Value of Reliability: Actual Commute Experience Revealed Preference Approach

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ABSTRACT

This research investigates the value placed by travelers on HOT lanes because of improvements in travel time reliability. This value depends on how the travelers regard a route with predictable travel times (or small travel time variability) in comparison to another with unpredictable travel times (or high travel time variability). For this purpose, commuters were recruited and equipped with Global Positioning System (GPS) devices and instructed to commute for two weeks on each of three plausible alternatives between their home in the western suburbs of Minneapolis eastbound to work in downtown or the University of Minnesota: I-394 HOT lanes, I-394 General Purpose lanes (untolled), and signalized arterials close to the I-394 corridor. They were then given the opportunity to travel on their preferred route after experiencing each alternative. This revealed preference data was then analyzed using mixed logit route choice models. Three measures of reliability were explored and incorporated in the estimation of the models: standard deviation (a classical measure in the research literature); shortened right range (typically found in departure time choice models); and interquartile range (75th - 25th percentile). Each of these measures represents distinct ways about how travelers deal with different sections of reliability. In all the models, it was found that reliability was valued highly (and statistically significantly), but differently according to how it was defined. The estimated value of reliability in each of the models indicates that commuters are willing to pay a fee for a reliable route depending on how they value their reliability savings. Furthermore, a meta-analysis is performed in order to explain the differences across valuation ratio estimates across studies. The results indicate differences are significant across regions, choice dimension (e.g. mode choice), travel time unit (e.g. data collected at AM or PM), and year of study.

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In the eternal words of argentinean rock band singer Gustavo Cerati. *"GRACIAS TOTALES"*.

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Chapter 1

Introduction

The issue of travel time reliability is becoming more critical to users of transportation networks. Historically, research on route choice behavior focused on expected travel time without consideration of its variability. However, surface transportation networks have matured in developed nations. This situation has been characterized by an inability to increase network capacity with additional links or lanes, because of small benefit-cost ratios (none to small economic advantage), possible negative effects (new links might make the network worse - as in the Braess Paradox), physical constraints (e.g. no space for expansion), difficulties in acquiring new rights of ways, and others. In contrast, travel demand (the number of users in the network) has been able to catch up or in some cases surpass the supply (network infrastructure), leading to congestion.

However, questions arise about which aspects of congestion are most costly, the higher travel times, the unpredictability of travel times (requiring earlier departures or causing potentially late arrivals), or the potential monetary cost of relieving congestion.

For this reason, considerable research into the connections between travel time variability and behavioral responses has been completed to date. This has generally included the development of theoretical models and empirical analysis of the relationships that affect both travel time reliability and traveler reactions. The focus has been directed mainly to four areas: departure time choice, traveler perception of reliability, mode choice, and route choice. In the case of route choice, the travel time of a particular path could be less important than how reliably the traveler can predict the duration of the trip. If travelers can ensure reaching their destinations in a time-certain manner, they may be willing to drive on paths with longer travel times rather than risking the use of paths that possess shorter travel times, but that entail greater risks of arriving late.

The main objective of this investigation is to estimate the value of travel time reliability of commuters using Interstate 394 in Minneapolis. This objective is the link to the implicit hypothesis that in addition to travel time both travel cost and travel time variability are significant factors in route choice preference, and it also leads to the hypothesis that travelers are willing to pay for enhancing their commute travel time reliability. In other words, the study will examine the extent to which the subjects value travel time reliability by comparing the variability of the time required to travel each of the three routes with the drivers' revealed preference (ascertained from global positioning system (GPS) tracking data) for the routes.

The remainder of this thesis is organized as follows: Chapter 2 presents a review of the literature on route choice theory, random utility theory, and travel time reliability; Chapter 3 introduces the data including sample descriptive statistics, experimental design and GPS data processing. Chapter 4 discusses the econometric models specified and the results estimated. Chapter 5 presents a meta-analysis in order to quantify the reasons of estimate differences across studies. The last chapter presents the implications of the results and concludes the thesis.

Chapter 2

Literature Review

Route Choice Behavior is an extensive and interdisciplinary topic of interest. In transportation, understanding route choice behavior of travelers is regarded as an important pillar on which travel demand models build. This literature review comprises two sections, the first covering Route Choice and Reliability, the second covering Economic Theory.. The first has several subsections, it begins by summarizing the main concepts in route choice behavior theory. The second subsection provides the background for travel time reliability including empirical and theoretical research. The third covers another behavior of travelers (departure time choice) usually associated with route choice, and the fourth discusses and summarizes the current knowledge on travel time reliability while identifying the limitations of the research. The section on random utility models provides the theoretical basis for the development of the mathematical model in this thesis; and it helps the reader by pointing them to the appropriate literature covering in detail these techniques.

2.1 Route Choice and Reliability

Route choice is anchored in spatial knowledge and behavior. It is a special case of human-environment interaction related to the act of traveling. Travel behavior mainly focuses on the refinement of humans' movements in their surroundings through spatial knowledge acquisition. This spatial information is comprised of two guiding processes: navigation and pathfinding or wayfinding. The former of these describes the actions required for unobstructed human travel by locating positions and plotting trajectories. The latter refers to the selection of paths connecting an origin-destination pair of interest. For this purpose, each individual designates points perceived as important (work, home, others) as anchor points or landmarks, in order to discern the locations of distinct places, and to facilitate the navigation among them.

As a side effect, individuals tend to have higher awareness of the spatial layout near their respective anchor points due to their inherent high familiarity. Many studies such as Golledge and Stimson (1997), Golledge (1999), and Golledge (1992) explain in further detail this interaction.

In the context of transport networks, route choice is a common decision-making process, where a traveler chooses a path connecting any two nodes from several known alternatives. This choice behavior is influenced by characteristics from both the traveler and the physical environment. The traveler's attributes consist of objective socio-demographic elements (age, gender, income,...) and subjective elements (preferences, perception, experiences...). In contrast, the physical environment is characterized by the built-up surroundings (the transport network infrastructure). Furthermore, this selection process is dynamic; it receives feedback from the traveler's previous decisions (Bovy and Stern, 1990).

Historically, transportation research in route choice behavior has focused on three categories: traveler's knowledge of alternative routes, route decision processes, and route choice preferences due to attributes of the traveler-road network system. The first consists of analyzing the criteria (shortest path, fastest path...) travelers adopt to generate their set of possible routes, the second focuses in the rules (preplanning, Markov process, and intermediate process) for the execution of the decision, and the last examines the effect of attributes in the route choice preference (Ben-Akiva et al., 1984).

Previous research has found travel time and distance as the main explanatory attributes for traveler's route choice preference (Trueblood (1952), Michaels (1966), Kansky (1967), Haefner and Dickinson (1974), Hamerslag (1981) and Vaziri and Lam. (1983)). For this reason, it is no surprise that travel time (and the value of that time) is a key factor in transportation planning studies such as cost-benefit analyses. Value of time (VOT) represents the marginal rate of substitution between the travel cost to the time spent in travel. Generally, values of time are calculated as the ratio between the parameters of travel time and travel cost, which are typically estimated from disaggregate econometric models. Further insight is detailed in Bruzelius (1977) (a theoretical economics approach), and Wardman (1998) (a summary of numerous empirical studies).

2.1.1 Travel Time Reliability

Route choice behavior is not entirely encapsulated by time and distance. Other factors (such as aesthetic scenery, network knowledge, and trip information) are also linked to the explanation of this phenomenon (Pal, 2004). In the case of reliability, the traveler is influenced by the quality of service provided by the links in a road network. This service is vulnerable to deterioration by recurrent (e.g., bottleneck congestion) or non-recurrent (e.g. crashes, weather, construction, or natural disasters) adverse forces. The detrimental effect of these forces can be quantified in performance measures such as connectivity and travel time reliability.

The genesis of these reliability measures has depended on road network problems in distinct periods of time. Connectivity was a major issue in the 1960s. The study of link disruptions was essential, because of the sparse nature of the network; the loss of a link resulted in long detours. On the other hand, travel time reliability has received increased attention lately. It is usually regarded as an indicator of the delays experienced by travelers because of the uncertainty present in the road network (Nicholson et al., 2003). This uncertainty is divided in three components by Wong and Sussman (1973): variation between seasons and days of the week; variation by changes in travel conditions because of weather and crashes or incidents; and variations attributed to each traveler's perception. Nicholson and Du (1997) lists also the components of uncertainty as variations in the link flows and variations in the capacity.

2.1.2 Theoretical Research

Traffic equilibrium (TE) by Wardrop (1952) is at the center of theoretical studies in travel time reliability. TE states two criteria for traffic assignment: User Equilibrium (fastest path or shortest objective travel time) and System Optimization (overall network travel time is minimized). User Equilibrium (UE) is widely used in conventional planning models, because the resulting flow patterns are similar to those observed in heavy congested networks. This is likely, as large time differences should be noticeable to most travelers. These flow patterns are obtained through optimization methods following the UE criterion. In these methods travel times are deterministic for given flow patterns, and the travelers know accurately the routes' travel times (an assumption in the UE criterion). For this reason, traffic models using Wardrop's TE are catalogued as *deterministic models*.

Other researchers proposed modifications to Wardrop's TE theory. For example, Daganzo and Sheffi (1977) transformed Wardrop's UE into a Stochastic User Equilibrium (SUE). The SUE criterion is based on the assumption that travelers select the routes with the shortest perceived travel times. Its mathematical formulation decomposes the perceived travel time into an objective travel time and an error term (a random variable capturing the traveler's perception error). In the case of "error-free" travelers, the traffic assignment criterion emulates Wardrop's UE. Traffic models of this type are referred to as *stochastic models*. However, these models do not capture the variability of each link's objective travel time in the network; they consider link travel times to be deterministic. Mirchandani and Soroush (1987) address this concern by allowing the objective travel time to also be a random variable, and consequently permitting the inclusion of travel time uncertainty in traffic models. Moreover, disutility functions are employed to model the distinct traveler responses to the introduced stochasticity by assuming different risk-taking behavior (averse, neutral, and prone). Risk averse and risk prone travelers consider the variance and expectation of the perceived travel time. The former (latter) exhibits preferences for low (high) variability, and it analyzes its trade off with the expected travel time. This balance depends on the degree of aversion (proneness) specified as a parameter in the disutility function. In contrast, risk neutral travelers only look at the expected perceived travel time (the type of behavior in the previous models). The form of the disutility function accords with decision analysis theory; linear disutility functions are typically used for risk neutral choice behavior, and exponential or quadratic for risk-averse and risk-prone behavior. (see Keeney and Raiffa (1993) for details).

In Chen et al. (2002), the TE models are classified by network uncertainty and perception error presence. For example, Wardrop's model corresponds to a deterministic network, and travelers without perception error. More importantly, the models are used to emulate the risk-taking behavior of the travelers in a small virtual network, and the numerical results of the simulation are compared. Some of the simulation findings include: risk-averse travelers are likely to pay to avoid uncertainty scenarios, and higher degrees of risk aversion among travelers translates to higher travel time, and lower travel time reliability. Nevertheless, the TE models (in the study) are single-class assignment, and consequently they consider the travelers to be homogeneous. Furthermore, they can only handle one risk behavior, which can be neutral or averse (prone) with a specified degree of aversion (proneness). A solution to this problem is by extending the TE models into multi-class assignment (see Dafermos (1972)). In this way, one model can emulate travelers with distinct risk behaviors. However, this solution will not account for the taste variation of travelers with the same characteristics, as some travelers may have different degrees of aversion or proneness. A way to account for this is by using a random coefficient logit model (see Train (2009)). These solutions are also noted by Chen et al. (2002).

The TE models discussed so far follow a normative approach; they assume travelers are rational decision-makers looking to select the route that maximizes their utility, or minimizes their travel costs. This interpretation has obvious limitations: it ignores the costs associated with spatial knowledge acquisition; overestimates human computational capabilities; and neglects to consider the influence of learning, experience, and other processes attributed to the development of human knowledge. For this reason, other models have diverged from the normative framework. For example, Mahmassani and Chang (1987) devised a traffic assignment model based on bounded rationality theory. They propose a model, where the traveler's behavior is described by "indifference bands" yielding a satisficing mechanism. This notion implies travelers do not change routes as long as the perceived difference in travel cost of the current route and the next available route does not exceed a limiting value. Therefore, a natural extension to a UE criterion (or Bounded Rationality User Equilibrium as it is referred in the study) is achieved when all the users are satisfied with their routes and do not want to change. Another model is formulated by Zhang (2006). This model is based on his proposed SILK behavior theory. This theory includes elements of travel behavior: searching for new routes; learning from previous experiences and new network information; and acquiring spatial knowledge, the same elements denoted in the SILK acronym. Furthermore, Zhang introduces a UE criterion (or Behavioral User Equilibrium as he refers to it) that is attained when all the travelers perceived search cost exceeds the expected gain from an additional search. It should be noted Zhang's SILK theory shares the same principles of the bounded rationality approach in modeling the limited human attitudes, and computational capabilities, but also includes other features such as the learning abilities of the travelers. The use of these models for travel time reliability simulation may shed more light in traveler responses to risk and uncertainty. This is possible, because of the increased similarity of the presented models to the observed travel behavior in comparison with the typical assumption of normative behavior.

2.1.3 Empirical Research

In the case of empirical research, the behavioral response of travelers to travel time reliability has been observed. For example, Abdel-Aty et al. (1997) used two stated preference techniques (a computer aided telephone interview and a mail-back survey) in order to investigate the effect of travel time reliability and traffic information on commuters. The first survey consisted of offering five options, each with two routes with distinct travel times (one with the same travel time for every day, and the other with different travel times on some days) for the travelers to choose, and the second one consisted of two routes (one presumably familiar to the subjects) with similar travel time variation scheme to the previous survey, but also included a section with traffic information. The analysis of the survey data was done with binary logit models including variables such as standard deviation, mean and gender. They found that commuters consider reliability characteristics in their route choice preference, and pay attention to travel information enough to be influenced in some scenarios to deviate from their usual routes. Another finding was that males tend to choose the uncertain route more than females.

In Jackson and Jucker (1981), a survey was administered to Stanford University employees; it consisted of paired comparison questions of hypothetical route alternatives. A pair was typically formed of two "usual" times and corresponding delays to each member of the pair. The highest delay was always given to the shortest "usual" time of the pair. The analysis of the subject's stated preference was done by optimizing an objective function (a linear programming problem) in which the expectation and variance of the travel times are variables. This method also allowed for the estimation of a degree of risk aversion parameter for the subjects. Jackson and Jucker found that some commuters prefer the more reliable route, even if the expected travel time is higher in comparison to other routes with shorter expected travel time, and higher uncertainty. This result agrees with the notion of a distribution of the degrees of risk aversion in the subjects. In addition, they noted that the mean-variance approach is useful and tractable.

Other more recent studies by Small et al. (2005) and Small et al. (2006) utilized data collected on California State Route 91 (CA-91) in the morning (AM). The collection consisted of three surveys: the first survey was a telephone interview of actual travel (revealed preference), and the other two were mail-back questionnaires (the first one about actual travel [revealed preference], and the other one about hypothetical scenarios [stated preference]). The set of actual alternatives was composed of High-Occupancy Toll lanes (HOT) and General Purpose Lanes (GPL). Commuters using the HOT lanes require an electronic transponder to pay a toll, which varies hourly. It should also be noted carpools (High Occupancy Vehicles (HOVs)) are allowed in the HOT lanes with a discount. The set of hypothetical alternatives remained the same as the actual with the exception of changing the values of variables such as time, cost and reliability. These changes allowed for the preferences of the subjects to be inferred based on their unique pattern of responses to trade-offs among the different hypothetical scenarios. The data was analyzed by a discrete-choice model; a utility function was specified containing attributes for the alternatives including toll, travel time and reliability. This statistical model approach allows for the estimation of the well known value of time (VOT), and the value of reliability (VOR). The latter value represents the susceptibility of the commuters to (un)reliability in monetary terms, and it is calculated as the ratio between the parameters of travel reliability and travel cost (toll cost in the study). This VOR represents the marginal rate of substitution between travel cost, and travel reliability. Right ranges (80th - 50th percentiles) on the travel time savings distribution (differences between travel time distributions of GPL and HOT) are used as (un)reliability measures. Another important feature of the model is the inclusion of a carpool variable in order to control for systematic bias. However, besides all these similarities the studies differ in certain key areas.

