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Impacts of User Heterogeneity and Attitudinal Factors on Roadway Pricing Analysis - Investigation of Value of Time and Value of Reliability for Managed Lane Facilities in South Florida

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IMPACTS OF USER HETEROGENEITY AND ATTITUDINAL FACTORS ON ROADWAY PRICING ANALYSIS – INVESTIGATION OF VALUE OF TIME AND VALUE OF RELIABILITY FOR MANAGED LANE FACILITIES IN SOUTH FLORIDA

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Md Sakoat Hossan

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To: Interim Dean Ranu Jung
College of Engineering and Computing

This dissertation, written by Md Sakoat Hossan, and entitled Impacts of User Heterogeneity and Attitudinal Factors on Roadway Pricing Analysis – Investigation of Value of Time and Value of Reliability for Managed Lane Facilities in South Florida, having been approved in respect to style and intellectual content, is referred to you for judgment.

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DEDICATION

I dedicate this dissertation to my parents, Md Solaiman and Momena Begum. Without their patience, understanding, support, and most of all love, the completion of this work would not have been possible.

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ABSTRACT OF THE DISSERTATION

IMPACTS OF USER HETEROGENEITY AND ATTITUDINAL FACTORS ON ROADWAY PRICING ANALYSIS – INVESTIGATION OF VALUE OF TIME AND VALUE OF RELIABILITY FOR MANAGED LANE FACILITIES IN SOUTH FLORIDA

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Managed lane refers to the application of various operational and design strategies on highway facilities to improve system efficiency and mobility by proactively allocating traffic capacity to different lanes. One of the key elements to understand the behavior changes and underlying causalities in user responses to managed lanes is to examine the value of time (VOT) and value of reliability (VOR). The breadth of this dissertation encompasses two major dimensions of VOT and VOR estimation – distributions or variations across different users and under different circumstances; and influences of unobserved attitudinal characteristics on roadway pricing valuation.

To understand travelers' choice behavior regarding the usage of managed lanes, combined revealed preference (RP) and stated preference (SP) data were used in this study. Mixed logit modeling was applied as the state of the art methodology to capture heterogeneity in users' choice behavior. The model revealed an average value of $10.68 per hour for VOT and $13.91 per hour for VOR, which are reasonable considering the

average household income in the region, and are well within the ranges found in the literature.

In terms of user heterogeneity, the mixed logit model was further enhanced by adding interaction effects of variables, which helped recognize and quantify potential sources of heterogeneity in user sensitivities to time, reliability, and cost. The findings indicated that travelers were likely to exhibit higher willingness to pay when they were female, younger (<35 years), older (>54 years), had higher income (> 50 K), driving alone, and traveled on weekdays.

Attitudinal aspects are rarely incorporated into roadway pricing analysis. The study herein presents an effort to explore the role of attitudinal factors in drivers' propensity toward using managed lanes. Model results boded for a significant contribution of attitudinal parameters in the model, both in terms of coefficients and model performance.

This study provides a robust approach to quantify user heterogeneity in VOT and VOR and capture the impacts of attitudinal attributes in pricing valuation. The results of this study contribute to a better understanding on what attributes lead to higher or lower VOT and VOR and to what extent.

TABLE OF CONTENTS

CHAPTER PAGE

LIST OF TABLES

TABLE PAGE

LIST OF FIGURES

FIGURE PAGE

CHAPTER 1

INTRODUCTION

1.1. BACKGROUND

Given the growing transportation needs, increasing congestion levels, emerging environmental issues, and continuing fiscal constraints, transportation agencies are challenged to seek solutions that promote the effective and efficient usage of transportation systems. For a number of reasons, roadway pricing is becoming a popular strategy among transportation agencies as an active transportation and demand management (ATDM) tool. Interest on roadway pricing increases as it accommodates benefits from both demand (e.g., travel demand management) and supply (e.g., maintain desired level of service on freeways) perspectives, and thereby is considered an alternative to traditional funding sources. It has the potential to fund new capacity improvement projects, promote effective management of congestion, and enhance the overall performance of transportation systems.

In the United States, managed lanes are the most prominent applications of roadway pricing, especially in the context of dynamic pricing (Perez et al., 2012). According to the Federal Highway Administration (FHWA), managed lanes are a set of lanes where operational strategies are proactively implemented and managed in response to changing conditions (FHWA, 2005). The first managed lane project was implemented during the mid-1990s on SR 91- Orange County, California. The success of this project triggered a rapid implementation of the concept across the nation. Within two decades, the managed lanes concept has been widely accepted as an effective active management tool.

Transportation agencies are facing multifaceted challenges to accommodate the managed lanes concept into existing infrastructure. Some of the concerns are related to determining the most efficient policies in pricing structure, revenue generation, transit operations, and social equity concerns. Agencies are also struggling to outline operational strategies for access control, vehicle eligibility, design flexibility, and enforcement. Understanding the demand and choice behaviors of managed lane users is essential for prescribing solutions to the aforementioned challenges.

This dissertation intends to contribute to a better understanding of travel behavior in the context of managed lanes through an in-depth examination of a series of influential factors that contribute to the use of managed lane facilities, as well as the exploration of a modeling framework that could better facilitate the policy and investment decisions for managed lanes.

1.2. Research Needs and Problem Statement

In the presence of managed lanes, travelers may demonstrate varying levels of willingness to pay to save travel time, or to improve reliability in travel time. Essentially, travel behavior emerges from the trade-off between travel cost and time/reliability of time. The trade-off can be reflected through two widely accepted parameters: value of time (VOT) and value of reliability (VOR). While a number of studies have focused on VOT and VOR in the past, there are large discrepancies in terms of the estimated values, which are generally attributed to the differences in the definitions, measurements, and modeling approaches adopted.

VOT represents the monetary equivalence of travel time savings. According to the theory of labor economics, “time” is a finite resource that can be used for work or leisure. Therefore, the value of “time” can be quantified at maximum equals to the wage rate and at a minimum equals to zero (Chiswick, 1967; Becker, 1965). Many empirical studies estimated VOT in terms of the average wage rate, and emphasized mainly the trade-offs between travel time and travel cost. This estimation process largely limited the scope of capturing the influence of traveler characteristics and travel characteristics on VOT estimation. Subjective assessments suggest that value of time depends on the attributes of a person's particular activity, and also the alternative activities that a person can be engaged in (DeSerpa, 1971; Shaw, 1992). Therefore, proper valuation of time should extend beyond the wage rate and incorporate influential factors on the overall time value of an individual. In order to understand how every individual values their time, there appears to be a massive vacant research space to fill. More research attempts are needed to find a proper estimation approach of time valuation.

VOR, similarly, represents the monetary value travelers place on reducing travel time variability. Since the inception of the term "reliability," the concept has gone through a process of evolution. In general, there are two approaches to defining reliability: reliability-based and variability-based. The first category defines reliability as the "probability" of non-failure over time and focuses on system performance evaluation and monitoring; whereas variability-based measures define reliability as the "unpredictability" of travel times and focus on travelers' perspectives (Elefteriadou and Cui, 2007). Originated from the differences in the definition of reliability, various measuring approaches and modeling techniques have been employed to quantify the value of travel time reliability. However, there are no standard practices developed yet in terms of defining and quantifying reliability, along with a formulated modeling framework, especially in the context of managed lanes. A clear picture is much needed, which will shed light on how to quantify reliability as a roadway pricing attribute through a formulated modeling framework, including the definition, measure, modeling approach, model structure, model development, and the overall estimation techniques.

Empirical studies revealed substantial variations in VOT and VOR estimations. Reported VOT estimates vary from $3.88/hour (Calfee and Winston, 1998) to as high as $47.50/hour (Patil et al., 2012B)), while VOR ranges between $2.31/hour (Tilahun and Levinson, 2010) and $68.90/hour (Asensio and Matas, 2008). In general, researchers attributed this variation to several aspects, including demographic characteristics, transportation alternative characteristics, and regional context. However, there is still a lack of uniform understanding on the underlying reasons for large variations, and the most suitable modeling approaches to quantifying VOT and VOR. An in-depth investigation is required to figure out the factors, which contribute to such a huge variation. In order to do that, every source of heterogeneity, either observed or unobserved, needs to be considered.

The user heterogeneity aspect of choice behavior is seldom incorporated into VOT and VOR studies to the full extent. Current practices usually assume single estimate of VOT and VOR to represent the entire population, or employ simple stratification (such as household income), which overlook the heterogeneity of preferences among the users. As a consequence, demand forecasting based on aggregate estimates are less convincing in terms of accuracy, reliability, and credibility. Proper identification of relative homogeneous user groups and targeted market strategies would greatly enhance modeling and planning decisions.

Moreover, most existing VOT and VOR studies explained travel behavior through observed characteristics (e.g., income, purpose, gender, etc.) only. These studies overlooked the unobserved characteristics (e.g., congestion tolerance level, attitude towards tolling, and on-time preference, etc.), which may have a significant influence on travel decision making. In addition to user heterogeneity, incorporation of unobserved characteristics into the modeling framework holds the potential to minimize VOT and VOR estimation variations and provide an appropriate treatment of discrepancies.

In light of the above discussion, it seems user heterogeneity and attitudinal aspects hold the potential to provide a realistic approach, which leads to identify potential reasons for VOT and VOR estimation variations, and provide a consistent approach that can estimate VOT and VOR in a more realistic, credible, and accurate manner.

1.3. GOALS AND OBJECTIVES

Given the above motivation, this study aims to clarify the intrinsic issues of time and reliability measurements that are responsible for the substantial variations in VOT and VOR estimates. Considering the prevailing deficiencies, the dissertation intents to contribute to the literature on facilitating the development of a comprehensive VOT and VOR estimation framework. In order to enhance the current estimation framework, two major dimensions of behavioral phenomena will be explored in the study, which are the user heterogeneity aspect and the attitudinal aspect. Herein, the dissertation will encompass two major objectives:

1. User Heterogeneity: VOT and VOR are usually estimated based on a specific study or within a specific context, for which the sample formation could be different for every study due to unique demographic, economic, geographic, and other associated factors. Therefore, heterogeneity among the users cannot be ignored in a VOT and VOR studies. However, the treatment of user heterogeneity needs to be appropriate in order to obtain accurate, reliable, and

credible VOT and VOR estimation. The objective of user heterogeneity analysis is to identify the influential factors for such variation from person to person and under different circumstances, and incorporate the factors to enhance behavior models. User heterogeneity is addressed through a variety of demographic and trip attributes.

2. Attitudinal Aspects: The majority of existing studies in VOT and VOR focus on the observed attributes, such as travel time, cost, income, departure time, and trip purpose. However, attitudes and perceptions also play an important role in choice behavior, especially in the context of managed lanes. This study will incorporate taste heterogeneity and latent preferences into the analysis framework to investigate whether and to what degree the attitudinal factors influence the propensity of using managed lanes. The study emphasized exploring travelers' attitudes toward congestion, tolling, and performance of managed lanes.

1.4. DISSERTATION ORGANIZATION

The rest of this dissertation is organized as follows: Chapter 2 will provide a nearly comprehensive review of the conducted research efforts in the field of roadway pricing, with an emphasis on VOT and VOR, along with the attitudinal aspect. Chapter 3 focuses on the stated and revealed preference data used in the study. Descriptive statistics for both observed and unobserved characteristics are also presented in this chapter. Chapter 4 provides the research methodology, which presents modeling approaches for both user heterogeneity and attitudinal aspects. Appropriate modeling tools are investigated for VOT and VOR estimation. Chapter 5 presents the results of the developed models. Mixed logit models are developed to identify the impact of user heterogeneity on VOT and VOR estimation, while multinomial logit models are adopted to capture the impact of the attitudinal aspect on VOT and VOR estimation. Finally, Chapter 6 provides general conclusions and further research opportunities.

CHAPTER 2

LITERATURE REVIEW

2.1. INVESTIGATING VALUE OF TIME

Probably no one would disagree with Benjamin Franklin that Time is Money. However, to put a price on time is not an easy task. In the past several decades, numerous studies have attempted to quantify the value of time. Some treated time as a resource/constraint, others as a commodity, or both. Earlier studies tend to associate VOT with hourly wage rate, while the concept of VOT has evolved later on from the sense that value is not inherent but subjective, meaning that value of time would depend on the attributes of the activity, as well as the alternative activities that a person could be engaged in.

Across the literature, another term has been widely used indicating the valuation of time, which is Value of Travel Time Savings or VTTS. Strictly speaking, VTTS would be more specific in the context of tolling representing the willingness to pay to reduce travel time, while VOT could be more generic representing the time allocation trade-off among alternative activities (including the time it takes to participate in the activities). For the purpose of this research, which is focusing on the impacts of managed lanes, both terms are treated the same.

2.1.1 Definition of Value of Time

VOT represents the monetary equivalent of travel time savings. Most studies defined VOT as the marginal rate of substitution between travel time and cost, where VOT can be derived as the ratio of the coefficient of travel time to the coefficient of cost obtained from choice models (Calfee and Winston, 1998; Lam and Small, 2001; Ghosh, 2001;

Hensher, 2001; Liu et al., 2004; Small et al., 2005; Brownstone and Small, 2005; Liu et al., 2007; Li et al., 2010; Tilahun and Levinson, 2010; Devarasetty et al. 2012A; Batley and Ibanez, 2012; He et al. 2012; Carrion and Levinson, 2013).

VOT represents a subjective marginal benefit of time spent in a certain activity. It does not necessarily depend only on any particular activity; it may be influenced by the next available alternative activity (Concas and Kolpakov, 2009). Possible time engagement on alternative activity is being referred as the opportunity cost of time. An individual's decision to participate in any particular activity or switching from one activity to another depends on the marginal utility level. That means individuals may value time differently at different times.

2.1.2 Measurement of Value of Time

VOT has been measured in reference to wage rate. Average wage rate has been used traditionally as a 'proxy' for value of time. According to Gronau (1976), average wage rate provided only 'crude' approximation of VOT and the estimation based on average wage rate exhibited substantial variation. Cherlow (1981) listed various studies where VOT estimates varied from 9% to 140% of the traveler's wage rate. Shaw (1992) indicated that VOT can go up to be equal to the wage rate at maximum and equal to zero at minimum. While Jara-Diaz (2002) asserted that VOT could be significantly higher or lower than the wage rate depending on the importance of activities. VOT estimated by Sheikh et al. (2014) exceeded the Atlanta's average wage rate. In a recent study, Devarasetty et al. (2012B) found VOT as 63% of average wage rate. FDOT (2000) estimated VTTS at 49% of average wage rate in Miami. The general rule of thumb for VOT estimation is to use 50% of wage rate but in the case of managed lanes, it tends to be higher.

Alternatively, less variation was observed when applying marginal wage rate instead of average wage rate. Therefore, marginal wage rate is preferred as more accurate measurement of VOT than average wage rate. However, marginal wage rate was not directly observable and can be attributed by different marginal utility/disutility related to work and travel (Concas and Kolpakov, 2009).

Other studies have raised an interesting perspective on whether the estimated VOT represent the true value that travelers place on travel time savings, since other trip attributes (such as comfort, convenience, and personal preference) may also contribute to the willingness to pay. For example, Devarasetty et al. (2013) found that 6% of the travelers choose tolled lanes during mid-day period, which implied that some travelers would choose tolled route even though there is little congestion on toll-free route. Those travelers were actually paying for the comfort in driving environment, not for travel time savings. According to Hensher (1976), most empirical studies failed to separate the pure value of time from other benefits brought by the tolled lanes, such as comfort and convenience.

Another factor that may complicate the estimation of VOT could be travelers' perceptions. Travelers make travel decisions based on estimation or the perceived travel time savings, which may not be accurate. A study found that, HOT users actually overestimate their time savings by an average of 11 minutes (Devarasetty et al., 2013).

2.1.3 Modeling Value of Time

This section discusses different approaches, modeling structures, as well as market segments and key variables that have been employed in the estimation of VOT.

2.1.3.1 Modeling Approach

The first attempt to quantify VOT can be dated back to the 1960's, when Beesley (1965) proposed a framework for the economic appraisal of transportation projects. Beesley measured VTTS in a study where the binary choice between two public transportation modes are modeled through the evaluation of two attributes – travel time and travel cost. Depending on the difference of travel time and travel cost between two alternatives, four options were offered to the travelers – more expensive and quicker alternative, more expensive and slower alternative, less expensive and quicker alternative, and less expensive and slower alternative. Finally based on a graphical representation of the survey data, the study identified travelers into two categories – traders, who found one alternative better on one attribute (either travel time or travel cost) and worse on another attribute (either travel cost or travel time), and non-traders who found both attributes were either better or worse for both alternatives. VTTS was estimated based on the extent of trade-off between travel time and travel cost.