The first study (Small et al., 2005) focuses solely in formulating a lane choice model (using mixed logit) by combining the RP and SP data. The results of the model indicate travel time and reliability to be significant, and that the heterogeneity in these factors is significant as well (thus implying the significance of the heterogeneity of VOT and VOR). In contrast, the second study (Small et al., 2006) models not only lane choice, but also vehicle occupancy and transponder acquisition. It also extends the previous study (Small et al., 2005) by using simulations to analyze distinct highway pricing policies besides the current one at CA-91. The policies simulated include: no toll, general purpose and HOV, general purpose and HOT, and combinations of the preceding cases. The objectives of these simulations is to point out the significance of the heterogeneous preferences of commuters to highway policymakers, and, as Small et al. points out, the current use of homogeneous preferences fails to account accurately for different policies working together. It should be noted that highway pricing policies are typically developed for congestion relief. The main notion being that congestion is a negative externality of the transportation system, and the use of pricing schemes will reduce any unnecessary trips, and persuade travelers to reconsider their activity patterns in time and space.

The limitations of the previous empirical studies are mostly related to their observational methodology. In the cases of Abdel-Aty et al. (1997) and Jackson and Jucker (1981), the observed route preferences of the subjects, as described earlier, are obtained by stated preference (SP) techniques; they consisted of hypothetical routes with distinct attributes (e.g. travel time). For this reason, the validity of the observed preferences may be affected by the lack of realism, and the subject's understanding of the abstract situations. Thus, the subject's route preferences may not be similar to the ones during their actual trips (see Louviere et al. (2000) and Hensher (1994) for discussions about SP vs. RP). In contrast Small et al. (2005) and Small et al. (2006) collected both RP (actual preferences of subject's lane choice) and SP (hypothetical scenarios to examine subject's lane choice) observations, and consequently enriched their statistical model by pooling both types of data. However, the nature of the survey methods employed didn't allow for some of the variables to be measured during each of the subject's trips. For example, travel time was obtained by field measurements (performed by others instead of the subjects) corresponding approximately to the travel periods of the subjects. Thus, these measurements may have affected the accuracy of the data in the model. Other data collection techniques such as equipping the subject's vehicles with Global Positioning System (GPS) devices would have avoided said difficulties, and possibly extend the lane choice model into a route choice model by considering arterials near the subjects. Furthermore, a GPS device can collect a wealth of detailed commute level data, including travel time and distance, origin and destination pair with link-by-link trajectory, commute start and end times, and trip itineraries. Therefore, it is no surprise that, with dropping equipment costs, these devices have been used as of late for travel behavior studies, especially for route choice behavior. A few examples of these studies are: Li et al. (2004) (an inspection of the travel time variability in commute trips, and its effects on departure time and route choice, including cases with trip-chaining), Li et al. (2005) (an analysis of attributes determining whether to choose one or more routes in the morning commute), and Zhang and Levinson (2008) (an estimation of the value of information for travelers, and a comparison of the impact of information with other variables such as travel time, distance, aesthetics, ...). Further detail about GPS application to transportation research, including GPS data processing using Geographical Information System (GIS) environment (matching of trip points to road network digital line graphs [DLG]) can be found in Li (2004).

2.1.4 Research in Departure Time choice

Other research has focused on analyzing travel time reliability considering solely departure time choice (also known as trip-scheduling choice). A factor that may influence route choice, as some travelers can change their departure times to combat the temporal effects of disadvantageous routes. This is likely especially for commuters, because they are usually bounded by time restrictions. Gaver (1968) is one of the earliest studies in this choice dimension. He introduced a theoretical framework for describing variability in trip-scheduling decisions. He considered distinct head start strategies for given delay distributions along with the costs of arriving early or late. In addition, statistical estimation procedures (non-parametric and parametric) are provided to estimate the probability density distribution of the trip delay, when it is unknown to the researcher.

Another important study is Small (1982). He formulates a theoretical model based on the traditional utility maximization framework (i.e. consumer behavior; see (Varian, 1978)) with insights from time allocation models (e.g. Becker (1965), DeSerpa (1971); see Jara-Diaz (2000) for a thorough review of these models). This model is presented as a static constrained optimization (maximization) problem as follows, (Small (1982) notation is preserved),

$$\mathbf{u} = \mathbf{U}(\mathbf{x}, \mathbf{l}, \mathbf{h}, \mathbf{s}) \tag{2.1}$$

$$\textit{subject to}$$

$$\mathbf{x} + \mathbf{c}(\mathbf{s}) = \mathbf{Y} + \mathbf{wh} \tag{2.2}$$

$$\mathbf{l} + \mathbf{h} + \mathbf{t}(\mathbf{s}) = \mathbf{T} \tag{2.3}$$

$$\mathbf{F}(\mathbf{s}, \mathbf{h}; \mathbf{w}) = \mathbf{0} \tag{2.4}$$

The objective function (2.1) is a utility function defined by two sets of choice variables: x (a numeraire good), and three types of time (leisure time [l], working time [h], and schedule time [s]). Thus, a consumer will derive the highest utility (or achieve the highest ranking of utility) from the solutions of these variables in the feasible set specified by the constraints (2.2, 2.3, and 2.4). These subsidiary conditions in order of appeareance represent: a monetary budget restriction (w and Y are given parameters representing wage rate and unearned income; and $c(s)$ is the cost associated with the "consumption" time of an activity scheduled at a time s); a total time constraint (T is a parameter representing the total time available; $t(s)$ is the "consumption" time of an activity not specified explicitly in terms of the utility function, but it depends on when it is scheduled [s]); and the last condition establishes a mathematical relation (without specification of its form) between schedule time and working time given wage rate as a known parameter (although as Small (1982) says wage rate may also depend on schedule time and working time). This (workplace) constraint represents penalties and time thresholds (flexible or inflexible arrival times) set by the workplace to its employees. Furthermore, the corresponding Lagrangian for this optimization problem is

$$\mathcal{L} = \mathbf{U}(\mathbf{x}, \mathbf{l}, \mathbf{h}, \mathbf{s}) - \lambda(\mathbf{x} + \mathbf{c}(\mathbf{s}) - \mathbf{Y} - \mathbf{w}\mathbf{h}) - \mu(\mathbf{l} + \mathbf{h} + \mathbf{t}(\mathbf{s}) - \mathbf{T}) - \nu\mathbf{F}(\mathbf{s}, \mathbf{h}; \mathbf{w}) \tag{2.5}$$

This theoretical framework has several implications, but only a few will be discussed. First, the workplace constraint is introduced into the value of (leisure) time. This can be seen by obtaining the marginal rate of substitution ($\frac{\partial U/\partial l}{\partial U/\partial x}$) between leisure time and the numeraire good (see eq. 2.6). This value indicates that individuals with higher job satisfaction (derive higher utility by being at the job) have a higher value than those who do not. The value of the latter is closer to the wage rate. Also, additional working hours may increase the costs of scheduling for the consumer.

$$\frac{\partial \mathbf{U}/\partial \mathbf{l}}{\partial \mathbf{U}/\partial \mathbf{x}} = \mathbf{w} + \frac{\partial \mathbf{U}/\partial \mathbf{h} - \nu \partial \mathbf{F}/\partial \mathbf{h}}{\partial \mathbf{U}/\partial \mathbf{x}} \tag{2.6}$$

Second, Small (1982)'s economic model presents a mathematical expression that can serve as an econometric specification. Equation 2.7 offers such an opportunity to test the model; think about the utility function (with the V notation) with the optimal choices when it is expressed in relation to $c(s)$, $t(s)$, and $F(s, h; w)$, and functional forms for these elements are specified (see eqs 2.8 and 2.9). It should be noted that $c(s)$ is neglected in the econometric form, because it is assumed such costs have little variation.

$$\frac{\partial \mathbf{U}}{\partial \mathbf{s}} = \lambda \frac{\mathbf{dc}}{\mathbf{ds}} + \mu \frac{\mathbf{dt}}{\mathbf{ds}} + \nu \frac{\partial \mathbf{F}}{\partial \mathbf{s}} \tag{2.7}$$

$$\mathbf{V}(\mathbf{c}(\mathbf{s}), \mathbf{t}(\mathbf{s}), \mathbf{s}) = \mathbf{U}(\mathbf{x}^*(\mathbf{s}), \mathbf{l}^*(\mathbf{s}), \mathbf{h}^*(\mathbf{s}), \mathbf{s}) \tag{2.8}$$

$$\mathbf{V}(\mathbf{c}(\mathbf{s}), \mathbf{t}(\mathbf{s}), \mathbf{s}) = \mu \mathbf{t}(\mathbf{s}) + \mathbf{f}(\mathbf{SD}(\mathbf{s})) \tag{2.9}$$

The last term of equation 2.9 represents the scheduling considerations (or constraints) of a consumer. In Small (1982) a linear-additive form is selected for the term as shown in equation 2.10, where the γ coefficients are parameters to be estimated. In this equation, the scheduling delays are divided by early (SDE) and late (SDL) arrivals at work, and a binary term DL to indicate whether it is a late arrival or not. One important note is that no reliability measures are considered in the model, nor in the econometric functional forms. Only costs of delay are accounted for. In other words, the effects of travel time uncertainty are not explicitly captured (they might be present in the estimates because of high correlation).

$$\mathbf{f(SD(s), S) = \gamma_1 SDE + \gamma_2 SDL + \gamma_3 DL} \tag{2.10}$$

In Noland and Small (1995), the previous specification (eq 2.10) is extended to include explicitly the uncertainty of travel time (e.g. non-recurrent congestion). This uncertainty is expressed in the form of a stochastic variable (the delay represented by t_r) with a given probability density. Thus, the optimization problem changes (also the utility function is traded for a trip cost form), and now the consumer minimizes the expected cost C after choosing the optimal s (see eq 2.11). The elements of 2.11 include the scheduling costs for early vs late arrival at work presented earlier, but also the last term employs the distribution of the stochastic delay in order to compute the probability of being late. P_L is simply $E(DL)$ depending on s. Therefore, the last term P_L also contains the costs of travel time unreliability as the dispersion (or variability) of the travel time distribution affects the calculated probabilities. In addition, travel time dispersion (or variability) may increase the propensity of early arrivals, and thus high earliness costs can be incurred. This implies variability and scheduling costs are related. Interestingly, previously discussed models in section 2.1.3 only considered travel time reliability measures (e.g. variance, standard deviation, difference of percentiles) without looking at scheduling-specific variables.

$$\mathbf{C^* = Min_s\ E(C(s, t_r)) = Min_s\ (\gamma_0 E(T) + \gamma_1 E(SDE) + \gamma_2 E(SDL) + \gamma_3 P_L)} \tag{2.11}$$

A thorough review of these studies and others is available at Noland and Polak (2002) and Small and Verhoef (2007). In addition (e.g. Tilahun and Levinson (2006)) examine various measures of travel time distributions including traditional ones such as mean-variance. Tilahun and Levinson (2006) also introduce a new travel time reliability measure consisting of two moments: the first representing on average how early the traveler has arrived by using that route; and the second representing on average how late that individual arrived by using that particular route. They assume that the deviation of the two moments (average late or average early) from the most frequent experience is a representative way of getting together the possible range and frequencies experienced by the travelers. Thus, this measure may considers scheduling constraints as well, albeit not separately from (un)reliability of travel time.

2.1.5 Discussion

This section of the literature review summarizes and evaluates studies assessing the effects of travel time reliability in route choice behavior. Both the empirical and theoretical approaches are presented, and the methodologies and results of each study are discussed. The main purpose of this review is to establish a compendium of what has been done, and what should be done in this area. The evidence is clear that traditional models (e.g. conventional planning model) based only on travel time and travel distance explain only a fraction of the travelers' real behavior. Several studies have found that other attributes such as travel time reliability are considered in the travelers' decision-making process. For this purpose, new theoretical models have focused on expanding the traditional Wardropian equilibrium theory into more realistic versions. These extensions concentrated on adding the travelers' perception of time, and the stochastic nature of the transportation network in the mathematical formulation. In addition, the models borrowed concepts (e.g. exponential forms for disutility functions) from decision analysis theory in order to incorporate travelers' risk behavior. The new models have been tested in small virtual networks with relative success. However, they are still prey to a lack of realism, as they must be further developed to consider heterogeneous travelers. Despite the current shortcomings, the new models are likely to perform better than the conventional model based on a Wardropian approach. Furthermore, the exploration of models relaxing the normative approach (perfect rationality) could lead to more realistic simulations of route choice behavior, and its connections to travel time reliability.

Another important aspect is the link between theoretical and empirical research. This connection refers to the need to further explore travelers' sensitivity to time reliability, in order to refine and to validate the theoretical models. However, a difficulty in the empirical research has been inherent to the RP data collection methods in the experiments. The current techniques (e.g. mail-back questionnaires, phone call interviews) are not able to fully capture very detailed commuter data for each of the subjects. These problems translate to having accurate revealed preferences, but lacking precise measurements of other important variables in the model such as travel time, travel cost, and others. These variables generally have been collected indirectly or not during the subjects trips. In the case of the SP data collection, the question has been more of validity, because the stated preferences may not reflect the actual preferences of the travelers. On the bright side, the availability of new technology such as GPS devices will help address these concerns.

Finally, a last important remark is related to the application of road pricing schemes. The recent use of value pricing or HOT lanes in limited access links have presented a strong case for the support of travel time reliability studies related to route choice (most of the research has focused on departure time choice). The main reason being policy evaluation; the desire to assess the consequences of HOT lanes as an effective method for controlling congestion. It is expected that new empirical research will allow planning agencies to use simulations in order to quantify the benefits of implementing such road pricing schemes. In other words, the improved understanding of travelers behavioral responses to time reliability improvements will probably lead to more effective policies for achieving these objectives.

A summary of selected studies of this literature review is presented in Table 2.1

Table 2.1: Summary of selected studies from the literature review

Study	Data (Source and Type)	Method	Results
Abdel-Aty et al. (1997).	Phone Interviews and Mail-back Surveys of the Los Angeles area morning commuters; Stated Preference (SP).	Choice Models (Binomial Logit).	Commuters consider variability in their route choices; Males tend to choose the uncertain route more than females.
Jackson and Jucker (1981).	Survey of Stanford University Employees; Stated Preference (SP)	LINMAP (Linear Programming technique).	Some commuters prefer reliable routes even if the expected travel time is higher.
Small et al. (2005) and Small et al. (2006).	Phone Interviews and Mail-back Surveys of California Route 91's morning commuters; Stated Preference (SP) and Revealed Prefrence (RP).	Choice Models (Mixed Logit),	Heterogeneity is significant in VOT and VOR estimates, and it must be taken in account for successful traffic congestion policies such as HOV and HOT.
Tilahun and Levinson (2009).	Phone Interviews and Mail-back Surveys of I-394 commuters; Stated Preference (SP).	Choice Models (Random Intercept Binomial Logit).	Commuters who are late have highest willingness to pay to avoid delays especially in the afternoon in contrast to those that are early/on time.
Tilahun and Levinson (2006).	Computer-Administered Survey; Stated Preference (SP).	Choice Models (Random Intercept Binomial Logit).	Commuters value reducing one minute of average lateness close to reducing travel time.

2.2 Random Utility Theory

In this thesis, the route choice behavioral models are developed according to qualitative (or discrete) choice methods obeying *Random Utility Theory*. These techniques are characterized by common elements representing a selection process; a group of *decision-makers* each choose an option from a set of *alternatives* given a list of *attributes*, and according to a specified *decision rule*. In addition, these elements establish certain properties in the model. For example, a decision-maker depicts an "individual" or agent performing the selection, and consequently imposes a disaggregate perspective to modeling the choices of a particular studied population. The set of alternatives must be mutually exclusive, exhaustive, and finite. The list of attributes are observable (or unobservable) characteristics that describe each alternative and the decision-makers. Lastly, the decision rules are axioms describing an assumed behavior the decision-makers follow in order to execute their choice. The specification of this last element requires both deterministic and stochastic components, because it is doubtful a choice model will accurately predict choices with exact certainty. This is understandable as the model simulates a complex human endeavor. Two traditional families of models can be formulated, depending on the assumption about the source of uncertainty (stochastic component). The first considers stochastic decision rules models with deterministic "desirability of attributes" and probabilistic decision process (e.g. "elimination by aspects" or EBA models developed in Tversky (1972a) and Tversky (1972b)). The second considers deterministic decision rules based on microeconomic theory (rational preferences, utility maximizing behavior, and complete relevant information is known), and the uncertainty is within the utility function formulation. These last models are known as *Random Utility Models (RUM)*. Generally, models with stochastic decision rules are given a *cognitive interpretation* (interpersonal variation of tastes for specific preferences), and RU models are given a *econometric interpretation* (incapability of the researcher to apprehend decision-makers behavior). Interestingly, the difference between EBA models and RU models is not as strong, and as McFadden (1981) shows every RUM could be specified as a broader class of EBA models ("elimination by strategy" [EBS]). This class includes the EBA models. The vice versa case was shown by Tversky (1972b) where EBA models could be reformulated as general RU models. Further detail about the genesis of random utility models can be found in McFadden (2002).