Later on, discrete choice modeling techniques have been applied in estimating VOT, although the basic concept of VOT remains the same. In choice models, travelers exhibit preferences among alternative travel routes, modes, or departure time choice, which involve a trade-off between higher monetary costs and lower travel time costs or lower monetary costs and higher travel time costs. The choice preference provides a direct indication of how much the travel time savings worth to the travelers.

A different modeling approach was undertaken by Li et al. (2009), where they proposed a single estimation to account for both travel time and travel time variability. While traditional choice modeling based on utility maximization theory usually employs linear utility specifications, Li et al. (2009) extended the theory in two stages - non-linear utility specification with linear probability and non-linear utility specification with non-linear probability weighting function. This model can accommodate observed variability in travel time for a specific trip and the associated likelihood of such variation in a more sensible way.

2.1.3.2 Model Structure

Bivariate logit /probit models have been used in many VOT studies with two alternatives (Lam and Small, 2001; Brownstone and Small, 2005; Tilahun and Levinson, 2007, 2010). In the cases with multiple alternatives, multinomial logit model structure has been widely used (Li et al., 2009). For example, VOT value was obtained by multinomial logit model for a feasibility study of a proposed road corridor in Florida (RSG, 2013).

More recently, mixed logit (ML) models have been gaining popularity in studies for VOT estimation. ML is considered as a powerful discrete choice modeling technique as it can incorporate both potential observed and unobserved user heterogeneity in the models. Several studies applied mixed logit modeling techniques in the context of route choice ((Liu et al., 2004; Small et al., 2005; Liu et al., 2007; Asensio and Matas, 2008; Li et al. 2010; He et al., 2012; Carrion and Levinson, 2012). Some studies also adopted mixed logit model structure in mode choice modeling (Ghosh, 2001; Devarasetty et al., 2012A). Hensher (2001) tested three model structures (multinomial logit, mixed logit –normal distribution, mixed logit –lognormal distribution). Batley and Ibanez (2012) modeled three different sources of randomness in Random Utility Model (RUM) namely preference orderings, outcomes, and attribute tastes using mixed Logit models.

Besides studies that focused on pricing/tolling choices, the influence of time on transportation-related choices was frequently observed in other studies such as residential location choice, activity participation etc. Residential location choice substantially affects the extent of travel cost, which increases as commute distance increases. When studying the trade-off between housing and commuting cost, Hochman and Ofek (1977) observed the influence of VOT in location choice using Partial Equilibrium model where time was considered as a constraint in the framework of consumer choice. Yamomoto and Kitamura (1999) formulated a discrete-continuous model to capture time allocation for discretionary activity. Participation in discretionary activities was captured by a doubly-censored (two limit) Tobit model structure, where a utility model was formulated as a function of the amount of time spent in the activities. Meloni and Loddo (2004) conducted a similar type of discretionary time allocation study, but their discrete-continuous model was nested-tobit instead of doubly censored tobit with similar specification for utility model. In the context of activity participation, Kockelman (2001) measured VOT via a multivariate negative binomial model structure, where the demand for activity participation was marginally represented by a negative binomial. The model described household preferences over activity participation and captured travel related trade off in a time-price setting.

Sheikh et al. (2014) estimated VOT without applying any discrete choice modeling techniques. They estimated aggregated travel time savings and aggregated toll amount separately. VOT was calculated as the ratio of the toll cost and travel time savings for different user groups based on the frequency of facility usage.

2.1.3.3 Key Data Variables

Key data variables used for VOT estimation are summarized in this section. The variables were classified into four categories – household variables, demographic variables, work variables, and trip variables.

Household Variables: annual household income, language, number of cars shared by the household, worker per vehicle, household type (single/two worker household), household size, number of vehicles in the household, number of children in the household, years at current home etc.

Demographic Variables: Education, age, race, gender, occupation, marital status, home owner, age Between 45 - 55, age between 35-55, and Dummy variable for professional etc.

Work Variables: Flexibility of work arrival time, work-hour flexibility, Years at current work etc.

Trip Variables: Congested travel time, uncongested travel time, expected driving time, travel cost (running cost and toll cost), dummy variable for truck allowance, trip distance, distance squared, trip purpose, impact of radio traffic reports, usual commute mode, car occupancy, travels by the carpool, fare, scheduled journey time, mean lateness at destination, mean earliness at destination, dummy variable for previous usage of specific route, dummy variable for the survey design technique etc.

Calfee and Winston (1998) applied interaction effect of income with other variables in their model to investigate the impact of income on VOT estimation. Interestingly, several studies estimate VOT without considering any socio-economic characteristics (Noland and

Small, 1995; Hensher, 2001; Li et al., 2010; Batley and Ibanez, 2012; He et al., 2012; Sheikh et al., 2014).

2.1.3.4 Market Segments

As VOT values may vary from person to person and under different circumstances, the focus of this section is to identify the influential factors for such variation.

Person level VOT variation can be attributed to traveler characteristics – income, gender, previous congestion experience, person type, frequent user etc. VOT has a direct association with income and high income traveler is expected to prefer travel alternatives that offer less travel time in exchange of higher travel cost. However Calfee and Winston (1998) found that; high-income commuters, having adjusted to congestion through their modal, residential, workplace, and departure time choices, simply did not value travel time savings enough to benefit substantially from tolls.

Travelers' previous congestion experience can influence travel decision making. Tilahun and Levinson (2007) separated travelers into two categories – early/on time arrival from previous experience and late arrival from previous experience. During the afternoon hours and off-peak hours, the travelers who had bad experience before exhibited higher VOT estimates.

VOT may also vary by gender, since male and female have different types of household responsibilities. Ghosh (2001) explored the influence of gender over VOT estimation and found that female travelers were more likely to use tolled facilities.

Li et al. (2010) estimated VOT for commuters and non-commuters and found that non-commuters had lower values of travel time savings (by 60%) than commuters.

Sheikh et al. (2014) grouped traveler into different category based on the frequency of the toll facility usage – infrequent user, frequent user, and very frequent user. Highest travel time savings was found for infrequent user group along with lowest VOT estimates, which implied that they were more selective on toll facility use and interested only when the benefits are higher than average.

Travel-related attributes that may have influence on VOT include time of day, day of week, trip urgency, trip purpose, ad trip distance, etc.

VOT varies substantially by time of day. For example, VOT is usually high for morning trips compared with traveling at any other time. Liu et al. (2007) estimated VOT for every half an hour between 5 a.m. to 10 a.m.. A consistent increase in VOT value was observed from 5 a.m., which reached the peak value at 7:00 -7:30 a.m., and then consistently decreased afterwards. Devarasetty et al. (2012A) estimated VOT in three different time of day periods (shoulder hours, peak hour, and off-peak hours) for both directions of the facility (eastbound and westbound) and found that VOT not only varied by the time of day but also by the direction of travel.

Day of week can influence VOT estimation also. He et al. (2012) estimated VOT across different weekdays. The result showed that, travelers placed higher VOT on Fridays than any other weekdays.

Travelers placed a much higher value on their travel time, when faced by an urgent situation. Patil et al. (2011) measured VOT for six different travel situations, with different urgency levels. The hypothesis was that, traveler's VOT would be higher in urgent situations than in ordinary situations. They found that based on the urgency level, a trip could have been valued three times more than a regular trip.

Trip purpose and travel distance also influence VOT estimation. Batley and Ibanez (2012) estimated mean and median value of journey time for two travel distance levels (short and long) and three purposes (business, commute, and other). They defined reliability ratio as the value of standard deviation of journey time to the value of the scheduled journey time and found higher estimates for long distance trips compared with short distance trips in case of business and commute trips.

2.1.4 Summary for VOT Estimation

Table 2-1 below provides a summary of existing studies in VOT estimation. Modeling approach, model structure, market segments employed (if any), and major findings are presented in the table.

Table 2-1 Synthesis of Value of Time Studies

Study	Modeling Approach	Model Structure	Segmen t	Findings

Jackson and Jucker (1982)	Traveler preferences over alternatives of mode and route choices were analyzed based on mean-variance approach. With the help of linear programming, a set of weights were developed for the various attributes that optimizes the model.	Linear program (LINMAP)		Mean travel time (related with VOT) should be included as part of the impedance function for both route choice and mode choice modeling process.
Noland and Small (1995)	The study optimized the cost function for morning commuters based on the assumption that, commuters face a probabilistic distribution of travel time and choose departure time to minimize an expected cost function. Travel time was divided into two components - time varying congestion component and random element specified by a probability distribution.	An expected cost function were developed and optimized.		For optimization of cost function, value of time was assumed as $6.40 per hour.
Calfee and Winston (1998)	13 route alternatives described by the congested and uncongested travel time, the travel cost (usually in the form of a toll), and an indication of whether trucks were allowed on the road.	Rank-ordered logit model	Two segments were observed in this study - income and urban area	Estimated mean VOT as $3.88 per hour, which is 19% of hourly wage. According to this study, high-income commuters, having adjusted to congestion through their modal, residential, workplace, and departure time choices, simply did not value travel time savings enough to benefit substantially from tolls.
Lam and Small (2001)	Five different combination of choice modeling has been performed - route choice alone or joint modeling of route choice with time of day/mode/transponder.	Binomial logit model		Joint model of transponder, mode, and route choice estimates VOT as $22.87 per hour, which is 72% of average wage rate. Significant factors for transponder installation are - income, gender, and language; whereas work-hour flexibility and trip distance influence route decision.

Table 2-1 Synthesis of Value of Time Studies (continued)

Study	**Modeling Approach**	**Model Structure**	**Segment**	**Findings**

Ghosh (2001)	Five mode alternatives - a) Free lanes, solo driver, no transponder b) Free lanes, solo driver, with transponder c) Express lanes, solo driver, with transponder d) Express lane, carpool, no transponder e) Express lanes, carpool, with transponder. Observed heterogeneity has been expressed as a function of demographic characteristics and travel attribute.	conditional logit, nested logit, heteroscedastic extreme value, and mixed logit models	VOT was estimated for morning and afternoon commute.	Mixed logit model estimates mean VOT as $20.27 per hour. This study found that VOT estimates using SP data are significantly lower than estimates using RP data. According to this study, high income, middle aged, homeowners, female commuters are more likely to use tolled facility.
Hensher (2001)	Cost attributes were assigned as fixed parameters, while travel time as well as VTTS was considered as random parameter. The alternatives are defined by six attributes; four related to expected driving time (free flow time, slowed down time, stopped/crawling time, uncertainty allowance) and two related to costs (running cost and toll cost).	Three models of varying degrees of disaggregation of time and cost MNL and RPL with two distributions for the random parameters - normal and lognormal.		Mean VTTS was estimated from MNL as $8.69/hr, from RPL (normal) as $9.38/hr, and from RPL (lognormal) as $9.42/hr. For normal distribution, median VTTS equals to the mean VTTS but for lognormal distribution they were different. In general, VTTS was likely to be estimated in MNL models compared with mixed logit model.
Liu et al. (2004)	Route choice utility functions included travel time and toll cost measures	mixed logit model		The median value of the time was $12.81. This study suggests that, travelers valued more highly a reduction in variability than in the travel time savings. However, substantial heterogeneity was observed in case of VOT.

Table 2-1 Synthesis of Value of Time Studies (continued)

Study	Modeling Approach	Model Structure	Segment	Findings

Small et al. (2005)	Route choice between tolled route and toll-free route	Mixed logit model		For RP data, median VOT was $21.46 per hour and for SP data, median VOT was $11.92 per hour. Therefore, RP data provided higher estimates for VOT than SP data.
Brownstone and Small (2005)	Morning commuters route choice between tolled and toll-free route. These choices were independent from the mode choice of public transportation, since the corridor accommodated very little public transportation.	Binary logit model		This study found VOT between $20 and $40 per hour. VOT estimated from RP data were at least twice of the estimates from SP data.
Liu et al. (2007)	A time variable was included in the utility functions to capture the time dependency of VOT. Two approaches for parameter estimation –Monte Carlo simulation & genetic algorithm, estimates observed from loop detector data.	Mixed logit model	Time of day	This study found greater median VOR than median VOT in the early morning (5:00 - 7:00) period and the reverse in the later period (7:00-9:30). Median VOT values varied within the range of $6.82 - $27.66 per hour.
Asensio, and Matas (2008)	Schedule delay early or late were included into the utility function for route choice modeling.	Random utility theory		VOT of 14.1€/h, or 77% of average wage rate, was obtained, which was significantly lower than VOR. This study reported high income and educational level as the reason for higher estimation of VOT.
Li et al. (2009)	Three different utility functions for route choice modeling. Utilized non-linear utility specification with linear and non-linear probability.	Multinomial logit model (MNL)		The mean REVTTS values estimated from the three models were $16.95, $17.95, and $19.08 respectively.

Table 2-1 Synthesis of Value of Time Studies (continued)

Study	**Modeling Approach**	**Model Structure**	**Segment**	**Findings**

Li et al. (2010)	Individual trade-off between different levels of trip time variability and various levels of proposed tolls was captured through route choice modeling using both Schedule Model and Mean-Variance model. Travel time and toll parameters were assumed as random parameters in the utility function.	Multinomia l logit and mixed logit model.	Commuters and non-commuters.	Based on schedule model, the mean estimate for VOT was $30.04 per hour. And based on mean-variance model, the mean VOT was $28.28 per hour. The findings suggest that, non-commuters had lower values of travel time savings (by 60%) than commuters. Like other studies, mixed logit provided better model fit compared to multinomial logit model.
Tilahun and Levinson (2007)	Reported flexibility on arrival time was included in the utility function. The alternative choices were whether to use the toll lane or toll free lane.	Random parameter logit model (Binomial logit)	Six categories based on time of day (morning peak, afternoon peak, off-peak) and previous experience (on-time, late), for subscribers and nonsubscribers (MnPass) separately.	VOT estimation varied from $9.54 to $25.43 per hour. Significant differences between on-time and late arrival was observed only for afternoon trips. The hypothesis was that, those who had delayed experience before would have higher willingness to pay than others. Significant differences in VOT estimations were observed between subscribers and non-subscribers of the facility (MnPass)
Tilahun and Levinson (2010)	Three different utility functions were developed based on the reliability measure for route choice modeling. Personal heterogeneity were captured through a random parameter.	Binomial logit model		VOT values varied based on how reliability has been defined and included in the utility functions in addition to travel time and costs. Three different values observed for VOT, which were $7.44, $8.07, and $7.82.

Table 2-1 Synthesis of Value of Time Studies (continued)

Study	Modeling Approach	Model Structure	Segment	Findings
Patil et al. (2011)	Captured preference heterogeneity. Four travel mode alternatives (combination of managed lane usage and vehicle occupancy) were given with different urgency levels. Travel time coefficients were assumed to have triangular distribution, whereas toll coefficients were assumed to be fixed but include two dummy variables to capture the observable heterogeneity in the toll. Two separate marginal utility equations were used to specify the parameters for the time and toll.	Mixed logit, Multinomial logit.	This study measured VOT for six different travel situations, which were urgent in some extent. The hypothesis was that, traveler's VTTS would be higher in urgent situations than in ordinary situations.	Travelers placed a much higher value on their travel time, when faced by an urgent situation. The mean VOT estimated for urgent trip varied from $8 - $47.5; compared to $7.4 - $8.6 per hour for ordinary trips. According to the study; since the VOT varied based on trip urgency, people from lower or medium income group could have higher valuation of time than high income people in an ordinary situation.
Devarasetty et al. (2012A)	Travel time and toll parameters were assumed as random parameters in the utility function. The hypothesis was that, each individual choose a mode alternative (combination of managed lane usage and vehicle occupancy) in a choice set that maximizes his/her utility.	Mixed logit model.	East-bound Vs West-bound measure of VOT by time of day (shoulder hours, peak hours, off-peak hours).	This study examined if travelers were using the managed lane in the same extent as they stated before opening managed lane and confirmed that they were actually using the facility in the anticipated manner. Mean VTTS was estimated as 48% of the sample hourly wage rate, which is $28 per hour.
Batley and Ibanez (2012)	Three different sources of randomness in Random Utility Model (RUM) namely preference orderings, outcomes, and attribute tastes were modeled in this study.	Mixed logit.	Six segment - combination of two distances (short and long) and three purpose (business, commuting, and other).	This study estimated mean value of schedule journey time as 25.62 pence/min and median value of schedule journey time as 18.55 pence/min.