According to McFadden (1980), and Train (2009), Random Utility Models can be specified as a utility function decomposed in two parts: one representing the attributes the researcher observes of the decision-maker and the alternatives; and the other representing the attributes unknown or unobserved by the researcher of the decision-maker and the alternatives. The first part is known as *representative utility or systematic utility*, and the second part is known as *unsystematic utility or error term*. This follows the econometric interpretation introduced in the previous paragraph.

The utility that decision-maker k in the set of decision-makers $\mathcal{N}$ associates with alternative j in the set of choices $\mathcal{C}$ is given by:

$$\mathbf{U_j^k} = \mathbf{V_j^k} + \varepsilon_\mathbf{j}^\mathbf{k} \tag{2.12}$$

$$\mathbf{k} \in \mathcal{N} = \{1, ..., K\}$$
$$\mathbf{j} \in \mathcal{C} = \{1, ..., J\}$$

where

- $\mathbf{U_j^k}$ is the utility function of the k decision-maker for the j alternative
- $\mathbf{V_j^k}$ is the systematic utility (deterministic component) of the k decision-maker for the j alternative
- $\varepsilon_\mathbf{j}^\mathbf{k}$ is the unsystematic utility (stochastic component) of the k decision-maker for the j alternative

The *systematic utility* of the j alternative is a function of the attributes of the alternative itself and of the k decision-maker. This can be written as

$$\mathbf{V_j^k} = \mathbf{V_j^k}(\mathbf{s_{jh}^k}) \tag{2.13}$$

where $\mathbf{s^k_{jh}}$ is a vector of H attributes ($h \in \{1, ...H\}$) for both the k decision-maker and alternative j. This function is generally defined as linear-additive with parameters β_h as

$$\mathbf{V^k_j} = \sum_{\mathbf{h=1}}^{\mathbf{H}} \beta_{\mathbf{h}} \mathbf{s^k_{jh}} \tag{2.14}$$

The *unsystematic utility* is represented by the random vector ε^k_j. The probability joint density of the random vector $f(\varepsilon^k_j)$ is selected according to the particular circumstances of the choice situation; different probability densities will allow distinct substitution patterns across alternatives in the model. Generally, the probability (P^k_j) of choosing an alternative j by the k decision-maker will be given by the following cumulative probability distribution

$$\mathbf{P^k_j} = \int_\varepsilon \delta(\varepsilon^{\mathbf{k}}_{\mathbf{j}} - \varepsilon^{\mathbf{k}}_{\mathbf{j'}} < \mathbf{V^k_{j'}} - \mathbf{V^k_j} \quad \forall \mathbf{j} \neq \mathbf{j'}) \mathbf{f}(\varepsilon) \mathbf{d}\varepsilon \tag{2.15}$$

where δ is a function defined as 1 when the expression inside is true; otherwise it is 0.

2.2.1 Mixed Logit

In this study, the focus is set solely to a class of *Random Utility Models* known as *Generalized Extreme Value (GEV)* models. These models follow a joint generalized extreme value distribution, and allow for distinct substitution patterns across alternatives. Detailed description of the GEV family, and the requirements ("Williams-Daly-Zachary-McFadden theorem") for consistency with random utility theory are covered in Train (2009) and McFadden (1980).

One type of these GEV models is the Mixed Logit (ML) also known as Mixed Multinomial Logit (MMNL) and also as Logit Kernel (LK). This model combines the flexibility of the Multinomial Probit model (correlation among utility alternatives) with the benefits of the GEV family models. The most prominent characteristics of this model are:

1. It can approximate any random utility model (Unique attribute of the Mixed Logit models).

2. It allows for random taste variation (like the Multinomial Probit).

3. It is not restricted to random coefficients with normal distributions (unlike the Multinomial Probit).

4. It allows for substitution patterns without restrictions (It does not exhibit *Independence of Irrelevant Alternatives (IIA)* like the Multinomial Logit).

5. It allows for correlation between unobserved factors over time.

The mixed logit models, like any random utility model, assume that the utility function a decision-maker k in the set of decision-makers $\mathcal{N}$ associates with alternative j in the set of choices $\mathcal{C}$ is given by:

$$\mathbf{U_j^k} = \mathbf{V_j^k} + \xi_\mathbf{j}^\mathbf{k} \tag{2.16}$$

$$\mathbf{U_j^k} = \mathbf{V_j^k} + [\eta_\mathbf{j}^\mathbf{k} + \epsilon_\mathbf{j}^\mathbf{k}] \tag{2.17}$$

In the equation (2.16), $\mathbf{V_j^k}$ is the systematic term, and $\xi_\mathbf{j}^\mathbf{k}$ is the unsystematic (or random) term. This is the standard functional form for any random utility model, and it follows the typical econometric interpretation. For the case of the mixed logit model, the functional form is given by equation (2.17). The random term is partitioned into two additive parts: The first (η_j^k) is a random vector following any probability distribution selected by the researcher, and the second (ϵ_j^k) is a random vector identically and independently distributed (i.i.d.) over alternatives and decision-makers following a extreme value type 1 (or Gumbel) distribution.

The choice probabilities for a mixed logit model are given by:

$$\mathbf{P_j^k} = \int_{\eta^\mathbf{k}} \frac{\mathbf{exp(V_j^k)}}{\sum_\mathbf{j=1}^\mathbf{J} \mathbf{exp(V_j^k)}} \mathbf{f}(\eta^\mathbf{k}|\theta)\mathbf{d}\eta^\mathbf{k} \tag{2.18}$$

In the equation (2.18), it can be noted that mixed logit probabilities are the integral of multinomial logit probabilities over the density of the η^k random term with parameter vector θ. Equation (2.18) can also be understood as the weighted average of the logit probability function evaluated at distinct values of η^k, with the weights given by f(η_j^k). The standard multinomial logit can be obtained when the probability density function of η^k is 1 for only one set of coefficients, and 0 for all others. In addition, for the case that the systematic utility ($\mathbf{V_j^k}$) is linear in the parameters then the choice probability becomes:

$$\mathbf{P_j^k} = \int_{\eta^\mathbf{k}} \frac{\mathbf{exp}(\beta^\mathbf{T}\mathbf{x_j^k})}{\sum_{\mathbf{j=1}}^{\mathbf{J}} \mathbf{exp}(\beta^\mathbf{T}\mathbf{x_j^k})} \mathbf{f}(\eta^\mathbf{k}|\theta)\mathbf{d}\eta^\mathbf{k} \tag{2.19}$$

The integrals in equation (2.18) and (2.19) generally do not have closed form solutions. Therefore, numerical procedures are required to estimate the parameters in the specified utility functions. These procedures tend to be grouped into Classical (or frequentists) Estimation (e.g. Maximum Simulated Likelihood) and Bayesian Estimation (e.g. Markov Chain Monte Carlo) methods.

Two interpretations, but equivalent mixed logit models can be given to our previous formulation: Random Coefficient Logit (RCL), and the Error Components Logit (ECL). The first allows for the random taste heterogeneity, and the second allows for the correlation among alternatives, and heteroscedasticity. Both interpretations may also be combined into a form of "Mixed Nested Logit" or "Mixed Cross Nested Logit" depending on the inter-alternative correlation structure imposed (see Hess et al. (2005*a*))

In this study, the author follows a Random Coefficient Logit interpretation. The RCL formulation allows for some elements in the systematic utility to be randomly distributed, and thus the η^k term represents deviation from the systematic utility because the coefficients β are not the same for all decision-makers. In this way, the choice model formulation depends on the probability distribution chosen for η^k, and consequently the selection of some elements of the systematic utility to be randomly distributed. Different probability distributions have been tried for applied research. The most popular distributions are: normal, lognormal, and truncated normal. However, each distribution may provide results that may be theoretically unsound, biased, or unjustified. For example, Hess et al. (2005*b*) discusses utility specifications when negative value of travel time savings (VOT) estimates can be obtained in random coefficient models.

For additional information about Mixed Logit models including RCL, ECL, and estimation procedures (e.g. simulation) the reader should refer to Train (2009), Hensher and Greene (2003), Orro-Arcay (2005) and Hess (2005). The last two cover specifically the mixed logit models, and discuss also the consequences of distinct probability distributions for the η^k term in RCL, and ECL models.

Chapter 3

Data

This chapter describes the methodology and instruments employed for the collection of the data, and it introduces the *actual commute experience revealed preference* (ACERP) approach. It is divided in several sections including: recruitment of the subjects; experimental design; GPS Data processing and others.

3.1 Recruitment

The subjects for this experiment were recruited through the use of distinct tools including: *Craiglist.org*, and *CityPages.com*; the free local weekly newspaper *City Pages*; flyers at grocery stores; flyers at city libraries, postcards handed out in downtown parking ramps; flyers placed in downtown parking ramps; and emails to more than 7000 University of Minnesota staff (students and faculty were excluded).

The recruitment process was repeated a total of three times. The first sample was selected in August 2008; the second in March 2009; and the third in September 2009. A total pool for the three recruitment attempts was of about 223 possible candidates. These possible recruits had to satisfy the following requirements in order to be part of the experiment:

1. Age between 25 and 65.

2. Daily commutes of at least twenty minutes.

3. Likelihood of using Interstate 394 for their commutes.

4. At least four regular work days per week.

5. Work location near or in downtown Minneapolis.

6. Single occupancy vehicle travelers.

7. Permission to install a GPS device in the vehicle.

8. Vehicle must allow continuous power supply to GPS device.

These criteria were developed to select a representative sample from the drivers using I-394 in the Twin Cities area. For example, there were two reasons that participants were selected with 20 minute commutes. First, they are likely to have more alternatives. Second, the statistical estimation will improve if the participants' commute distances are similar. In addition, I-394 must be a likely route for the participants, because it is doubtful any participant will participate in (or remain with) the study if they have to stray too far from their regular routes. Furthermore, participants needed to have simple commuting patterns, because more complicated patterns (chained trips) would have been a confounding factor in the study. Other factors like non-home/non-work destinations might have played the central role in the route choice process.

A total of 54 participants were recruited for the study. Only 18 finished due to a high dropout rate (see section 3.4) and unfortunate GPS equipment failure (see section 3.4.2). Each of the participants that completed the study successfully (followed instructions as described by the experimenter) was given compensation of USD $125.00.

3.2 Experimental Design

3.2.1 Description

After the subjects were recruited, an experimenter equipped immediately the subject's vehicle with a MnPass transponder (the subjects only received it for their HOT assigned route, and the last two free choice weeks) to allow subjects to use the HOT lanes, and a logging Global Positioning System device (QSTARZ BT-Q1000p GPS Travel Recorder powered by DC output from in-vehicle cigarette lighter), in order to track their commute. The former provides information about toll data (amount, time, and date). The latter allowed the measurement of detailed commute level data including: travel times for each commute trip; distance traveled for each commute trip; and time of day.

After a one to two week period of free travel to establish baseline travel choices (the amount varies as installations were often done midweek, while the protocol for assigned routes began the assigned route blocks on Mondays), the subjects were required to drive on three parallel alternative routes in the Twin Cities during the study period: I-394 High-Occupancy Toll lanes (HOT), I-394 General Purpose lanes (untolled), and signalized arterials close to the I-394 corridor (e.g. Hwy 55, Hwy 7). The order of these routes was randomly assigned to each participant to control for effects of order; a Chi square test was performed and the hypothesis of presence of order effects was rejected. Each participant drove each of three routes both in the morning and evening for two-week blocks. In this way, the subject's existing knowledge of alternative routes was augmented. This set a "before learning" route choice period vs. an "after learning" choice period as they selected among these routes freely only during the first week and the last two weeks. Additionally, each of these routes provided reasonable and convenient ways of traveling between the subject's home and work. However, the exact routes depended on the subject's home and work locations.

Each week, the experimenter asked the subjects to complete a survey about their current daily route three times (Mondays, Wednesdays, and Fridays). This was done during 6 weeks to guarantee each of the alternative routes were reviewed by the subjects. In addition, at the end of the study period the subjects completed a final survey where they stated their final route choice preference. In this way, the degree of familiarity that the subjects already had with the alternate routes was determined. It should be noted that this degree may vary with the relative locations of each subject's home and work place. In addition, subject demographics (age, gender, income) and details of the drivers vehicle (make, model, and age of the vehicle) were collected. This was done to compare the sample of the study to the population in the Minneapolis - St. Paul metro area (see section 3.5).

After the completion of the study period, the GPS receiver and MnPass Transponder were recovered from the subjects, and the GPS data extracted. The drivers were debriefed and fully compensated for their participation even though they believed that there was no reimbursement for using the MnPass transponder during their free choice period in the last 2 weeks. The stated preference (surveys) and revealed preference (GPS and Transponder) data acquired from each of the participating drivers during the eight-week period was processed and employed to estimate the behavioral route choice models in this study. It should also be noted that transponder data was enriched by a database of toll information detailed by the time, date and entrance station. This database was provided by the Minnesota Department of Transportation (MnDOT).

Readers can refer to Tables 2 and 1 for the observed route choices and observed travel time distributions per subject.

3.2.2 Comparison to others techniques

Generally, route choice studies can be divided according to the nature of the measured data (stated preference [SP] or revealed preference [RP]), and the data collection techniques employed (e.g. phone interviews). In Bovy and Stern (1990), two types of data sources for a route choice study are emphasized: (quasi) laboratory experiments, and field observations (i.e. actual trips). Furthermore, the most prominent data collection techniques are grouped under these two categories. Laboratory experiments include: paper-based experiments (e.g. multiple choice questions), experiments with visual aids (e.g. questions with charts, maps), and simulations (e.g. computer-based simulations, and fixed-base vehicle simulators). On the other hand, field observations include: interviews in person or through the phone; self-completion questionnaires; and stalking/shadowing the subjects (e.g. license plate matching). This last list can be expanded by including GPS tracking as a new item, or contained within stalking/shadowing the subjects. Although, it might not fit perfectly as the subjects are usually aware that their trips are being recorded.

Both classes of data collection techniques (Laboratory and Field) have advantages and disadvantages. According to Bovy and Stern (1990), the main attributes that vary from technique to technique are: cost and resources; realism and validity; degree of control of the researcher over the experiment; researcher's ability to monitor the experiment; and degree of difficulty of separating a variable's effects from others. The first characteristic refers to the material, equipment, and labor costs. The second refers to how closely the experiment emulates a real route choice situation, and thus bring questions about its validity. The third and fourth refers to the level of management the researcher has over the elements in the experiment, and the ability to measure or collect data of variables during the experiment, respectively. The last refers to the level of complexity of the experiment due to a high number of factors interacting, and thus confounding any possible insights and/or statistical estimation. For these reasons, a researcher must consider the trade off he/she makes (e.g. lower cost but less realistic, actual route choices [RP] vs. hypothetical choices [SP]) when selecting a specific technique or more for their study.

In this research experiment, GPS tracking data was used along with questionnaires to gather information about each subject and their revealed preferred choice (the most used route according to their GPS data). This is also considering that each subject was randomly assigned to drive for two weeks on each route, and thus form their own opinions about each route (see 3.2 for more details). The author refers to this experimental design as *actual commute experience revealed preference* (ACERP). This technique's advantages include: real choices in an actual urban environment; subjects are familiarized with route alternatives; subject's origin (home) and destination (work) are preserved (i.e. not assigned); detailed objective measures of travel distance, travel time and other variables; and multiple records per route in order to enrich the statistical analysis. However, this method has several disadvantages including: expensive as the cost of a GPS device increases if more features (e.g. wireless communication) are required (this study used logging GPS, avoiding communications cost, but limiting ability to gather real-time information from subjects); subjects might dislike having to drive the same unpreferred route for two weeks, especially if the route requires them to adjust their departure time; and additional funds need to be allocated in order to reduce attrition rate in the experiment.

A summary of selected studies for each data collecting technique is presented in Table 3.1.

Table 3.1: Summary of data collection techniques in route choice studies

Method	Data Type	Features	Examples
Questionnaires with Hypothetical Scenarios.	SP.	Controlled choice situations; Unrivaled freedom in defining choice situations, alternatives, and variables; Automatic format for fast data processing.	Jackson and Jucker (1981); Pal (2004); Abdel-Aty et al. (1997); Tilahun and Levinson (2009); Khattak et al. (1993).
Questionnaires with Hypothetical Scenarios including visual aids.	SP.	Inclusion of subjects unfamiliar to a specific analysis area; Clear presentation of choices and variables.	Tilahun and Levinson (2006); Goldin and Thorndyke (1982); Bartram (1980).
Computer-Based Simulator.	SP.	Interactive systems under controlled choice situations; Flexible and dynamic regulation of subject's interaction with the environment.	Mahmassani and Herman (1989); Leiser and Stern (1988).
Fixed-base Vehicle Simulators.	SP.	Dynamic virtual environments with colors, perspectives, and image combinations; Simulation of weather and light conditions.	Blaauw (1982); Scott (1985); Godley et al. (2002).
Virtual Experience Stated Preference (VESP).	SP.	Physical Simulators are used to generate dynamic environments; Subjects are monitored during the experiment; Subjects follow several scenarios assigned by the researcher.	Levinson et al. (2004); Levinson et al. (2006).
Field Experience Stated Preference (FESP).	SP.	GPS devices are used in subjects' vehicles; Subjects' routes and origin-destination pair are assigned by the researcher.	Zhang and Levinson (2008).
Field Self-Completion Questionnaires.	RP.	Maps and images help the subjects mark their preferred routes.	D'Este (1986) Duffell and Kalombaris (1988).
Field Interviews.	RP.	Subjects report choices through the phone or in-person; Information about perception can be extracted.	Small et al. (2005); Small et al. (2006).
Stalking/Shadowing.	RP.	Subjects are followed stealthily in order to determine their preferred routes.	Chang and Herman (1978).
Field GPS Tracking.	RP.	GPS devices are used to track very detailed trip data for each subject.	Li et al. (2004); Li et al. (2005); Li (2004).
Actual Commute Experience Revealed Preference (ACERP).	RP.	See section 3.2.	None.*

* It is unknown to the author whether there are other studies similar to this one.

3.3 Surveys

Web-based surveys are used for collecting profiles, attitudes, and stated preferences (SP) of the subjects. These offer significant advantages over paper-based surveys:

- reduced computational time spent processing the data;
- use of audiovisual features; restrictive control of answers (e.g. leaving questions blank);
- less active participation of experimenters; and others.

For this project, three web-based surveys were employed. The first survey filtered the prospective participants for the experiment according to the requirements listed in Section 3.1. The second survey captured subject's weekly perceptions of route attributes (e.g. congestion level) for morning and afternoon commutes; and individual evaluation of the tolling costs for using the HOT lanes (only filled during their 2 weeks of driving assigned HOT lanes). The third survey collected the final stated preferences (after the 8-week period was concluded) of the subjects with regards to their assigned routes. This survey included questions about: socio-demographics (e.g. age, income); perceived attributes (e.g. travel time predictability) of each assigned route for both morning and afternoon commutes; individual evaluation of the tolling costs for using the HOT lanes; route preferences for morning and afternoon commutes; reasons (e.g. travel time) for selecting a route instead of others; stating threshold of willingness to pay a toll cost (using only HOT lanes) for distinct travel time savings; and stating threshold of willingness to pay for distinct travel time reliability savings.

The weekly web-based survey was completed by the study participants each Monday, Wednesday and Friday. In contrast the final survey was completed only at the end of the experiment.

3.4 Issues with subjects and technology.

3.4.1 Subjects: Recruitment and Retention

The main issues in the study were subject recruitment and subject retention. In the case of recruitment, the difficulty was finding enough subjects that allowed for a larger sample. A possible reason was the restrictive selection criteria; although a total of about 223 possible candidates applied, only 54 satisfied the requirements. Unfortunately, these restrictions could not be lifted as subjects with stable commutes (e.g. at least 4 days of work), likelihood of using I-394, and GPS devices installed inside their vehicles were indispensable conditions. In addition, 3 possible candidates reported they were interested in participating if the compensation of USD $125.00 were higher. This leads to the possibility that higher compensation could have helped to increase our sample size. However, additional recruiting efforts were done to obtain a larger overall sample size.

In the case of retention, the nature of the experimental design seemed to disenchant some of the participants. Three classes of subjects left the study. The first one occurred when a subject was required to use a customized arterial route (selected according to home and work location). Initially, subjects drove it without complaining, but later during the same week or the next week, they withdrew of the study giving reasons such as: travel time was too high; route was highly inconvenient; resistance to using arterial routes; and many others. The second one occurred when a subject was required to use the I-394 (General Purpose lanes or HOT lanes). For this path, subjects withdrew immediately usually within 2 days. Reasons for leaving included: lack of accessibility to desired commercial zones; and other perceived benefits of using the arterial over the freeway. The third one included miscellaneous cases with distinct reasons such as: vehicular accident; vehicle stolen; death of a family member; injury of participant requiring hospitalization; vehicle requiring prolonged stay at the mechanic; and many others.

3.4.2 Technology: Data failure

The GPS device became an additional issue for the study. For some of the subjects, the device did not collect complete experimental data (none or only a fraction of the study period were retrieved). These devices were sent to QSTARZ for analysis, and more importantly to recover the lost data. Fortunately, the QSTARZ team was able to extract data from some of the devices. In addition, the QSTARZ team performed several tests to determine the underlying cause of the GPS device failure while it was deployed in the field. However, they did not find conclusive evidence for failure to be attributed solely to the equipment itself. Another possibility for the failure of the device could be attributed to subjects unplugging the equipment. This GPS device requires continuous power supply from the vehicle's battery in order to function properly. Therefore, if the device is unplugged for long periods, it will cease logging data, and in the worst case it will require resetting to log data again (this method clears the memory). Unfortunately, the experimenter was unable to know when exactly the device stopped working. For this, the experimenter requires more expensive equipment, with permanent or semi-permanent installation, that allows day-to-day monitoring.

In the end, the Table 3.2 shows the number of participants that fulfilled the study's criteria (denoted as initial subjects), the participants who left study, GPS data failure, and remaining subjects.

Table 3.2: Actual Subjects vs. Initial Subjects

Sample	**Initial Subjects**	**Dropouts**	**Data Loss**	**Remaining Subjects**	**% Retained**
Aug-08	28	10	6	12	42.86%
Mar-09	11	8	1	2	18.18%
Sep-09	15	7	4	4	26.67%
	54			**18**	**33.33%**

3.5 Descriptive Statistics

3.5.1 Socio-Demographics

Table 3.3, summarizes socio-demographic information of the subjects. Main difference of the sample vs. the population of the Twin cities include: higher proportion of females; and subjects are on average older, more educated, and have higher income. Other characteristic of the sample is the variation of the subjects' time living at their current work and home location is high. In other words, the sample has subjects ranging from those living several years in their current work and/or home locations to those living a few months in their current work and/or home locations.

Table 3.3: Socio-Demographics attributes of the sample

Number of Subjects			18	
		Sample	Sample (%)	Twin Cities
Sex	Male	7	39.89%	49.40%
	Female	11	61.11%	50.60%
Age (Mean, Std. Deviation)			(52, 10)	(34.47, 20.9)
Education	11th grade or less	0	0.00%	9.40%
	High School	2	11.11%	49.60%
	Associate	5	27.78%	7.70%
	Bachelors	8	44.44%	23.20%
	Graduate or Professional	3	16.67%	10.10%
Household Income	$49,999 or less	4	22.22%	45.20%
	$50,000 to $74,999	5	27.78%	23.30%
	$75,000 to $99,999	2	11.11%	14.60%
	$100,000 to $149,999	5	27.78%	11.00%
	$150,000 or more	2	11.11%	5.90%
Race	Black/African American	2	11.11%	6.20%
	White or Caucasian	16	88.89%	87.70%
	Others	0	0.00%	6.10%
Years at Current Work (Mean, Std. Deviation)			(13.86, 11.12)	
Years at Current Home (Mean, Std. Deviation)			(9.83, 7.93)	

Minneapolis' Population statistics are obtained from the *2006-2008 American Community Survey 3-Year Estimates, Minneapolis-St. Paul-Bloomington, MN-WI Metropolitan Statistical Area, Retrieved November 25, 2009.* (n.d.)

3.5.2 Routes: Preferences, and Attributes

Figure 2 presents the routes' rankings according to the subjects. The HOT Lanes are the most preferred, while the preference for General Purpose Lanes or Arterials differs. This preference is likely related to the perceived low congestion level, and high travel time predictability stated by the subjects in Figure 4. In contrast, the General Purpose Lanes and the Arterials had a wider variation in their perceived congestion and travel time predictability levels. In addition, the subjects stated a high preference for HOT lanes for their work to home trips (W2H) over their home to work trips (H2W). Furthermore, the high preference for HOT also agrees with the the subjects' stated reasons for choosing a route (Figure 3). The two most important reasons for choosing a route indicated by the subjects are travel time, and travel time predictability. especially for their work to home trips (W2H). Other important reasons ranked first include: distance and travel cost (including tolls). This last reason is interesting, because even though it was considered important the subjects still preferred the HOT lanes. This is probably due to the high value most subjects place for travel time and travel time predictability coupled with the perceived low congestion and high travel time predictability levels as stated before. Some subjects may have answered their preference ignoring cost, just examining the quality of the trip, while others may have answered including cost.

Other subjective factors (easiness of driving and pleasantness) further corroborate the HOT Lanes as the most preferred route. This can be inferred because of the high levels of these factors as stated by the subjects in Figure 4. In the case of General Purpose Lanes and Arterials, the subjects indicated a wider variation in their levels of easiness of driving and pleasantness. However, the subjects considered the Arterials slightly more pleasant than the General Purpose Lanes. Furthermore, the readers can refer to Table 3 for the stated preferences and attributes per subject.

3.6 GPS Data Processing

The raw data generated by the GPS device consisted of a list of codes with detailed trip information including: record ID, latitude and longitude, date and time, and instantaneous speed. Each of the codes represent one point per 25 meters in the travel trajectories of each vehicle. In ideal conditions, the displacement of the vehicles are accurately captured by the GPS. In some situations, the records are not accurate, because it might take the GPS device a few minutes to initialize after the vehicle's engine is on. These points were excluded from the dataset. In addition, out-of-town trips during holidays (e.g. Thanksgiving) were also excluded. The actual routes used for the analysis were built by merging these points with a GIS map. This map is referred to as the *TLG network*, which is maintained by the Metropolitan Council and The Lawrence Group (TLG). It covers the entire 7-county Twin Cities Metropolitan Area and is the most accurate GIS map of this network to date. The TLG network contains 290,231 links, and provides an accurate depiction of the entire Twin Cities network at the street level. Twenty-meter buffers are used for all roads, in order clip the GPS records. All points outside of Twin Cities area as well as off-road points were excluded. The remaining points were regrouped into trips; these trips contained all points between one engine-on and engine-off events for each subject. In this way, all trips by each subject were identified along with the characteristics of each trip, including the starting time, the ending time, the path used, and travel speed on each link segment along the route. Another process (or algorithm) was also developed in order to determine the *commute trips* for each subject, and identify each of the routes (e.g. I-394) followed by each trip. The algorithm worked by matching trip origins to home location, and trip destinations to work location, and vice versa. The distance tolerance between origins (destinations) to home (work) locations was set to 600 meters. In addition, a threshold was set for the start of a new trip at 5 minutes. This temporal constraint guarantees that the trips are mostly direct, and avoids confounding difficulties such as chained trips. This complete process was done inside the ArcGIS environment. An example can be seen in Figure 1.

Chapter 4

Models and Results

4.1 Econometric Models

The models are divided by their complexity and number of choices. The first category refers to the GEV models: random coefficient logit (RCL), and multinomial logit (MNL). The second category refers to the subject's route choices (dependent variable): binomial (Non-freeway vs. Freeway), lane (General Purpose Lanes [GPL] vs. High Occupancy Toll Lanes [HOTL]), and multinomial (Arterial vs. GPL vs. HOTL). Furthermore, the models' dependent variables are defined as the subjects' chosen route (or class of route for the binomial) for each of their direct commute trips after they experience the routes in the previous 6-weeks (see Section 3.2 and 3.6). Additionally, the explanatory variables selected for the models are based on travel time measures, travel cost, and socio-demographic factors. The details of these variables are in Section 4.1.

In the RCL models, the coefficients of the travel time measures are considered to be random, because it is hypothesized that travelers may have distinct responses to their perception of time (both travel time, and its variability). For example, these responses can be explained by assuming that travelers possess different risk-taking behaviors (averse, neutral, or prone). Risk averse and risk prone travelers consider the variance and expectation of the perceived travel time in their choice process. The former (latter) exhibits preferences for low (high) variability, and it analyzes its trade off with the expected travel time. Risk neutral travelers are indifferent to travel time variability. Other reasons might also include flexible work entry time, and consequently travelers not feeling pressured to be at their jobs on a specific time. These traveler constraints and others are unknown to the researcher, and thus end up being neglected in the models' systematic utility. Unfortunately, these unobserved preferences are typical in disaggregate microeconomic data as Trivedi and Cameron (2005) points out. Moreover, the normal distribution was selected as the probability density distribution (or population distribution as it is referred) of the coefficients. The reason for selecting this distribution instead of others (e.g. lognormal) is because the normal distribution performance was adequate despite the potential of yielding values of coefficients that might be theoretically unsound (e.g. positive travel cost). Other distributions considered include the log-normal and the truncated normal. The log-normal distribution was disregarded because it tends to yield very high values of the coefficients that are likely to be improbable, and more importantly, we were not able to estimate (achieve convergence) in most of our models. The truncated normal distribution was also disregarded, because it is difficult to tell whether the parameter values (and its associated calculated valuation measures such as VOT) were biased by the selection of the bounds. Finally, this analysis follows the recommendations by Sillano and Ortuzar (2005) to keep cost as a fixed parameter for calculating valuation measures (e.g. VOT) in order to avoid the problems associated with taking ratio of random variables. Readers are referred to Sillano and Ortuzar (2005), Cherchi (2009), Orro-Arcay (2005), and Hess (2005) for more details.

Both RCL and MNL models are divided (see Travel Time Variability in 4.1) according to the travel time reliability measure used to estimate *Value of Reliability* (VOR) of the sample. This value is defined as the marginal rate of substitution between toll cost and travel time reliability. In microeconomic theory (Varian, 1978), this is represented as the ratio of the marginal utility of travel time reliability to the marginal utility of toll cost. Formally,

$$\mathbf{VOR} = \frac{\partial \mathbf{U_j^k} / \partial \mathbf{R_j^k}}{\partial \mathbf{U_j^k} / \partial \mathbf{C_j^k}} \tag{4.1}$$

The *Value of Time* (VOT) and the *Reliability Ratio* (RR) are defined respectively as

$$\mathbf{VOT} = \frac{\partial \mathbf{U_j^k} / \partial \mathbf{T_j^k}}{\partial \mathbf{U_j^k} / \partial \mathbf{C_j^k}} \tag{4.2}$$

$$\mathbf{RR} = \frac{\partial \mathbf{U_j^k} / \partial \mathbf{T_j^k}}{\partial \mathbf{U_j^k} / \partial \mathbf{R_j^k}} \tag{4.3}$$

All the models are estimated using free software called BIOGEME. The procedure selected for the estimation is BIOMC (an algorithm based on simulated maximum likelihood) with 1500 Halton draws. Details about this tool are found at Bierlaire (2003).

Systematic Utility for the models

The additive linear in parameters systematic utility for the previously introduced models is:

$$\mathbf{U_j^k} = \mathbf{f}(\mathbf{T}, \mathbf{V}, \mathbf{C}, \mathbf{S}, \mathbf{A}) \tag{4.4}$$

where

- T: Expected travel time
- V: Travel time variability
- C: Expected toll cost
- S: Socio-demographic
- A: Alternative specific constants (ASC)

Expected travel time

This variable is a measure of the average travel time of each assigned route for each subject during their route assignment (6-weeks) period. This variable is used to represent the traveler's travel time "expectation" when choosing one of the alternatives. It is normally and i.i.d. in the RCL models. It is measured in minutes.

Travel time variability

It is a measure that is inherently linked to the travel time unreliability of a route. Distinct measures have been theorized and developed in order to establish a more direct connection between travel time variability and travel time unreliability, and consequently measure the latter accurately.

Based on Tilahun and Levinson (2006), three travel time unreliability measures are used in the RCL models, all are normally i.i.d. :

- Model 1: Standard deviation; a classical measure in the research literature. A VOR estimated with this model is useful for comparison purposes, as it is a commonly found among travel time reliability studies. Two variations of this model (RCL-1) are estimated: 1a with a gender interaction term, and 1b without it.

- Model 2: Shortened right range of the travel time distribution (90th - 50th percentile), typically found in departure time choice models.

- Model 3: Interquartile range of the travel time distribution (75th - 25th percentile).

The different formulations offer insight into how each unreliability variable is traded off in decision making with travel time and travel cost. The first considers that decisions are motivated by avoiding the overall travel time variability without differentiating the value decision-makers might place on lateness vs. earliness. The second considers that decisions are motivated by extreme values of the right range, which should translate to values decision-makers place solely on lateness. The third consider that decisions are motivated by avoiding the overall travel time variability as denoted by the interquartile range. This variable is measured in minutes.

Expected toll cost

This variable indicates the average toll that would have been paid by subjects at the time they used the I-394 HOT lanes. It is measured in current US Dollars.

Socio-demographic

These are a set of variables describing the attributes of each of the subjects. In this study, one variable was specified: Gender (1=male, 0=female).

Alternative specific constants (ASC)

These are specified for the binomial, lane and multinomial choice models. For each of these models, the alternative specific constants (Non-freeway, GPL, and Arterial, respectively) are fixed to zero.