Table 2-1 Synthesis of Value of Time Studies (continued)

Study	Modeling Approach	Model Structure	Segment	Findings
He et al. (2012)	Route choice model with utility function including travel time, travel time variability, and out of pocket cost. Preference heterogeneity was captured through random coefficients. This study applied 'instantaneous' travel time, which includes travel time of all segments, when the vehicle enters into the system.	Mixed Logit Model. Simulated maximum likelihood estimation (SMLE) technique was applied.	Weekday (Monday, Tuesday, Wednesday, Thursday, Friday)	Travelers placed higher VOT on Friday than any other weekdays. In addition, the mean VOT was always smaller than VOR for any weekdays.
Carrion and Levinson (2013)	Utility functions for route choice model included travel time and toll cost measures.	Random utility model (mixed logit model)	Total six segments - two centrality measures (mean and median) and three dispersion measures (Standard deviation, shortened right range, and interquartile range).	Estimated VOT values were almost similar for six models $9.15, $7.92, $7.31, $7.77, $7.30, and $7.31. However in case of Median/standard deviation and Median/Inter-quartile range, confidence interval included $0.00 as a possible value.
Sheikh et al. (2014)	No choice modeling was performed in this study. The travel time on the corridor was calculated based on the difference between the timestamps of two detections.		Frequency of facility usage - infrequent user, frequent user, and very frequent user. Both AM peak and PM peak.	Median VOT was reported for Morning Peak - $36/hour & Evening Peak - $26/hour. Estimated VOT were greater than the hourly average wage rate.

2.2. INVESTIGATING VALUE OF RELIABILITY

Travel time saving is widely accepted as one of the most critical factors in the forecasting and appraisal studies of transport projects. Recent empirical studies suggest that travelers also place significant value on the reliability of the transportation network in addition to travel time. The impact of reliability on travel behavior is crucial. Therefore, reduction in travel time variability has been included as a major source of benefit in benefit-cost analysis of transportation projects. Some countries around the world already recognized the importance of a reliable transportation system. For example, Netherlands, Australia, UK government regarded improving travel time reliability as one of the top most priority for their transport ministry.

Travel time variability imposes uncertainty over the scheduled arrival time at respective destinations. There are many factors that could result in variations or uncertainties in travel time. A few to be mentioned are - differences of vehicle mix on the network, differences in driver reactions under various weather and driving conditions, differences in delays experienced by different vehicles at intersections, random incidents (vehicle breakdown, signal failure) etc.

The following sections will focus on different aspects of Value of Reliability – definition, measurement, modeling approach, model structure, and key data variables.

2.2.1 Definition of Reliability

Travel time variability is an integral feature of transportation systems, which incurs additional cost and uncertainty for travelers. Similar to VOT which is defined as the monetary value travelers place on travel time savings, value of VOR can be defined as the monetary value travelers place on reducing travel time variability.

Since the inception of travel time reliability, the concept has gone through a process of evolution. Micro-economic theory defines VOR as the marginal rate of disutility between travel time reliability and out-of-pocket toll cost. Several studies assumed variability as the source of disutility (Jackson and Jucker, 1982; Pells, 1987; Black and Towriss, 1993).

There are several ways to define travel time reliability. Elefteriadou and Cui (2007) separated travel time reliability definitions into two main categories: reliability based and variability based. First category defines reliability as the probability of non-failure over time, whereas variability based measures defines reliability as the 'unpredictability' of travel times.

Few example definitions of travel time reliability have been listed below.

- National Cooperative Highway Research Program defines travel time reliability as a measure of variability that can be measured using the standard deviation of travel time (Cambridge Systematics, 1998).
- Federal Highway Administration defines travel time reliability as the consistency or dependability in travel times, as measured from day-to-day and/or across different times of the day (TTI, 2006).
- Florida Department of Transportation defines reliability as the percentage of travel that takes no longer than the expected travel time plus a certain acceptable additional time (FDOT, 2000).
- Center for Urban Transportation Research, CUTR defines reliability as the percent of trips that reach their destination over a designated facility within a given travel time (or equivalently, at a given travel speed or higher (Concas et al., 2009).
- The Texas Transportation Institute (TTI) Urban Mobility Report makes a distinction between variability and reliability of travel time. Variability is

refers to the amount of inconsistency of operating conditions, while reliability refers to the level of consistency in transportation service (TTI, 2003).

2.2.2 Measures of Travel Time Reliability

Across the literature different definitions of reliability have been introduced which eventually leads to different reliability measures. Three general approaches in measuring travel time reliability have been found in the literature, which are – mean-variance, scheduling delays, and mean-lateness.

Mean-variance approach assumes that travelers seek to maximize the option's return while minimizing the associated risk. Most of the reliability measures of this category are concerned with the distribution of travel time. Jackson and Jucker (1982) first applied the concept in transportation contexts, where the objective function minimizes the sum of the two terms - expected travel time and the travel time variability of the trip. The expected travel time refers to the centrality measure (e.g., mean) of the travel time distribution. The travel time variability refers to the dispersion measure (e.g., standard deviation) of the travel time distribution.

Several empirical studies applied mean-variance measures to estimate value of travel time reliability (Ghosh, 2001; Liu et al., 2004; Small et al., 2005; Brownstone and Small, 2005; He et al., 2012; Carrion and Levinson, 2013). These measures include:

- Mean travel time
- Median travel time
- Mode travel time (most frequent travel time)
- Standard deviation of travel time

- Variance of travel time
- Co-efficient of variance of travel time
- Inter-quartile range (75th % - 25th %) of travel time
- 90th % - 50th % travel time
- 80th % - 50th % travel time
- 90th % - Instantaneous travel time

To facilitate reliability measure comparison between travel corridors with different length, the percentile travel time difference needs to be normalized by the mean or median of travel time. In the presence of outliers, median travel time is preferred over mean travel time. Lam and Small (2001) found that application of median instead of mean, and the difference between percentiles instead of standard deviation improve the log-likelihood ratio of the model.

Schedule delay approach stands in accordance with departure time adjustment, which is the most common response from travelers facing a transportation network that offers variable travel times. Schedule model considers disutility incurred by not arriving at the preferred arrival time (PAT), either early or late. Delay is defined as the difference between the PAT and the actual arrival time. Mahmassani and Chang (1986) found that, when the arrival is more than 5 minutes away from the PAT, it incurs schedule disutility.

Several empirical studies applied the mean-variance approach to measure travel time reliability (Noland and Small, 1995; Lam and Small, 2001; Asensio and Matas, 2008; Li et al., 2010). Reliability measures of this category are related to the preferred travel time. The measures include:

- Actual late arrival – Usual travel time

- Early arrival time – Preferred arrival time
- Late arrival time – Preferred arrival time

Mean-lateness approach was proposed by the Association of Train Operating Companies (Towriss, 2005). The framework is becoming standard for analyzing passenger rail transport especially in the UK. Mean-lateness consists of two elements: schedule journey time, and the mean lateness at destination. Schedule journey time refers to the travel time between the actual departure time and the scheduled arrival time, and means lateness refers to the mean of the lateness at destination. The difference between scheduling model and mean lateness model is that mean lateness model considers only the scenarios of being late at both the departure and destination relative to the scheduled timetable; while the scheduling model addresses both early and late arrival with respect to the preferred arrival time.

Batley and Ibanez (2012) extended Towriss's (2005) model by adding train fare and the mean lateness at the boarding station. Reliability measures of this category are listed below:

- Schedule journey time
- Mean lateness at destination
- Standard deviation of the in vehicle journey time

In the case of departure time choice modeling, schedule delay approach is the most appropriate and convenient to apply. Hollander (2006) explored the mean-variance approach and stated that it was inappropriate for modeling departure time choice, following the underestimation of VOR measurement. Asensio and Matas (2008) explored both approaches separately as well as in combinations and were in favor of the schedule delay approach.

Bates et al. (2001) argued that schedule delay approach is suitable only when the passengers are able to adjust departure time continuously and therefore, not suitable in the context of public transport as departure time choice is discrete and constraint by fixed time table offered by public transport. However, Hollander (2006) was able to measure VOR through schedule model in context of public transport (bus).

Therefore, mean-variance and schedule delay are the two most common reliability measures. When information on preferred arrival time is available, schedule delay approach is preferred. According to Bates et al. (2001), a mean-variance model can approximate a schedule model under some specific assumptions.

2.2.3 Modeling Value of Reliability

This section discusses various issues related to the modeling of VOR, including the approach, model structures, key variables, and market segments, etc.