4.2 Results and Discussion

A first step in this study was to identify the characteristics affecting the route choice process of the subjects after allowing them to acquire new information about the alternatives. This information refers to the 6-weeks route assignment period used to familiarize the subjects with each of the studied alternatives (see Section 3.2 and Section 4). Each of the Models (see Tables 4.1 and 4.2) found as statistically significant the following factors: travel time, travel time variability, and toll cost. Both the expected travel time and travel time variability are directly linked to the travel time distribution experienced by each traveler. Therefore, the fact that both are statistically significant factors in explaining the route choice variation is likely to translate into an added influence to the behavioral decision-making process of the subjects.

In addition, observed (for the first model, Tables 4.1, 4.2, and 4.3) and unobserved heterogeneity (for the first, second, and third models, Table 4.1) of the travelers were found to be statistically significant as well. In the case of observed heterogeneity, males were found to be more risk-prone than females. This illustrated by the fact that they have a smaller disutility for choosing routes with higher variability, in contrast to the females which have higher disutility. This behavior is illustrated more directly in the binomial and lane choice models (Tables 4.2 and 4.3). This result corroborates Abdel-Aty et al. (1997). In the case of unobserved heterogeneity, additional sources (e.g. individual idiosyncrasies) unknown to the researcher were found to influence the route choices of the travelers. This result agrees with Small et al. (2005) and Small et al. (2006), because of presence of the effect, nevertheless it'll be discussed in detail in the subsequent paragraphs.

A second step was examining the performance, and likely meaning of the travel time variability measures. In the multinomial, and binomial choices (Tables 4.1, and 4.2), the RCL-3 and MNL-3 models fit the data better, and statistically significant at 5% according to likelihood ratio tests. However, both models do not seem to outperform each other, and the MNL-3 model does not seems to outperform the RCL-1a. This result indicates that the interquartile range models are the best fit for this data, and the shortened right range has the lowest goodness of fit of these three measures. In contrast, RCL-2 and MNL-2 models fit the data better, and statistically significant at 5% for the lane choices (Table 4.3). The difference of fit is interesting, because it implies that right range measures of variability were found more adequate for this type of lane choice model (GPL vs. HOTL). Furthermore, the coefficients of travel time variability measures exhibit distinct magnitudes. The coefficient of std. deviation (MNL-1 and RCL-1) has the highest magnitude, probably because the other measures are contained within it.

A third step was to analyze the results of the random coefficients in the RCL models. In the binomial and lane choice (Tables 4.2, and 4.3), the RCL models converged to MNL models. This indicates an homogeneous view of the benefits of driving on a freeway vs. an arterial (or GPL vs. HOTL) by the subjects. In other words, travelers are likely to concern themselves more with the travel time (expected and variability), and the travel cost rather than other factors (e.g. personal beliefs) when deciding between driving on Freeway vs. Arterial (or GPL vs. HOTL) for a given commute trip. In the multinomial choice (Table 4.1), the RCL-1, RCL-2, and RCL-3 models exhibit a statistically significant variation across the population for the expected travel time, and only the RCL-1 model has also a statistically significant variation for the travel time variability. This result is interesting because it indicates that travelers differ on the disutility they gain for similar average travel times, also for travel time variability at least for the RCL-1 model case. Additionally, the normal distribution seems like a good choice for our random coefficients as the percentage of theoretically unsound values (e.g. positive travel cost) is small (less than 8%). The exception is RCL-1b because the value is less than 18%. Moreover, the homogeneous outlook of the subjects (lack of unobserved heterogeneity) for the lane choice model disagrees with Small et al. (2005) and Small et al. (2006) as they found presence of this effect for their lane choice models. However, these can be explained by the key differences between the studies (only Small et al. (2005) will be considered, because Small et al. (2006) includes other choice dimensions that are not comparable to this study) that should be covered for research purposes. Firstly, both models use distinct data collection techniques. In this study GPS devices are placed on subjects' vehicles (see Sectio 3.2). In contrast, Small et al. (2005) utilizes questionnaires (only for the RP surveys) and Field measurements by researcher's own vehicle driving (for reconstructing the travel time distributions experienced by the RP surveys' subjects). The two RP surveys were collected by the Brookings Center on Urban and Metropolitan Policy and the California Polytechnic State University at San Luis Obispo, separately. In addition, both RP surveys indicate differences between the samples specifically for travel distances, and also the surveys were collected for the 1999-2000 period prior to the field measurements. Secondly, both studies use distinct distribution of travel times. In this study, the distributions correspond to each of the routes during the assignment period (see Section 3.2) for each subject. In contrast, Small et al. (2005) utilizes a distribution of travel time savings (differences between travel time distributions of GPL and HOTL) obtained through field measurements by the researcher at several times of day for 11 days. In terms of results, both models agree that travel time attributes are significant factors in lane choice behavior. However, both studies disagree in other factors such as gender interaction (not statistical significant in Small et al. (2005); significant in this study), and unobserved heterogeneity (as mentioned previously). In addition, this study's lane choice model has a better goodness of fit (a likelihood ratio index as high as 0.8) in comparison to Small et al. (2005) (a likelihood ratio index as high as 0.4).

Finally, the last step was the estimation of the value of reliability (VOR), value of time (VOT), and the reliability ratio (RR) for the three models specified according to Section 4 for both the binomial, lane, and multinomial choices.

The first model (see Table 4.4) is based on a mean-standard deviation approach. This model implies that higher standard deviation (denoted as travel time variability in the model) is a source of disutility, and thus travelers will prefer the HOT lanes as long as there are any reliability (or less variability) benefits.

In the multinomial choice, women (high VOR) were found to be risk averse in comparison to men (low VOR). In the case of the VOT, both MNL-1 and RCL-1 values are similar and higher than the mean VORs as the reliability ratio (RR) of 0.7 and 0.8 for MNL-1 and RCL-1 points out.

In the binomial choice, the travelers (especially female travelers) are more concerned about VOR than VOT in decisions between arterials or the freeways.

In the lane choice, travelers are equally concerned about VOR and VOT in decisions between GPL and HOTL in terms of avoiding overall variability. Unfortunately, the RCL-1 model did not converge.

The second model (see Table 4.4) is based on a shortened right range approach. This model implies that extreme values of travel time are undesirable. This model assumes travelers place more value on lateness than earliness. It is also a measure that mainly considers lateness by each subject.

In multinomial, binomial and lane choices, the VORs were found to be the smallest, but still representing a significant fraction approximately 20% to 30% of other models' VORs (except for MNL-3 and RCL-3 where the proportion is about 60%).

The third model (see Table 4.4) is based on a interquartile range measure for travel time unreliability. It considers a shortened range of the travel time distribution. This range assumes travelers place equal value to earliness and lateness, but does not consider extreme values as they are unlikely.

In the multinomial choice, the VOT are similar to the second model (MNL-2 and RCL-2), and the VOR are about one third of the mean VORs of the first model (MNL-1 and RCL-2).

In the binomial choice, the VOT and VOR values are the highest of the 3 binomial choice models.

In the lane choice, the VOR values differ by roughly \$1 h^{-1}between each of the 3 lane choice models.

In addition, population distributions of VOT and VOR for the multinomial choice model are shown in Figures 5 and 6 for illustrative purposes.

Interestingly, the VOT and VOR values for the binomial choice models are the highest, and look more plausible according to other studies (see Small and Verhoef (2007)) in comparison to the multinomial and lane choice values which are smaller. This difference is likely to be attributed to self-selection bias because of two reasons: travelers that choose arterials over freeways probably don't have tight time constraints, and the high attrition rate of the subjects (potential subjects with high values of time would be unwilling to drive on unpreferred routes).

Finally, other specifications were considered including weather related variables, and income level dummy variables but were dropped because they were not statistically significant. Furthermore, another model was specified with a travel time variability measure of a shortened left range (50th - 10th), but this variable was not statistically significant as well. For this reason, the model was dropped.

Table 4.1: Econometric Models - Multinomial Choice

Multinomial Choice	**MNL-1**	**RCL-1a**[e]	**RCL-1b**[e]	**MNL-2**	**RCL-2**	**MNL-3**	**RCL-3**
Arterial vs. GPL vs. HOTL	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**
Expected Travel Time[a]							
μ	-0.219***	-0.367**	-0.763**	-0.280**	-0.384**	-0.296**	-0.332**
σ		0.250**	0.615**		0.192**		0.110**
% positive		7.11	10.74		2.28		0.13
Travel Time Variability[b]							
μ	-0.268**	-0.360**	-0.547**	-0.0644**	-0.0771**	-0.126**	-0.121**
σ		0.222**	0.587**		0.000427		0.00218
% positive		5.24	17.57		0.00		0.00
Expected Toll Cost[c]	-2.28**	-4.25**	-9.60**	-4.34**	-5.96**	-5.16**	-5.86**
Male-Std. Deviation[d]	0.225**	0.312**					
$ASC_{GeneralPurposeLanes}$	0.734**	0.820**	0.725**	-0.0230	-0.106	-0.226	-0.227
$ASC_{HighOccupancyTollLanes}$	-0.100	-0.312	0.940	-0.353	-0.175	-0.674	-0.527
Log-likelihood (LL)	-121.531	-117.75	-127.810	-124.650	-121.979	-116.075	-115.400
Likelihood ratio index (ρ^2)	0.497	0.513	0.471	0.484	0.495	0.520	0.523

** is 5% significance level, *** is 1% significance level

[a]It is the average travel time per route, and it's the same for all models. For the RCL models the coefficient is i.i.d. $N(\mu, \sigma)$.

[b]The variability measures are Std. Deviation, Right Range, and Interquartile range for each model pair (e.g. MNL-1 and RCL1) respectively. For the RCL models the coefficient is i.i.d. $N(\mu, \sigma)$.

[c]It is the average MnPass toll paid by each subject.

[abc] Readers should refer to section 4 for more information.

[d]It is an interaction variable between gender and the respective travel time variability measure.

[e]Two variations of this model are estimated: 1a with a gender interaction term, and 1b without it.

Table 4.2: Econometric Models - Binomial Choice

Binomial Choice	**MNL-1**	**RCL-1**	**MNL-2**	**RCL-2**	**MNL-3**	**RCL-3**
NonFreeway vs. Freeway	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**
Expected Travel Time[a]						
μ	-0.141***	-0.141**	-0.159**	-0.156**	-0.194**	-0.194**
σ		0.00587		0.00758		0.00473
% positive		0.00		0.00		0.00
Travel Time Variability[b]						
μ	-0.225**	-0.225**	-0.0672**	-0.0672**	-0.172**	-0.172**
σ		0.00446		0.000265		0.00184
% positive		0.00		0.00		
Expected Toll Cost[c]	-0.797**	-0.797**	-1.06**	-1.07**	-0.566**	-0.566**
Male-Std. Deviation[d]	0.145**	0.145**				
$ASC_{Freeway}$	0.282	0.282	-0.229	-0.229	-0.208	-0.208
Log-likelihood (LL)	-83.212	-83.208	-91.826	-91.821	-79.150	-79.146
Likelihood ratio index (ρ^2)	0.454	0.513	0.398	0.398	0.481	0.481

** is 5% significance level, *** is 1% significance level

[a]It is the average travel time per route, and it's the same for all models. For the RCL models the coefficient is i.i.d. $N(\mu, \sigma)$.

[b]The variability measures are Std. Deviation, Right Range, and Interquartile range for each model pair (e.g. MNL-1 and RCL1) respectively. For the RCL models the coefficient is i.i.d. $N(\mu, \sigma)$

[c]It is the average MnPass toll paid by each subject

[abc] Readers should refer to section 4 for more information

[d]It is an interaction variable between gender and the respective travel time variability measure.

Table 4.3: Econometric Models - Lane Choice

Binomial Choice GPL vs. HOTL	MNL-1 Estimate	MNL-2 Estimate	RCL-2 Estimate	MNL-3 Estimate	RCL-3 Estimate
Expected Travel Time[a]					
μ	-0.243***	-0.672***	-0.672***	-0.446***	-0.446***
σ			0.0000166		0.000226
% positive			0.00		0.00
Travel Time Variability[b]					
μ	-0.390***	-0.228***	-0.228***	-0.280**	-0.280**
σ			0.0000241		0.0000854
% positive			0.00		0.00
Expected Toll Cost[c]	-3.91***	-6.94***	-6.94***	-5.29***	-5.29***
Male-Std. Deviation[d]	0.343**				
ASC_{HOT}	0.0421	-2.23**	-2.23**	-1.67	-1.67
Log-likelihood (LL)	-35.467	-13.999	-13.999	-19.485	-19.485
Likelihood ratio index (ρ^2)	0.654	0.864	0.864	0.810	0.810

** is 5% significance level, *** is 1% significance level

[a]It is the average travel time per route, and it's the same for all models. For the RCL models the coefficient is i.i.d. $N(\mu, \sigma)$.

[b]The variability measures are Std. Deviation, Right Range, and Interquartile range for each model pair (e.g. MNL-1 and RCL1) respectively. For the RCL models the coefficient is i.i.d. $N(\mu, \sigma)$

[c]It is the average MnPass toll paid by each subject

[abc] Readers should refer to section 4 for more information

[d]It is an interaction variable between gender and the respective travel time variability measure.

Table 4.4: Comparison of VOT and VOR estimates

Multinomial Choice	**VOT (US$/Hr)**	**VOR (US$/Hr)**			**Reliability Ratio**
Arterial vs. GPL vs. HOTL	Mean[a]	Men	Women	Mean[a]	Mean[a]
MNL-1	5.76	1.13	7.05	4.76	0.83
RCL-1a[b]	5.18	0.68	5.08	3.57	0.69
RCL-1b[b]	4.77			3.42	0.72
MNL-2	3.87			0.89	0.23
RCL-2	3.86			0.78	0.20
MNL-3	3.44			1.47	0.43
RCL-3	3.40			1.24	0.36
Binomial Choice					
NonFreeway vs. Freeway					
MNL-1	10.61	6.02	16.93	12.75	1.20
RCL-1	10.61	6.02	16.93	12.75	1.20
MNL-2	9.01			3.80	0.42
RCL-2	9.01			3.80	0.42
MNL-3	20.56			18.23	0.89
RCL-3	20.56			18.23	0.89
Lane Choice					
GPL vs. HOTL					
MNL-1	3.73	0.72	5.98	3.93	1.05
MNL-2	5.81			1.97	0.34
RCL-2	5.81			1.97	0.34
MNL-3	5.05			3.18	0.63
RCL-3	5.05			3.18	0.63

[a] It is the weighted average when the values differ by gender. In the other cases, see section 4.

[b] Two variations of this model are estimated: 1a with a gender interaction term, and 1b without it.

Chapter 5

Meta-Analysis of travel time reliability research

Several studies (see Chapter 2) have focused in the valuation of travel time reliability in traveler's choices as of late. Nevertheless, differences still exist especially in modeling approaches, methodology, and in results (including estimated values). Furthermore, no unanimous agreement has been achieved, neither on the order of magnitude of the estimates nor on how to measure travel time reliability (typically used interchangeably to mean variability).

In other fields (mainly in social sciences), a quantitative method known as *meta-analysis* has been used to analyze and summarize the results of various studies. This method analyses data at a higher level; it searches for patterns in the results of other studies through statistical tools (e.g. meta-regression). Furthermore, these patterns (or differences) can be understood with the use of several regressors incorporating several key characteristics (e.g. sample size) of each study (See Guzzo et al. (1987) and Arnqvist and Wooster (1995) for more details).

In this thesis, a meta-analysis is performed to identify the sources of variations in travel time reliability estimates, and to provide an objective summary of current state of research in this area. This chapter is organized as follows: Section 1 presents a brief literature review of the application of meta-analysis in transportation research; Section 2 and 3 discusses the data set assembling procedures and techniques undertaken for comparable estimates across studies; and presents the statistical models utilized in this meta-analysis; and Section 4 interprets the results, and discuss their implications.

5.1 Brief Literature Review

Button (1995) is one of the earliest works utilizing meta-analysis in transportation research. His paper centered around three main themes: value of time (VOT), traffic noise, and the impact of transportation on land use. His method of analysis for each of the motifs was a simple meta-regression using ordinary least squares (OLS) estimators and linear additive functional forms. However, his results (especially for the VOT part) are plagued with lack of statistical significance in most of the regressors; the reasons are possibly related to small sample (or studies) sizes, and sources of bias inherent in the studies themselves.

In the United Kingdom, Wardman (1998) and Wardman (2004) performed a meta-analysis on a large body of literature concerning to the values of in-vehicle travel time for passenger car users, and value of in-vehicle travel time, walk time, wait time and headway for public transport, respectively. For both studies, Wardman employs a log-log functional form (He reports a better fit over the linear additive form) for all the continuous variables. In addition, categorical variables are also present in the model to control for methodological differences. His results (e.g. VOT for commute trips are higher than leisure trips) for the most part agree with those found in the mainstream literature of VOT (see Chapter 2 and Small and Verhoef (2007) for more information).

Another valuation study from Europe is de Jong et al. (2004). They used results (several simulation runs) of various national models to develop a meta-analysis in order to develop a comprehensive and simple framework for demand forecasting, and policy formulation for both passenger and freight transport for numerous years up to 2020.

Other more recent studies are Zamparini and Reggiani (2007*b*), Zamparini and Reggiani (2007*a*) and Shires and de Jong (2009). The first and second carried out meta-analyses on VOT for intermodal passenger (including car, train, bus, airplane) and freight (including only road and rail modes) transport in Europe and North America, respectively. The third performed meta-analyzes on VOT for intermodal passenger transport in North America, Europe, Asia, South America and others. In Zamparini and Reggiani (2007*b*), they use a meta-regression with OLS estimators and linear additive functional forms. They consider the following five sets of regressors as relevant for the analysis: country-specific variables, trip mode, trip purpose, year, and GDP. However, the only sets with statistical significance variables are trip purpose and trip mode. In Zamparini and Reggiani (2007*a*), the meta-regression specification and estimation is similar to their previous study with the exception of logarithmic functional form specified. The types of regressors used are: region-specific, trip mode, GDP, and the ratio of haulage to goods. GDP, region and mode variables were found to be statistical significant. In the case of Shires and de Jong (2009), a linear panel model with random effects, and log-log functional forms are specified for the meta-regression. The explanatory variables considered in their study includes: data type (SP, RP or both), trip mode, GDP, country-specific, travel distance, years, and of course the variance of the random effect (specific for country of origin for a study). In addition, the sample of studies is very comprehensive by including a diverse set of countries. Results from this study include: income elasticities of VOT by trip purpose (0.5 for business travel, 0.7 for commuting, and 0.5 for other passenger transport), significant differences in VOT estimates by trip purpose, trip mode, and region of the world.

In terms of valuation of value of travel time reliability (VOR), there are not many meta-analysis studies. The author after an extensive search only found one: Tseng (2008). This study identifies various differences between VOR estimates, probably because so far there's no consensus in data collection methodology, modeling approaches, and reliability measures in VOR research. In terms of the meta-regression, weighted least squares models are used with different weighting (e.g. samples sizes), and one with a stochastic random effects variable. His results with regards to reliability ratio (RR) indicate negative effects of RR estimates, when scheduling and reliability measures are present in the model; the reason is high correlation between both measures. In addition, RR estimates from the reliability measure of the differences between maximum and minimum travel times tend to have higher values, in comparison to other reliability measures (e.g. standard deviation).

5.2 Data

A data set was assembled after an extensive search of studies with comparable estimates and methodology in transportation research journals, Google (scholar) search engine, and other articles' databases. Empirical studies were included according to the following criteria:

- Contained estimates of VOT, VOR, or RR that could be made comparable across studies;
- Stated explicitly and clearly how the expected travel time and travel time (un)reliability were measured;
- Sample size of the data was provided;

Table 5.1 presents the studies selected for the meta-analysis. Data Type refers to Stated Preference (SP), or Revealed Preference (RP) or both. Observations refers to the number of Reliability Ratio (RR) estimates available in each study, and the average of RR provides the mean among those observations. Maximum and Minimum values are included as well.

It should be remember that the *Reliability Ratio* (RR) is defined as the marginal rate of substitution between (expected) travel time and travel time reliability. In microeconomic theory, this is represented as the ratio of the marginal utility of (expected) travel time to the marginal utility of travel time reliability. Formally,

$$\mathbf{RR} = \frac{\partial\mathbf{U}/\partial\mathbf{T}}{\partial\mathbf{U}/\partial\mathbf{R}} \tag{5.1}$$

$$\mathbf{RR} = \frac{\mathbf{VOR}}{\mathbf{VOT}} \tag{5.2}$$

The *Value of Time* (VOT) and the *Value of Reliability* (VOR) are defined respectively as

$$\mathbf{VOT} = \frac{\partial\mathbf{U}/\partial\mathbf{T}}{\partial\mathbf{U}/\partial\mathbf{C}} \tag{5.3}$$

$$\mathbf{VOR} = \frac{\partial\mathbf{U}/\partial\mathbf{R}}{\partial\mathbf{U}/\partial\mathbf{C}} \tag{5.4}$$

Table 5.1: Summary of selected studies

Study	Data Type	Observations	Average RR	Min	Max
Ghosh (2001)	SP & RP	7	1.17	0.91	1.47
Yan (2002)	SSP & RP	19	1.47	0.91	1.95
Black and Towriss (1993)	SP	1	0.55	-	-
Tilahun and Levinson (2006)	SP	1	0.89	-	-
Small et al. (2005)	SP & RP	2	0.65	0.26	1.04
Bhat and Sardesai (2006)	SP & RP	1	0.26	-	-
Hollander (2006)	SP	1	0.10	-	-
Current Thesis (2010; see 4)	RP	6	0.91	0.47	1.20

5.3 Methodology

The current differences among research in valuation of travel time reliability are a key problem in comparing estimates across studies. The main differences are classified by Tseng (2008) in:

- Data Type (RP, SP, Joint RP & SP);
- Scheduling vs. Reliability Measures;
- Various Travel Time Reliability Measures (e.g. Standard deviation, interquartile range);
- Travel time unit;
- Presence of Heterogeneity (Observed and Unobserved);
- Choice Dimensions (Mode, Route, Transponder, and joint choices).

The Data type differences (RP vs. SP) are mostly centered around perception issues for subjects, and multicollinearity of statistical estimates in econometric models. Succinctly, the validity of the preferences collected from SP data may be affected by the lack of realism, and the subject's understanding of the abstract situations. Thus, the subject's route preferences may not be similar to the ones during their actual trips (see Louviere et al. (2000) and Hensher (1994) for discussions about SP vs. RP). However, new modeling techniques (see Louviere et al. (2000)) have been developed to combine RP and SP data, and to correct for the scale issues of one over the other. The idea behind these techniques is to ground stated choices (SP) to real choices (RP), and to use SP data to stabilize RP data allowing to obtain more precise estimates. In terms of marginal rates of substitution (e.g. VOT, VOR, RR), distinct data types may provide estimates differing by order of magnitude. Generally, transportation researchers hypothesize that valuation ratios of SP estimates are smaller than RP estimates.

Reliability and Scheduling (Section 2.1.4) are related concepts. The former refers to the disutility because of the inconvenience and possible penalties attributed to the unreliability of travel times. The latter refers to the disutility of arriving either too early or too late, when the traveler has time restrictions (e.g. inflexible vs flexible schedules). These two may interact as travelers may have time restrictions and experience unreliable travel times, and thus obfuscate the contribution of each in the utility models estimates. This is important to remember as most of the valuation of travel time reliability studies have focused in commuters; a subset of travelers typically with time constraints. In other words, valuation ratios may depend on controlling for the contribution of both reliability and scheduling. However, most of the VOR studies have focused on using only reliability measures, and consequently not allowing this study to test for this in the meta-analysis.

There are three main distinctions among studies with regards to travel time. First, there are various measurements of travel time reliability in empirical studies including but not limited to: standard deviation, difference between 90th and 50th percentiles of travel time distribution, and others. Second, distinct travel time distributions have been used such as travel time of savings (difference between HOT Lanes and General Purpose Lanes' travel time distributions; see Small et al. (2005)), and the actual travel time distribution of each (e.g. current thesis). Third, travel time may depend on when it is evaluated during the day. The time of day has influence over the travel time. It is likely that measures from off-peak hours may differ from peak hours. In other words, valuation estimates may depend on the described effect. At the moment, most of the valuation of travel time reliability research has focused in the morning commute. A few (including current thesis) have considered afternoon commute. In this study, these differences in travel time are referred as travel time unit. This lack of agreement generates difficulties for the comparison of empirical estimates across studies. Therefore, results of each valuation research must be examined by considering the assumptions of travel time distribution, reliability measures, and travel time unit.

Two types of heterogeneity can be included in the utility specification: observed and unobserved. The observed heterogeneity in the estimates can be evaluated by adding interaction terms of traveler attributes (e.g. age, gender) with travel time, reliability, or cost variables. In contrast, the unobserved heterogeneity (using mixed logit models; see Section 2.2.1) is evaluated by adding another stochastic term that allows to consider the individual units as draws from a population distribution. However, there are difficulties (especially for observed heterogeneity) in the calculation of valuation ratios, because the interaction terms enter in the marginal rate of substitution partial derivatives. This effect could be fixed by obtaining weighted means, but the more interaction terms included and lack of statistics (socio-demographics data) serves as additional obstacles. In the meta-analysis, observed heterogeneity is neglected. In contrast unobserved heterogeneity, it is included in the utility models through the use of advanced econometric modeling (mixed logit or multinomial probit). However, it is unclear whether unobserved heterogeneity leads underestimates or overestimates the valuation ratios. For example, Ghosh (2001) presented low estimates for the valuation ratios for his most general model, in contrast to his other models. Unobserved heterogeneity is considered in the meta-analysis.

Finally, the estimation of the marginal rates of substitution may be affected by distinct choice dimensions (e.g. route choice, mode choice). There might be differences in the choice behavior of travelers between mode and route (perhaps even departure time). In addition, these differences could also be attributed to the modeling (perhaps even endogeneity issues supporting joint choice models). In the meta-analysis, these difference of estimates are explored to identify the trend of the estimates with regards to these results. Furthermore, a procedure is outlined for making estimates comparable for the meta-regression in the correction of estimates section, and the variables of interest are covered along with the econometric model used in the meta regression section.

5.3.1 Correction of estimates

In discrete choice models (consistent with RUT; see Section 2.2), an utility function is specified and estimated, in order to obtain the marginal rate of substitution among distinct quantities of interest. In valuation of travel time reliability, the quantities of interest are measures of travel time, travel time reliability, and travel cost. However, the estimates of the utility function depends on the measures used for each variable. For example, a researcher could choose standard deviation (SD) as the (un)reliability measure, and another may choose the difference of the 90th and 50th percentiles (90D50). Assuming linear-additive in parameter function forms for both models, the utility functions are given in equations (5.5) and (5.6). It is trivial to notice that $\beta_2 \neq \beta_2'$, and thus the computed valuation ratios (VOR and RR) are different, because of measure rather than observations (samples). Furthermore, another difficulty is the travel time distribution used by the researcher (travel time of route vs. travel time savings) as it was mentioned in the previous section.

$$\mathbf{U} = \mathbf{ASC} + \beta_\mathbf{1}\mathbf{E}(\mathbf{T}) + \beta_\mathbf{2}\mathbf{SD} + ... \tag{5.5}$$

$$\mathbf{U}' = \mathbf{ASC}' + \beta_\mathbf{1}'\mathbf{E}(\mathbf{T}) + \beta_\mathbf{2}'\mathbf{90D50} + ... \tag{5.6}$$

The best solution to both problems consists of using a standard methodology (i.e. same travel time distributions), and same (un)relability measures on the same observations for each study. However, this requires reestimating, and performing transformations to the data sets. Unfortunately, these changes are not possible unless the data sets were available to the public (not necessarily a possibility as data sets can be costly). Other methods (as the ones outlined here) can be used to obtain reasonable solutions, although not necessarily better.

First, the different measure problem can be fixed by using "transformation ratios" (similar to Tseng (2008)). These ratios are obtained by normalizing for one measure to transform all measures to a common form (e.g. standard deviation). However, this requires an strong assumption on the shape of the travel time distribution. For example, the standard deviation (SD) and the difference of the 90th and 50th percentiles (90D50) can be obtained analytically or numerically for various theoretical distributions, and it can be normalized to transform one to the other or vice versa. In the case of travel time following an uniform distribution, the transformation ratio (0.723) of 90D50 to SD is obtained by taking the ratio of (5.8) to (5.7), where a and b are the parameters for an uniform distribution.

$$\mathbf{90D50} = \frac{\mathbf{8}}{\mathbf{20}}(\mathbf{b} - \mathbf{a}) \tag{5.7}$$

$$\mathbf{SD} = \frac{\mathbf{1}}{\mathbf{2\sqrt{3}}}(\mathbf{b} - \mathbf{a}) \tag{5.8}$$

In this thesis, a normal distribution was selected for the transformation ratios because the distribution shape is hypothesized to be similar to the true distribution of travel times, it is tractable, and the transformation ratios are between uniform and triangle distributions (cases with no peak and peak travel times). The transformation ratios are grouped in Table 5.2.

Table 5.2: Transformation ratios for a Normal distribution

Measure	**Ratios**
Standard Deviation	1.000
90th - 50th Percentiles	0.780
80 - 50th Percentiles	1.188
75th - 25 Percentiles	0.741

In terms of travel time distribution differences, only three studies (Ghosh (2001), Yan (2002), and Small et al. (2005)) use the travel time savings approach. However, it can be noted that as the studies mention the HOT lanes are mostly operating at free flow conditions. Therefore, the travel times tend to be rather constant. This means that the travel time savings distribution is likely to resemble the GPL distribution but reduced by a constant for each value. It is trivial to show that if it is assumed that all values are reduced by a constant then the dispersion measures remain unaffected.

Other corrections with regards to travel cost unit (monetary value) are neglected, because in this meta-analysis only the reliability ratio is considered, and VOR and VOT are not analyzed. The main reason was to avoid including more confounding because of assumptions with respect to exchange rates, and the present value of capital.

5.3.2 Meta-regression

A meta-regression is a multivariate regression or any of its extension according to the required characteristics (e.g. heteroskedasticity, autocorrelation) of the data. Therefore it follows that a meta-regression is defined as

$$\mathbf{y_n} = \beta_\mathbf{0} + \beta_\mathbf{1n}\mathbf{x_{1n}} + \beta_\mathbf{2}\mathbf{x_{2n}} + \beta_\mathbf{3}\mathbf{x_{3n}} + ... + \beta_\mathbf{k}\mathbf{x_{nk}} + \epsilon_\mathbf{n} \tag{5.9}$$

Where y represents the reliability ratio (RR), x are the k regressors (outlined in subsequent paragraphs), ϵ is the gaussian white noise (ϵ i.i.d. $N(0, \sigma^2)$), and n are the number of observations.

The regressors are grouped into six classes. These are:

Unobserved Heterogeneity:

This is a categorical variable representing studies that included unobserved heterogeneity. This is a binary variable (denoted as Het), where 0 = did not include (base case), and 1 = included.

Travel Time Unit:

This class contains two categorical variables representing the time of day the data was collected. These are: AM, and PM. The base case is PM.

Data Type:

This class contains three categorical variables representing the data type. These are: SP, RP and joint SP & RP. The base case is joint SP & RP.

Region:

This class contains four categorical variables representing the regional differences. There are: Minnesota (MN), California (CA), Texas (TX), and United Kingdom (UK). The base case is UK.

Year of study:

This is a quantitative variable representing the trend of the estimates with regard to years of publication.

Choice Dimension:

This class contains three categorical variables representing the distinct choices. There are: mode choice, route, and joint choices (e.g. route choice + transponder choice). The base case is joint choices.

The reader can refer to Wooldridge (2009) and Trivedi and Cameron (2005) for a complete review and additional information about these statistical (or econometric as there is overlap) models.

5.4 Results and Discussion

Table 5.3 presents the results. There are four estimated models. All utilize the Reliability Ratio value as the dependent variable, and also the regressors as outlined in the previous section. First, a multivariate regression with Ordinary Least Squares (OLS) estimators was performed. However, most of the estimates turned out to not have statistical significance with the exception of a regional variable (California). A reason for this lack of statistical significance can be attributed to inefficient estimators (as standard errors enter in T-Statistics), because of heteroskedasticity. Therefore, a Breusch-Pagan test was performed and the homoskedasticity assumption of OLS was rejected at the 5% significance level. Second, a multivariate regression with OLS estimators and robust standard errors (RSTDE) was performed. This regression identified additional variables that did not have statistical significance for lack of OLS estimator efficiency. Furthermore, two additional models were considered to handle heteroskedasticity explicitly: Weighted Least Squares (WLS), and a Feasible (also known as estimated) Generalized Least Square estimators (FGLS).

The weights for the WLS model are the average sample size divided by number of observations per study. In this way, the impact of many observations per study (a likely source for heteroskedasticity) is reduced. The multiplicative weight function is added to the OLS estimators, and the model is re-estimated. The variables found statistical significance with the WLS were also identified by the OLS estimators with robust standard errors as well. In the case of the FGLS model, the function that determines the heteroskedasticity (referred here as heteroskedasticity function) is estimated using an exponential functional form, and then the fitted values of this function are used as weights for the estimation of the model. The result is the highest goodness of fit in comparison to the other models, and also all variables found statistical significant with the OLS with robust standard errors are identified.