2.2.3.1 Modeling Approach

Utility maximization is the most basic approach for modeling VOR. Rational travelers are expected to counter act variability of travel time by choosing the travel options (route/mode/departure time) which offer lowest disutility or highest utility. Trip making has been considered as a disutility from traveler's perspective, since any travel incurs costs (travel time or monetary cost). Disutility functions are comprised of two parts – deterministic disutility and stochastic disutility. Deterministic disutility accounts for the observed disutility of the travel and are derived as the linear multiplication of the cost vector and parameter vector. In most of the studies, the cost vector includes three different types of cost – travel time cost, travel time variability cost, and out-of-pocket monetary cost. Travelers may have different preference to these three costs based on the travel circumstances. These preferences are related to the stochastic disutility and can be captured by a random term which is generally unknown.

Most studies in VOR estimation encountered the choices of route and/or mode. Several studies estimate VOR through route choice modeling (Liu et al., 2004; Small et al., 2005; Brownstone and Small, 2005; Liu et al., 2007; Li et al., 2009, 2010; Tilahun and Levinson, 2010; He et al., 2012; Carrion and Levinson, 2013). Some other studies estimate VOR under the context of mode choice (Prashker, 1979; Jackson and Jucker, 1982; Ghosh, 2001; Devarashetty et al., 2012). In general, utility functions are specified for each route/mode alternative, where the cost vector of each alternative is different and travelers choose the alternative which offers the highest utility.

Another approach applied in VOR modeling is the safety margin approach. Travelers prefer to allocate a 'safety margin' between their average arrival time and work start time and reduce the probability of arriving late (Knight, 1974). Safety margin influences departure time choice, since it is a function of marginal utility of time spending at home, arriving early to work and arriving late to work. From traveler's perspective, they want to maximize their time spending at home and minimizing the frequency of late arrival. Safety margin helps travelers to achieve both objectives – allocation ensures timely arrival and magnitude of safety margin can optimize the time spending at home (Pells, 1987).

The safety margin approach has been applied in VOR modeling especially in the case of departure time choice modeling. To understand travelers' departure time choices, Small (1982) investigated "shifting peak" phenomenon where traveler's preferences over traveling under congested conditions or traveling at preferred time of day in presence of highly peaked congestion were modeled using econometric theory. The model revealed that traveler's decision on when to make travel was affected by the worker's official work hours, occupational and family status, work-hour flexibility, and car occupancy. Traveler's departure time choice modeling was further extended by Noland and Small (1995), where they consider 'uncertain' property of travel time. They formulated travel time as a summation of two components – time varying congestion component and a random component specified by a probability distribution and found that 'uncertain' component accounted for large proportion of morning commute cost. Hollander (2006) explored departure time choice in context of public transport users and found that bus users placed penalty for both early and late arrival to the destination with higher penalty for late arrival.

2.2.3.2 Model Structure

Various forms of logit structures for choice modeling have been applied in VOR estimation, including binomial logit, multinomial logit, conditional logit, nested logit, heteroscedastic extreme value (HEV) model.

Lam and Small (2001) applied binomial logit model for route choice and nested logit while modeling joint choices (route and mode, route and time of day). Ghosh (2001) explored several model structures - conditional logit, nested logit, mixed logit and heteroscedastic extreme value (HEV) in mode choice modeling.

Multinomial logit model has also been used extensively for VOR estimation. However the IIA (Independence from Irrelevant Alternatives) property of MNL model has limited its applications, especially to accommodate user heterogeneity in travel choices.

Mixed logit has been increasingly applied in reliability studies (Devarasetty et al., 2012A; Patil et al., 2011; He et al., 2011; Li et al., 2009; Liu et al., 2004; Carrion and Levinson, 2013; Lam and Small, 2001; Ghosh, 2001; Liu et al., 2007). The main assumption of mixed logit model is that the coefficients in the model are realization of random variables. This assumption generalizes the standard multinomial logit model (MNL) and allows the coefficient to vary with decision maker. The variable property of coefficients allows mixed logit model to conveniently capture user heterogeneity. A simulated maximum likelihood estimation (SMLE) technique can be applied for mixed logit model for coefficient estimation. Normal distribution is the most commonly accepted distribution for mixed logit models. Some studies applied log-normal distribution and triangular distribution to reveal motorists preference. Patil et al. (2011) showed that mixed logit model exhibits better model fit than multinomial logit model (MNL).

2.2.3.3 Key Data Variables

Key data variables in VOR estimation are classified into four categories – household variables, demographic variables, work variables, and trip variables.

Household Variables: Presence of Children, Number of children in the household, Household Size, Household Structure (single worker household, two worker household), Household Income (high income, low income), Language in the household, Number of Vehicles, Number of Worker per vehicle, number of cars shared by the household, Years at the current home etc.

Demographic Variables: Age, Language, Marital status, Occupation, Gender, Person Type, Education, Race, Home Owner, Proxy variable for wage rate, Degree of risk aversion, Age between 45-55, Age between 35-55, etc.

Work Variables: Employment location, Working in paid work, Work hours, Flexibility of work arrival times, Number of years at the current work, etc.

Trip Variables: Mode of travel, Total travel time, Door-to-door travel time, Trip purpose, Mean travel time, Median travel time, Standard deviation of travel time, Distance squared, 90th percentile of travel time – 50th percentile of travel time, Toll cost, Time of day, Day of week, Car occupancy, Probability of time of arrival, Impact of radio traffic reports, Travels by carpool, Dummy variable for alternate route usage, Dummy variable for alternate time of day choice, Fare, Schedule journey time, Mean lateness at destination, Mean earliness at destination, Lateness penalty, Per minute penalty for early arrival, Per minute penalty for late arrival, etc.

Some studies considered Flexibility of work arrival times or Work hour flexibility in choice models and found significant impacts especially in the case of morning commute (Small et al., 2005; Brownstone and Small, 2005; Lam and Small, 2001). Asensio and Matas (2008) found that restriction of arrival time to work place has a significant impact on VOR and applied market segmentation of commuters based on the extent of flexible entry time.

2.2.3.4 Market Segments

Similar to VOT, VOR values may vary from person to person and under different circumstances. The focus of this section is to identify the influential factors for such variation.

Person level VOR variation can be attributed to traveler characteristics: person type, gender, private car ownership etc. VOR estimation may vary based on car ownership characteristics of travelers. Prashker (1979) found that car users and transit users exhibit different patterns of reliability valuation.

VOR may vary by person type (e.g., commuters and non-commuters). Li et al. (2010) estimated VOR for commuters and non-commuters and found that non-commuters had lower values of reliability (by 46%) than commuters.

VOR may also vary by gender, since male and female may have different household responsibilities. Ghosh (2001) explored the influence of gender over VOR and found that female travelers were more likely to use tolled facilities. Lam and Small (2001) estimated VOR for men and women separately and found higher estimates for woman. The reasons for higher VOR of women may be attributed to the child-care responsibilities of women, which reduce their scheduling flexibility.

Trip specific characteristics, such as time of day, day of week, trip purpose, trip distance etc., are also found to have influence on VOR (Liu et al., 2007; Devarasetty et al., 2012A; He et al., 2012; Batley and Ibanez, 2012).

2.2.4 Summary for VOR Estimation

Table 2-2 below summarizes the studies in VOR estimation, in terms of reliability measures, modeling approach, model structure, key segments, and major findings.

Table 2-2 Synthesis of Value of Reliability Studies

Study	Measures	Modeling Approach	Model Structure	Findings
Prashker (1979)	21 attributes were considered for reliability measures. Importance scale of all reliability attributes were rated also.	Utility functions consist of multiple attributes including in-vehicle travel time, waiting time, and parking time. Mode choice was dependent on the level of satisfaction derived from many performance characteristics of the alternatives.	Homogeneous population groups were identified using a basic classification tool, MANOVA. Regression analysis was carried out over the attributes.	a) Reliability of out-of-vehicle activities is more important than in-vehicle activities, b) Reliability of finding a parking place on time is more important than in-vehicle reliability, c) Car and transit users exhibit different VOR, d) Gender had significant impact on VOR, and e) reliability is highly valued.
Jackson and Jucker (1982)	Five mean-variance measures: a) mode and STD of mode b) mode and variance of mode c) mode and STD d) mode and variance e) Mode and coefficient of variance	Traveler preferences over alternative mode and route choice were analyzed by minimizing the impedance function which included a non-negative parameter that represents the degree to which the variance of travel time was undesirable to any traveler.	Linear programming technique (LINMAP) was used, a set of weights were developed for the various attributes that optimizes model.	This study suggest that variance of travel time (related with VOR) should be included as part of the impedance function for both route choice and mode choice modeling process.
Noland and Small (1995)	schedule delay measure: Schedule delay early (SDE) and Schedule delay late (SDL)	Departure time choice for morning commutes through that analysis of two probability distributions (uniform and exponential).	An expected cost function were developed and optimized.	This study found that uncertainty associated with travel time accounts for the large proportion of the morning commute cost.
Ghosh (2001)	mean-variance measure, 90th % - 50th % travel time	Five alternatives between GP and ML combined with occupancy and the use of transponders.	conditional logit, nested logit, heteroscedastic extreme value, and mixed logit	Commuters are more sensitive to variations in travel time in the morning, especially during the peak, than in the afternoon.
Lam and Small (2001)	mean-variance measure, 90th % - 50th % travel time	Five different combination of choice modeling has been performed - route choice alone or joint modeling of route choice with time of day/mode/transponder	Binomial logit model	The estimated VOR for men is $15.12 per hour and for women is $31.91 per hour, which are 48% and 101% of average wage rate.