The reliability error according to the FGLS and OLS-RSTDE varies in size by the following statistical significant variables: travel time unit, region (MN and CA), year of study, and the choice dimension (route). It is prudent to look at all classes of regressors (even if they are not statistically significant) as there could be reasons or further insight into why they were not found "important" in describing the variation of the RR variable. The classes following previous order of appearance are:

Unobserved Heterogeneity:

The presence of unobserved heterogeneity was not found statistically significant. This is plausible as the RR estimates of models including it might not be as different as models without it. The differences are ameliorated by taking ratios of VOR to VOT (both estimates might reduce or increase by similar proportion). It is likely that meta-regressions for VOT or VOR could find this effect significant.

Travel Time Unit:

The time of day when the data is collected was found statistical significant. The results indicate that the RR value calculated in the morning is smaller in comparison to the one in the afternoon. This agrees with Tilahun and Levinson (2009), and Liu et al. (2007). The former indicated different VOTs between the morning and afternoon commute. The afternoon commute presented the highest VOT. The latter estimated VOT and VOR as functions of time, and thus indicating that values reduce with time of day. The values were higher for regular peak hours. It should be noted that in order for RR to be higher either VOT reduces or VOR increases or both values increase by distinct proportions, but VOR must increase more.

Data Type:

The RR estimate seems unaffected by Data type (SP or RP or joint SP & RP). This result disagrees with mainstream opinion with regards to SP estimates vs. RP estimates. However, the reason for lack of statistical significance is probably attributed to both VOT and VOR estimates reducing in size by similar proportions rather than the optimistic idea of similarity of SP estimates to RP estimates. Ghosh (2001) and Yan (2002) find RP estimates to be of higher value (about twice) in comparison to SP estimates.

Region:

The regional differences were found statistical significant. This is plausible as market conditions may differ regionally (and more by country). Both California (CA) and Minnesota (MN) experienced higher RR estimates in comparison to the United Kingdom studies. The magnitude of California was even higher. There are several reasons that can explain this, but a very likely one for California is congestion.Yan (2002)'s trip-based and person-based models of the SR-91's congestion experiment (in LA, CA) agree with this statement.

It should be noted that individual study differences are captured by the regional variables.

Year of study:

This variable was found statistically significant. It indicates that the RR estimates are reducing slightly in time. This result is puzzling, but it might be related to the nature of the studies. First, most of the earlier studies used SP estimates, while the latter focused on RP estimates or joint SP & RP estimates. Therefore, this time trend needs to be further explored by increasing the sample of studies, and no final conclusions should be drawn.

Choice Dimension:

The route variable was found statistical significant. However, it should be noted most of the studies were based on the route choice dimension. Therefore, this result like year of study needs to be further explored by adding more estimates of published journal articles from transportation research literature.

Table 5.3: Results of Meta-Analysis

Class	**Variables**[e]	**OLS**[a]	**OLS (Robust)**[b]	**WLS**[c]	**FGLS**[d]
Unobserved Heterogeneity	Het	-0.02 (-0.1)	-0.02 (-0.1)	0.11 (0.7)	0.19 (1.58)
Travel Time Unit	AM	-0.31 (-0.9)	-0.31 (-3.18)***	-0.33 (-4.11)*	-0.33 (-4.22)***
Data Type	SP	0.21 (0.4)	0.22 (0.61)	0.47 (1.34)	0.42 (1.26)
	RP	0.05 (0.4)	0.05 (0.25)	0.23 (1.04)	0.15 (0.74)
Region	MN	0.74 (1.4)	0.74 (9.25)*	0.76 (11.27)**	0.76 (11.4) ***
	CA	1.36 (1.8)**	1.36 (5.68)***	1.47(6.34)***	1.44 (6.36) ***
	TX	0.34 (0.5)	0.34 (1.13)	0.49 (1.58)	0.35 (1.17)
Year of study	Year	-0.03 (-1)	-0.03 (-1.96)**	-0.03 (-1.91)**	-0.03 (-3.1) ***
Choice Dimension	Mode	-0.01 (-0.01)	-0.01 (0.95)	-0.09 (0.18)	0.05 (0.32)
	Route	0.32 (1.4)	0.32 (1.87)*	0.27 (1.47)	0.41 (2.47) **
	Constant	59.6 (0.97)	50.60 (1.95)**	54.56 (1.89)**	78.45 (3.08) ***
R^2		0.6376	0.6376	0.9111	0.9387
Obs		38	38	38	38

* is 10% significance level, ** is 5% significance level, *** is 1% significance level

[a] Multivariate regression with OLS estimators; Coefficient (T-Statistic).

[b] Multivariate regression with OLS estimators using Robust Standard Errors; Coefficient (T-Statistic).

[c] Multivariate regression with WLS estimators using average sample size divided by number of observations per study as the weight; Coefficient (T-Statistic).

[d] Multivariate regression with FGLS estimators using an estimate for the heteroskedasticity function; Coefficient (T-Statistic).

[e] See Section 5.4 for variable descriptions.

Chapter 6

Conclusions

The prominent features of this thesis are: the experimental design (ACERP) employed for the GPS/Survey/Transponder data collected; and the use of mixed logit models to estimate the VOT, VOR and RR for this RP data. The first component allowed the generation of plausible scenarios (assigned routes with actual OD pairs) for the subjects to experience in real life conditions. This provided several benefits already mentioned despite its main difficulty being the high attrition rate. This experimental design serves as a basis for researchers. In addition, the study found to be beneficial the experience with GPS devices for travel behavior research. These were found to be quite useful for obtaining detailed commute level data. It permitted direct measurement of travel time and variability values for each of the subject's trips and specific routes. The wealth of information obtained has yet to be fully exploited. The second component allowed for the investigation of the effects of travel time reliability in the route choice behavior of travelers. These effects were evaluated in two parts. First, the attributes (including unobserved heterogeneity) of the subjects that were significant for route choices were recognized. Readers should refer to Tables 4.1 and 4.2. Second, values of reliability were estimated according to distinct proposed travel time variability measures. A summary of VOT, VOR and RR can be found in Table 4.4. Furthermore, the results were reasonable despite the low VOT/VOR estimates obtained from the data.

A meta-analysis on RR estimates was also performed in order to understand the differences of estimates between and within studies. The results of the meta-regression pointed to several variables including: the time of day for collecting the data; regional differences; year of the study; and the choice dimension. However, the last two must be further explored in order to detect whether they are truly important.

Future research includes the development of models using this RP and SP data to develop VOR as function of time similar to Liu et al. (2007), in order to asses the different time periods for which users will be willing to pay higher tolls. This leads to the possible interpretation that VOR as a function of time could possibly help set toll prices more effectively than traffic flow measures by itself. However, this hypothesis needs to be tested.

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Appendix

Table 1: Comparison of Before and After Observed Route Choices

Observed Choices	**Before**[a]			**After**[a]			**Change?**
Subject ID	**Arterial**	**GPL**	**HOTL**	**Arterial**	**GPL**	**HOTL**	**(Yes/No)**
1	0.00%	100.00%	0.00%	21.05%	31.58%	47.37%	Y
2	100.00%	0.00%	0.00%	0.00%	100.00%	0.00%	Y
3	100.00%	0.00%	0.00%	0.00%	50.00%	50.00%	Y
4	0.00%	100.00%	0.00%	53.85%	46.15%	0.00%	Y
5	100.00%	0.00%	0.00%	47.37%	0.00%	52.63%	Y
6	0.00%	100.00%	0.00%	0.00%	100.00%	0.00%	N
7	100.00%	0.00%	0.00%	50.00%	50.00%	0.00%	Y
8	50.00%	50.00%	0.00%	100.00%	0.00%	0.00%	Y
9	100.00%	0.00%	0.00%	0.00%	100.00%	0.00%	Y
10	0.00%	100.00%	0.00%	0.00%	100.00%	0.00%	N
11	0.00%	100.00%	0.00%	100.00%	0.00%	0.00%	Y
12	0.00%	100.00%	0.00%	85.71%	14.29%	0.00%	Y
13	0.00%	100.00%	0.00%	44.44%	55.56%	0.00%	Y
14	33.33%	66.67%	0.00%	0.00%	50.00%	50.00%	Y
15	11.11%	88.89%	0.00%	25.00%	75.00%	0.00%	Y
16	20.00%	80.00%	0.00%	83.33%	0.00%	16.67%	Y
17	10.00%	90.00%	0.00%	6.80%	82.45%	10.75%	Y
18	0.00%	100.00%	0.00%	8.60%	76.56%	14.84%	Y

[a] See section 3.2 for details.

Table 2: Travel Times of Subjects per Observed Routes

	Statistics of Subject's Travel Time Distributions (Minutes)																			
	Free Week (Before)[a]						Assignment Period						Free Week (After)[a]							
Subject ID	Arterial		GPL		HOTL		Arterial		GPL		HOTL		Arterial		GPL		HOTL		Average Toll ($USD)	Gender (M/F)
	Mean	Std. Deviation[b]	Mean	Std. Deviation[b]	Mean	Std. Deviation[b]	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation[b]	Mean	Std. Deviation[b]	Mean	Std. Deviation[b]		
1			28.71	4.36			42.07	13.15	31.34	8.52	24.55	3.99	44.87		30.41	4.58	29.48	2.55	0.71	F
2	33.22	2.96					41.75	10.46	42.17	7.95	29.70	7.19			42.39	6.12			1.42	M
3	20.00	1.23					22.12	3.74	26.26	8.34	26.01	7.86			21.71	2.19	20.63	1.40	0.40	F
4			20.49	2.66			33.06	16.81	26.05	16.57	28.34	15.54	26.39	18.09	26.78	5.72			0.25	F
5	25.79	6.76					28.90	7.15	34.70	7.33	30.09	4.46	23.73	9.16			25.93	3.40	0.28	F
6			30.86	8.74			37.05	10.32	31.19	7.62	25.91	7.61			29.30	8.51			1.11	F
7	41.80	12.65					42.28	8.33	49.99	19.70	42.40	2.77	43.66	9.35	49.16	13.82			0.46	M
8	24.46	2.64	22.33	2.57			33.99	10.17	32.69	13.25	34.36	12.78	31.41	10.52					0.30	F
9	41.59	7.82					61.98	66.72	28.20	5.51	34.76	13.69			35.27	5.87			1.40	M
10			46.75	4.62			33.59	3.77	28.80	10.12	32.81	1.67			34.81	16.95			1.02	F
11			39.27	12.71			36.30	40.91	40.77	13.22	39.60	13.05	41.42	19.33					0.78	F
12			45.84	12.71			60.76	56.85	42.75	29.07	26.37	24.73	56.34	51.00	35.38	10.80			1.04	F
13			34.00	9.80			37.91	6.94	32.10	13.08	30.44	7.51	35.20	10.86	31.38	10.19			2.43	F
14	37.33	9.16	23.49	5.91			34.45	8.61	29.00	7.13	32.65	8.74			34.59	9.19	22.86	2.77	0.66	F
15	43.24	6.85	31.26	15.46			40.85	9.13	40.83	29.36	35.89	12.25	44.04	8.98	35.10	16.63			0.30	M
16	29.08	5.08	36.93	4.47			25.94	2.86	35.92	9.31	29.56	7.33	24.61	3.86			29.85	6.87	1.26	F
17	32.95	6.13	32.72	7.64			38.31	17.24	34.55	12.88	31.46	9.45	37.16	15.68	33.86	9.21	25.75	3.40	1.02	F
18			33.09	7.94			38.08	17.50	34.75	13.15	31.90	9.79	36.39	15.68	34.14	9.60	25.00	3.57	0.83	F

[a] See section 3.2 for details.

[b] Std. deviations for the Free periods depend on the number of trips made by the subjects. In some cases, there is only one trip, or less than five. This is especially true for the first free period (before) because it consisted of just a week or 4 days for each subject. The case of not enough trips to calculate the std. deviation is Subject 1 (After), and the cases of less than 5 trips are Subjects 2 (Before), 8 (Before), and 9 (Before).

Table 3: Subjective Attributes of Routes and Stated Preferred Routes per Subject

Subject ID	Subjective Attributes of Routes: Arterial				GPL				HOTL				HOTL Saves Time? (Yes/No)	Toll paid worth time saving? (Too High/Just Right/ Too Low)	Stated Preferred Route Ranking			Gender (M/F)
	Congestion	Predictability	Ease	Pleasantness	Congestion	Predictability	Ease	Pleasantness	Congestion	Predictability	Ease	Pleasantness			1st	2nd	3rd	
1	4	2	4	1	4	5	5	5	1	5	7	7	Y	TH	HOTL	GPL	Arterial	F
2	2	6	6	5	6	1	2	2	3	4	3	3	Y	TH	HOTL	GPL	Arterial	M
3	4	6	6	5	5	3	6	5	2	7	5	6	N	TH	Arterial	HOTL	GPL	F
4	3	6	4	4	5	3	6	4	2	6	7	7	Y	TH	Arterial	GPL	Arterial	F
5	4	2	5	5	5	4	2	3	1	6	7	7	Y	TH	HOTL	N/A	N/A	F
6	5	5	5	6	5	3	5	3	1	6	6	6	Y	TH	HOTL	HOTL	GPL	F
7	5	3	5	5	3	5	6	4	1	1	7	5	N	TH	HOTL	GPL	Arterial	M
8	4	5	5	5	5	5	3	2	4	4	5	4	N	TH	Arterial	N/A	N/A	F
9	6	4	3	3	3	5	5	5	1	7	7	7	N	TH	GPL	HOTL	Arterial	M
10	2	6	6	5	5	3	4	5	3	5	6	5	Y	JR	Arterial	GPL	HOTL	F
11	5	3	3	3	4	5	5	3	1	6	5	5	Y	JR	Arterial	GPL	Arterial	F
12	5	6	6	5	6	3	5	2	1	2	7	6	Y	TH	Arterial	Arterial	GPL	F
13	5	5	5	5	6	1	1	2	3	6	6	6	Y	JR	HOTL	GPL	GPL	F
14	5	1	1	1	4	7	4	4	3	3	3	4	N	TH	HOTL	HOTL	Arterial	F
15	3	3	3	3	3	3	3	3	1	2	1	1	Y	JR	HOTL	GPL	Arterial	M
16	3	5	5	5	6	1	2	3	2	5	5	5	Y	JR	Arterial	Arterial	GPL	F
17	5	4	3	3	4	4	5	5	2	5	5	6	Y	TH	GPL	N/A	N/A	F
18	5	4	4	4	6	4	6	6	4	6	6	5	Y	TH	GPL	N/A	N/A	F

[a] See sections 3.2 and 3.5.2 for details. For summary statistics refer to Figures 2, and 4.