Table 2-2 Synthesis of Value of Reliability Studies (continued)

Study	Measures	Modeling Approach	Model Structure	Findings
Liu et al. (2004)	mean-variance measure,75th% - 25th% travel time	An indirect method, where coefficients were not estimated using maximum likelihood method, that applied genetic algorithm to identify the coefficients of route choice model that best match with loop detector data.	Mixed Logit Model	The median VOR was $20.63. This study suggests that, travelers valued the reduction in variability more than in the travel time savings. Substantial heterogeneity was observed in VOR.
Small et al. (2005)	mean-variance measure, 80th % - 50th % travel time	Route choice between tolled route and toll-free route	Mixed logit model	For RP data, median VOT was $19.56 per hour, much higher than that from the SP data, $5.40 per hour.
Brownston and Small (2005)	Mean-variance measure, 90th % - 50th % travel time.	Morning commuters' route choice between tolled and toll-free route. These choices were independent from the mode choice of public transportation, since the corridor accommodated very little public transportation.	Binary logit model	This study found that, reliability was being valued highly (not estimated in an exact amount). However, they were unable to isolate the substantial heterogeneity that existed among travelers.
Hollander (2006)	Mean-variance measure, standard deviation of travel times; schedule delay. Mean-variance approach seemed inappropriate and underestimated VOR.	Departure time choice for bus users, considering - minimize mean travel time, minimize travel time variability, depart as late as possible, minimize mean lateness, and minimize mean earliness.	For departure time - Ordered generalized extreme value (OGEV) and MNL (finally preferred).	Based on the scheduling approach; mean earliness was estimated 5.2 pence per minute and mean lateness was estimated 14.4 pence per minute. According to this study, bus users placed a similar penalty on the mean travel time and on early arrival to the destination; the penalty on late arrival was much higher.

Liu et al. (2007)	Mean-variance measure, 75th - 25th percentile.	Route choice model estimated VOR for every half an hour interval of morning commute. VOR was expressed as a continuous function of time. Genetic algorithm was used to identify the parameters that produce best match with loop detector data.	Mixed logit model	This study found greater median VOR than median VOT in the early morning (5:00 - 7:00) period and the reverse in the later period (7:00-9:30). Median VOR values varied within the range of \$17.49 - \$39.24 per hour. Within a small time interval, travelers exhibited consistency in terms of toll payment.

Table 2-2 Synthesis of Value of Reliability Studies (continued)

Study	Measures	Modeling Approach	Model Structure	Findings
Asensio and Matas (2008)	Explored three different types of reliability measures - mean variance, schedule delay, and combination of both.	Choice of route alternatives that differ in terms of monetary cost, travel time, travel time variability, and departure time.	Random utility theory	Delayed arrival time varied from 51.4 €/h to 21.0 €/h based on the flexibility of work start time. Early arrival time has been found significant only for fixed entry commuters, which is 9 €/h, as expected much lower than delayed arrival. Men and commuters with more children were more likely to choose tolled route.
Li et al. (2009)	VOR is measured as Standard Deviation of REVTTS using schedule delay framework.	Three different utility functions were used for route choice modeling. This study extended the utility maximization theory in two stages - non-linear utility specification with linear probability and non-linear utility specification with non-linear probability weighting function.	Multinomial logit model (MNL)	The mean REVTTS values estimated from the three models were \$16.95, \$17.95, and \$19.08 respectively. The empirical evidence suggest that, the extension of the utility function addressed individuals choice made under risk properly, although the model estimates were almost similar in terms of attitudes toward risk.
Li et al. (2010)	Mean-variance measure, standard deviation of the travel time; schedule delay measure	Individual trade-off between different levels of trip time variability and various levels of proposed tolls was captured for route choice modeling.	MNL and ML with triangular distributions (provided better fit than normal distributions).	For schedule delay approach, the mean estimate for schedule delay early was \$24.1 per hour and for schedule delay late was \$38.86 per hour. And based on mean-variance model, the mean VOR was \$40.39 per hour. The findings suggest that, non-

				commuters had lower values of reliability (by 46%) than commuters.
Tilahun and Levinson (2010)	Three measures for reliability were explored - moment of inertia (measured from the mode travel time), range coupled with lateness probability, and standard deviation.	26 route alternatives based on different combination of travel time distributions and toll cost. A random parameter was included into the model to account for personal heterogeneity.	Binomial logit model	Higher VOR value was observed for all three types of measures. Obtained VOR values were - \$7.44, \$2.31, and \$6.39 respectively. Reliability ratio implies that, reliability was valued 38% - 41% more than travel time.

Table 2-2 Synthesis of Value of Reliability Studies (continued)

Study	Measures	Modeling Approach	Model Structure	Findings
He et al. (2012)	Mean-variance measure, 90th % - the instantaneous travel time (which include travel time of all segments) on the general purpose lanes.	Route choice model with utility function including travel time, travel time variability, and out of pocket cost. Preference heterogeneity was captured through random coefficients.	Mixed Logit Model. Simulated maximum likelihood estimation (SMLE) technique was applied.	Travelers placed higher VOR on Friday than any other weekdays. In addition, the mean VOR was always larger than VOT for any weekdays.
Devarasetty et al. (2012A)		Travel time and toll parameters were assumed as random parameters. The hypothesis was that, each individual choose a mode alternative (combination of managed lane usage and vehicle occupancy) in a choice set that maximizes the utility.	Mixed logit model.	VOR was estimated as 56% of the sample mean hourly wage rate, which was \$33/hr. The study suggested that travelers subconsciously placed higher value for reliability than their estimated valuation.
Batley and Ibanez (2012)	Reliability ratio was estimated here as a measure of variability, which was the ratio of the standard deviation of journey time to the value of scheduled journey time.	The focus of this study was primarily on random variability (ex. Incident) rather than systematic variability (ex. Peak hour). Three different sources of randomness in Random Utility Model (RUM) namely preference orderings, outcomes, and	Mixed logit.	This study estimated mean reliability ratio as 2.07 and median reliability ratio as 0.85. Based on the distribution of the reliability ratio, this study inferred a predominant behavior of aversion to journey time risk.

		attribute tastes were modeled in this study.		
Carrion and Levinson (2013)	Mean-variance measures - standard deviation, shortened right range, and interquartile range (75th % - 25th %).	Choice for three route alternatives (Managed Lane Vs General Purpose Lane Vs Arterial Lane). To estimate confidence interval, parametric bootstrap approach was used.	Random utility model (mixed logit model)	VOR (average) values were observed as: $5.99, $4.25, $4.40, $11.31, $5.98, and $7.68. However in case of Median/standard deviation and Median/Inter-quartile range, confidence interval included $0.00 as a possible value. Woman placed significantly higher value on reliability compared with man.

2.3 Investigating Attitudinal Aspects of Pricing

Observed trip attributes and individual characteristics such as trip purpose, trip length, income, gender, and age are usually the major focuses of roadway pricing studies as influential factors. Due to the multidimensional subtle complexities in choice behavior, choice analysis requires adequate attention towards both observed and unobserved characteristics. While attitudinal attributes hold the potential to represent unobserved characteristics of the traveler, they have rarely been incorporated in roadway pricing analysis.