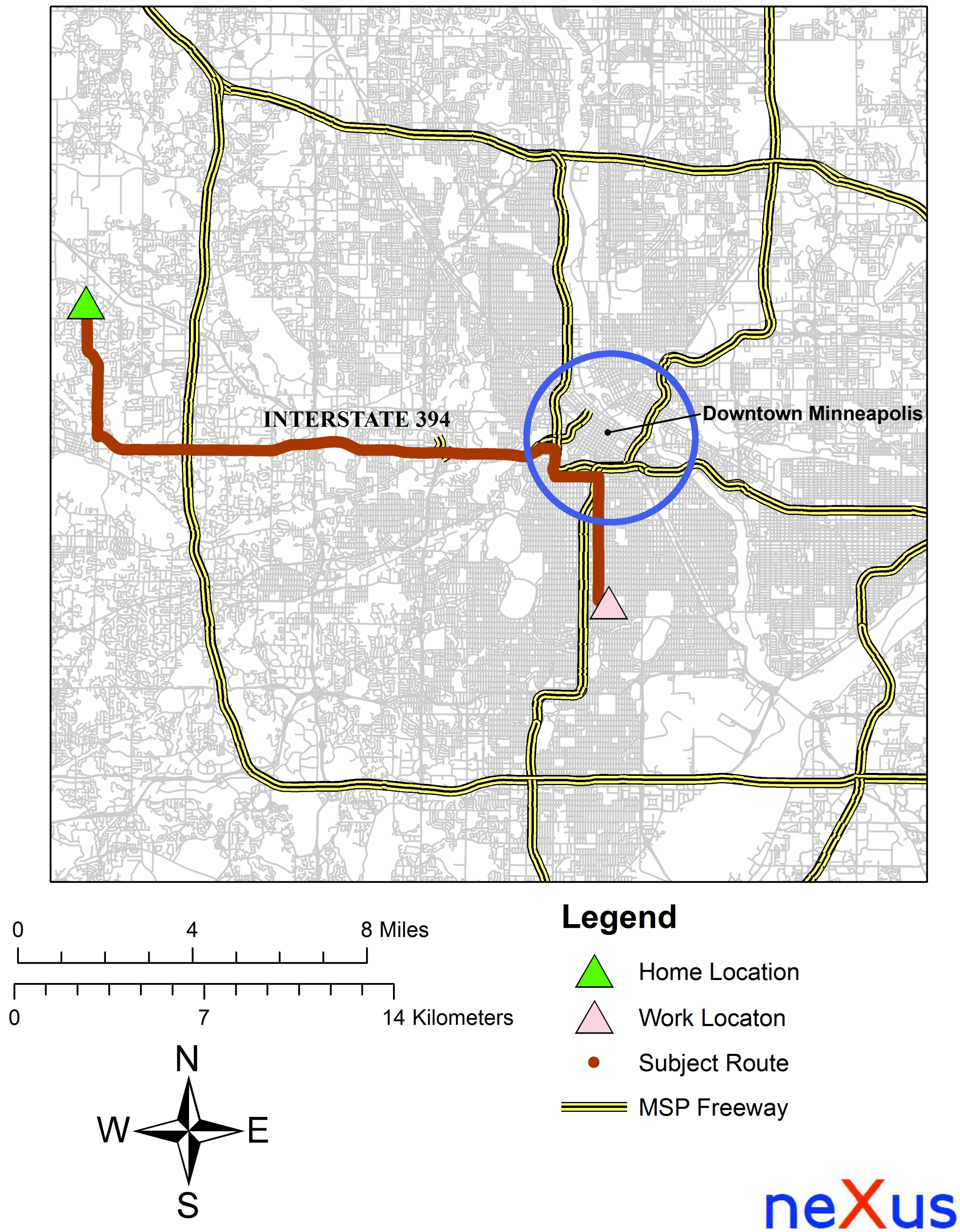

Figure 1: Example of a subject's commute trip using I-394

Figure 2: Routes Preference Top 3 Rank

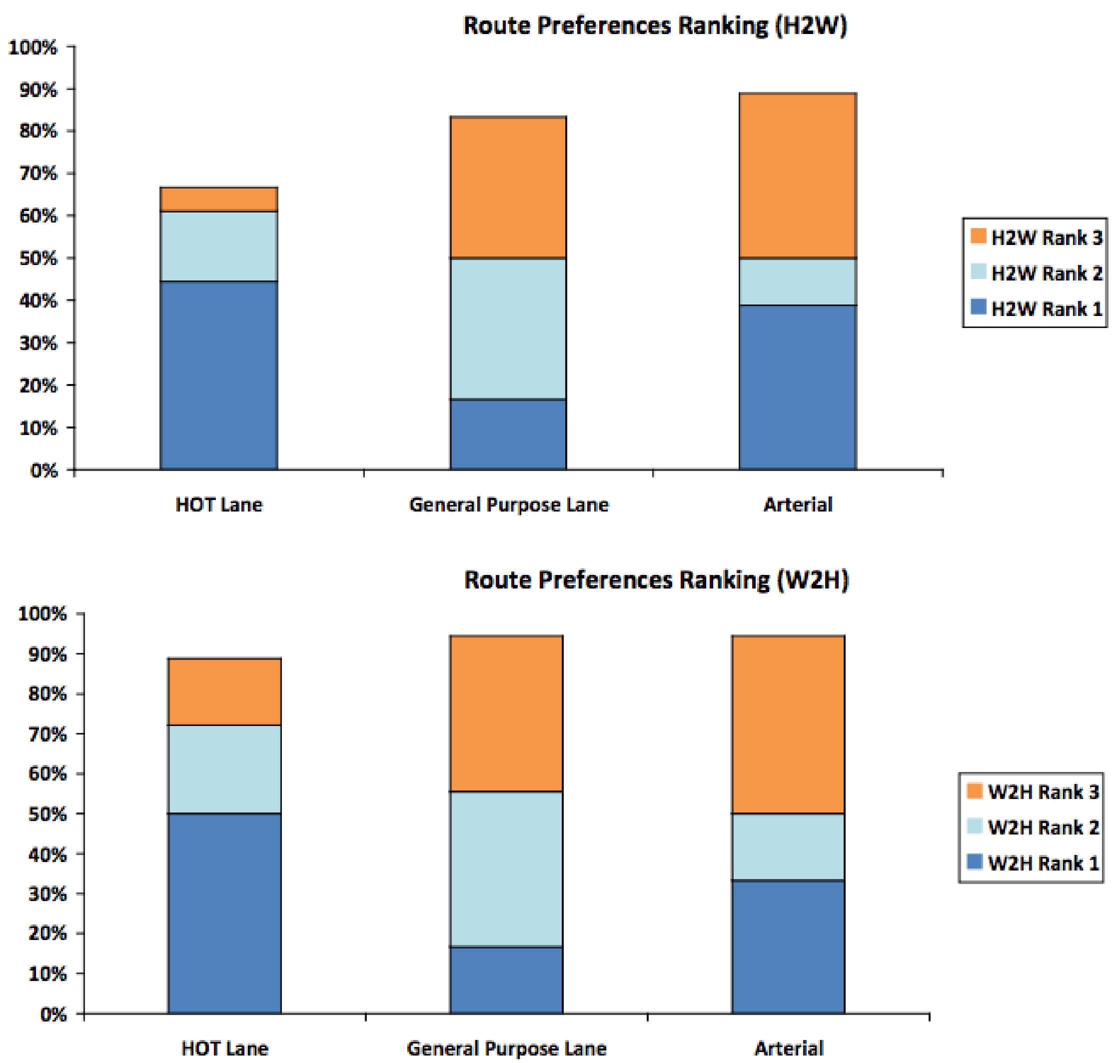

Figure 3: Reason behind route preferences Top 3 Rank

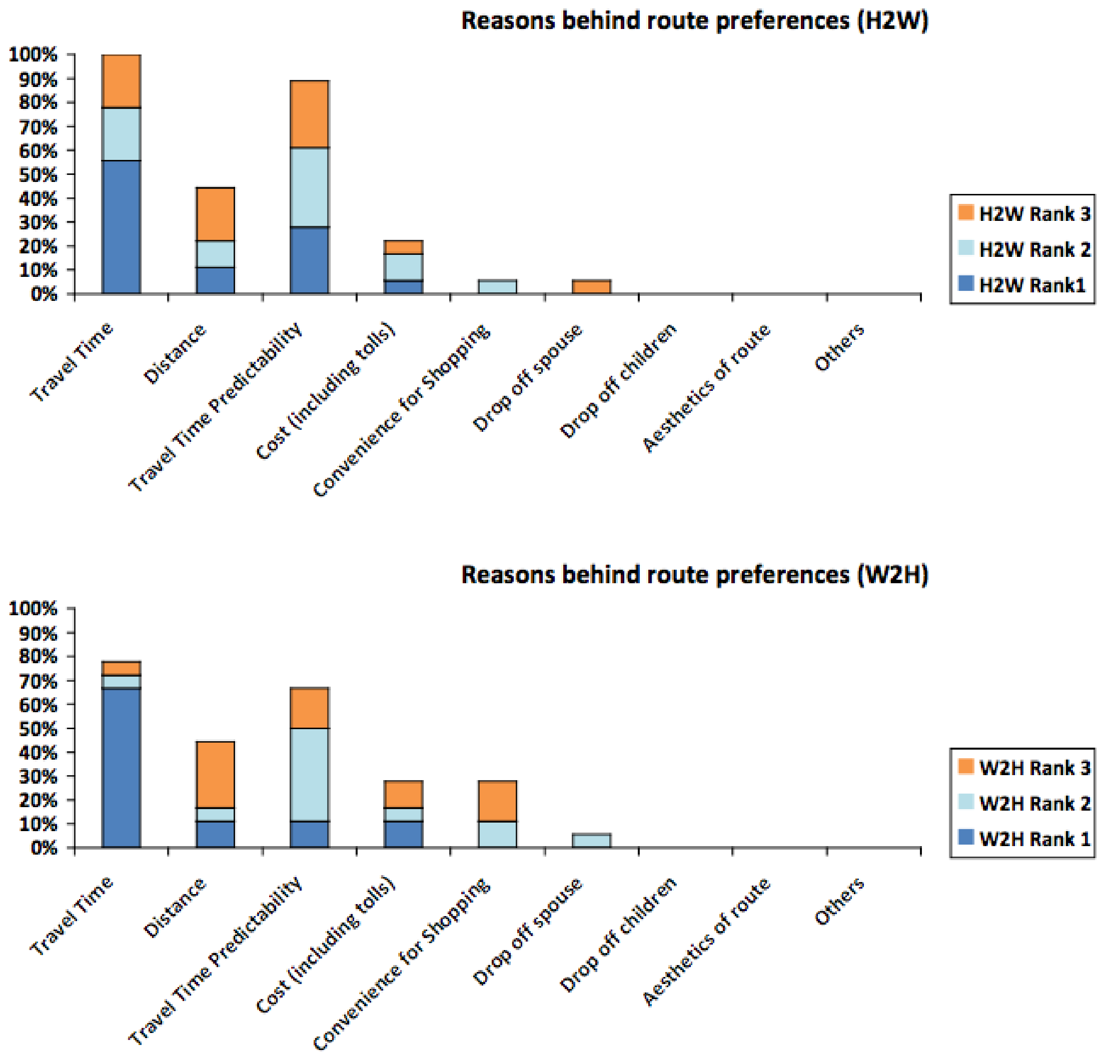

Figure 4: Route Attributes

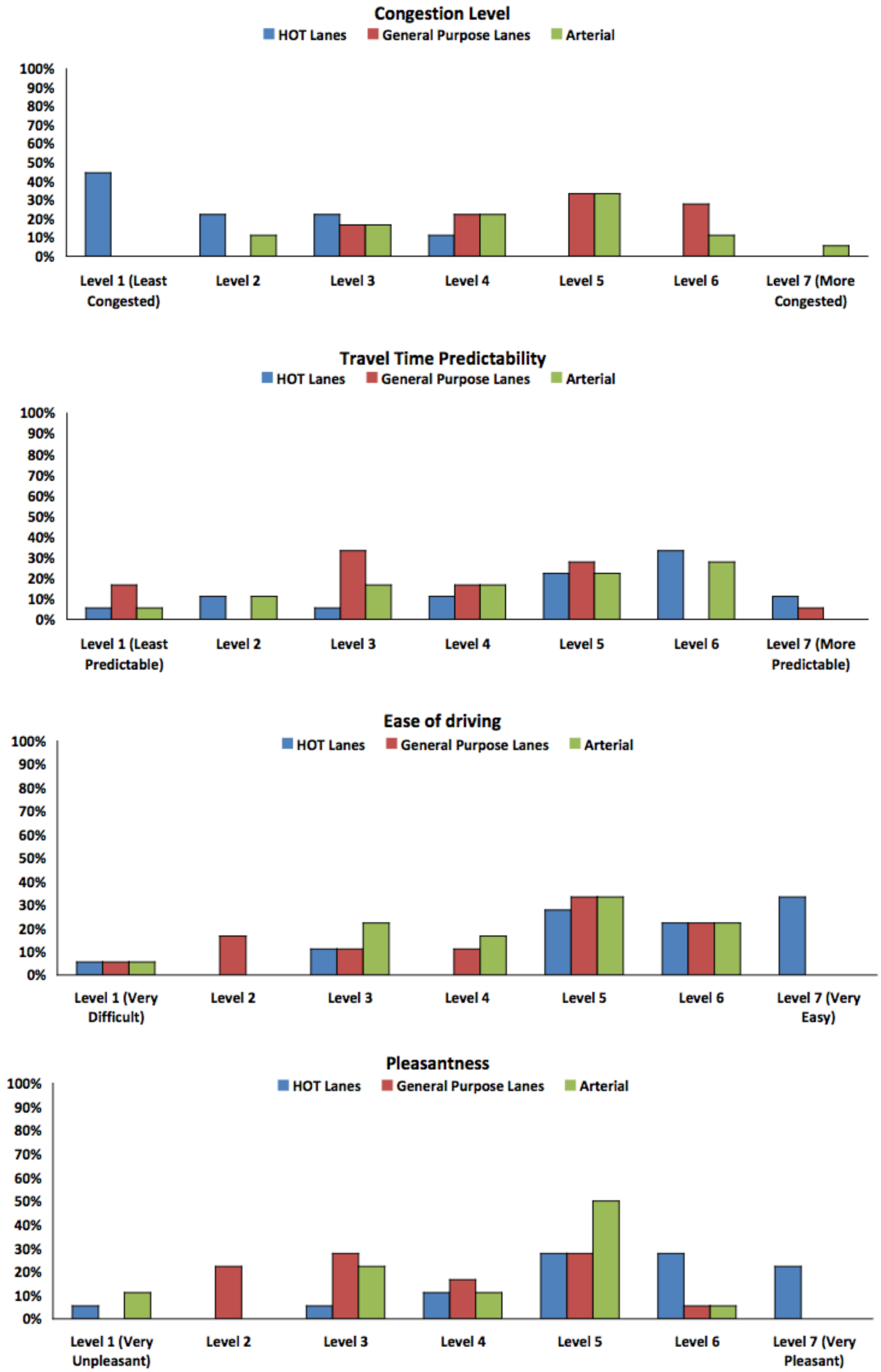

Figure 5: VOT Distributions

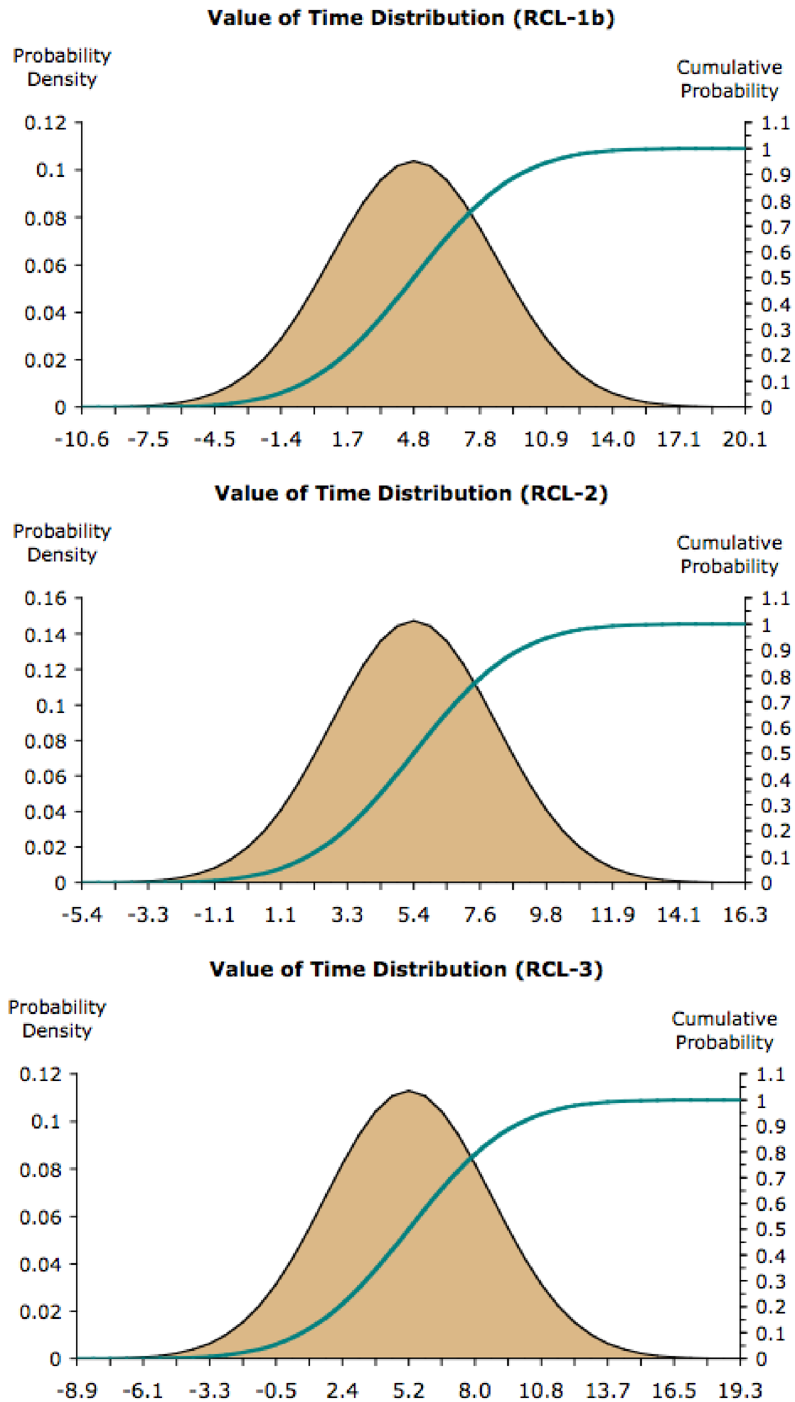

Figure 6: VOR Distributions