2.3.1 Implications of Attitudinal Aspects

Attitudinal aspects of travel behavior are originally derived from a psychological theory, known as theory of planned behavior (TPB). According to Ajzen (1991), intensions to perform actions of different kinds can be predicted with high accuracy based on attitudes toward those actions. Therefore, incorporation of attitudinal characteristics in travel behavior analysis is expected to provide the opportunity to increase the explanatory power of the models and reveal the intentions.

The focus of this dissertation is to analyze and evaluate the impacts of attitudinal parameters on drivers' propensity toward using managed lanes. As a relatively new concept of roadway pricing (introduced about two decades ago), managed lanes offer roadway users some appealing features, including travel time savings and reliability improvements (Burris et al., 2015). In particular, the literature suggests that travelers favor managed lanes over increasing or placing of tolls on expressways (Greene and Smith, 2010). With increasing emphasis on managed lanes strategies in the US, it is critical to understand the behavior changes and underlying causalities in responding to managed lanes, in order to evaluate the program impacts and effectiveness.

A number of studies were conducted in order to estimate traveler's sensitivity toward travel time, travel time reliability, and toll cost. In most cases, the sensitivity was estimated without considering the attitudinal aspects of individuals. Only few studies focused on exploring the propensity of managed lane usage based on unobserved characteristics. Devarasetty et al. (2012) and Larsen et al. (2013) considered several psychometric measures as the explanatory variables of managed lane usage, but the measures were found insignificant. Thus, previous efforts on addressing attitude were not sufficient. Given this context, this study aims to incorporate attitudinal variables (as indices of latent preferences) into roadway pricing analysis. The study will investigate whether and to what degree the attitudinal factors influence the likelihood of using managed lanes among drivers.

2.3.2 Applications of Attitudinal Aspects in Roadway Pricing

The literature in attitudinal applications in transportation planning can be broadly grouped into three categories – a) employed attitudinal factors as a set of explanatory variables, b) considered attitudes as an instrumental variable for market segmentation, and c) incorporated attitudes as latent variables in hybrid choice models (HCM) to make the model more realistic (Bolduc et al., 2008; Johansson et al., 2006; Kamargianni and Polydoropoulu, 2013). Although HCM is the most powerful behavioral modelling technique used to analyze attitudes/perceptions, the focus of this paper is to capture the influence of attitudinal factors on the propensity of managed lane usage which can be addressed using simple forms of logistic models.

The role of traveler attitudes and perceptions is often analyzed in mode choice contexts. Kuppam et al. (99) analyzed 40 attitudinal variables in order to capture the latent preferences of respondents toward any specific mode. They developed three multinomial logit models – model included only demographic and socio-economic variables, model included only attitudinal factors, and model included both type of variables. Likelihood ratio test of model results implied that contribution of attitudinal variables was nearly twice compared with the contribution of demographic variables. Namgung and Akar (2015) examined the influence of 39 attitudinal factors on public transportation (transit) usage. They developed two binary logit models – with and without consideration of attitudinal variables. Model comparisons indicated that the explanatory power of the model increased significantly when attitudes were included in the model. Van et al. (2014) analyzed 31 attitudinal responses from six Asian countries in a mode choice context with three options – car, public transport, and other modes (walking/motorbike/bicycle etc.). Attitudinal variables were incorporated into seven multinomial logit models – one combined model and six models for six countries. They identified barrier attitudes of using public transportation, and found that behavioral intention of using cars was strongly related to attitudes.

For analysis purpose, studies often require large amount of attitude information. In general, attitudinal responses were collected in a Likert scale or bi-polar adjective scale. The level of Likert scale varied across the studies from four levels, five levels, seven levels, to ten levels. To manage the large number of attitudinal variables, the most popular statistical technique to regroup homogeneous variables is factor analysis. The major objective of factor analysis is data reduction, where the main challenge is to identify the minimum number of factors that can explain most of the variances. The major criterions for selecting the number of factors include Eigen value (>1), minimum factor loadings, Cattell scree plot method (elbow point), and percentage of variance explained by the factors. Based on the criterions, Kuppam et al. (99) reduced 40 attitudinal variables into 8 meaningful factors, Van et al. (2014) found 3 distinct factors from 31 attitudinal statements, Shiftan et al. (2006) reduced 38 attitudinal variables into 7 meaningful factors, Chao et al. (2011) extracted 6 factors from 36 service attributes, Beirao and Cabral (2008) transformed 35 attitudinal questions into 8 factors, and Anable (2005) identified 17 meaningful factors from 105 attitudinal statements. No uniform requirements of minimum factor loading and the percentage of variances explained were observed in the studies. For example, Van et al. (2014) considered 0.4 and Chao et al. (2011) considered 0.5 as minimum factor loadings, whereas Kuppam et al. (99) accepted lower factor loadings (0.29). The ‘sign’ of factor loading may be negative also. Similarly, Van et al. (2014)’s study explained 52.6% variances, whereas Chao et al. (2011)’s model explained 66.70% of the total variance. To obtain distinct factors and minimize overlap across the factors, factor loading needs to be rotated. In the literature, principal component analysis was the most preferred factor analysis method, whereas Varimax rotation was the popular factor rotation method as it ensures that each factor has a small number of large loadings and a large number of small loadings. The name of any factor was defined based on the correlation among the variables included in a factor set. Factor scores against each observation were used to transform them into variables.

Another application of attitudinal data in transportation planning is market segmentation analysis. Some studies applied attitudinal data to identify distinct markets, mainly in public transportation usage. The process involved two stages – reduction of attitudinal dimension by either factor analysis or structural equation modelling (SEM), and assigns each observation to a corresponding factor through cluster analysis.

Attitudes were found to be influential in several behavioral aspects of transportation applications, including the perception regarding public transportation features, consciousness on vehicle emission reduction, assessment of a new transportation alternative, obligation to time saving and flexibility, and sensitivities to costs and stress (Parkany et al., 2005). Regarding roadway pricing, there are not enough empirical evidences on application of attitudinal data for travel behavior analysis. Some studies partially focused on quantifying the impact of attitudes on willingness to pay (WTP) estimation. For example, Abou-Zeid et al. (2010) and Lowery et al. (2011) quantified attitudinal impact on VOT (value of time), but ignored the attitudinal impact on reliability (VOR). In some cases, researchers claimed to address attitude in analyzing roadway pricing behavior, but they actually failed to separate the concept of ‘attitude’ from ‘preference’. Rather than analyzing latent characteristics, they were more focused with observed characteristics. Therefore, willingness to pay were influenced mainly by the observed characteristics, such as income, age, trip purpose, time of day, trip distance, and thereby did not reflect latent preferences. For instance, Li et al. (2002) identified potential managed lane users based on trip purpose, gender, age group, and income attributes. They did not consider any latent characteristics of the responder, rather assumed observed characteristics as attitudes. Similarly, Zmud et al. (2008) developed binary logit models for tolled facilities, but attitudes were only incorporated in survey design and respondent recruitment stage. In another study, Lowery et al. (2011) found that respondents in a suburban area who sensed congestion in upcoming years were more interested to use managed lane. However, sense of congestion is more like a perception rather than a behavioral attitude.

Based on a study in Edinburg (UK), Allen et al. (2006) showed that even a well prepared congestion pricing scheme can be rejected if the scheme failed to accommodate different attitudinal aspects of its potential users. Thereby, attitudinal aspects of behavioral modelling is reasonable and worth exploring from transportation planning perspectives. In light of above discussion, it can be inferred that many studies were conducted on estimating the impacts of attitudinal factors in the broad area of travel behavior analysis. A significant number of efforts were also given on estimating roadway pricing parameters, such as VOT and VOR (Carrion and Levinson, 2012). However, a distinct gap in the literature can be observed regarding the contribution of attitudinal factors on VOT and VOR estimation.

2.4 DATA USED IN VOT AND VOR STUDIES

Stated Preference (SP) and Revealed Preference (RP) are the two main data sources for VOT and VOR studies.

2.4.1 Stated Preference (SP) Survey

Stated preference survey is the major data source for the studies related to VOT and VOR estimation. Stated preference survey provides information related to travel time and reliability of travel time through hypothetical scenarios. The survey design accommodates both 'frequency' and 'magnitude' aspects of reliability. The main challenge is to present all the information in a concise but explanatory manner without causing cognitive burden to responder.

Bates et al. (2001) considered SP as the preferred approach for collecting travel time reliability data. However, Ghosh (2001), Hensher (2001), Brownstone and Small (2005), and Black and Towriss (1993) found that typical stated preference survey underestimate VOT compared with RP studies (approximately half).

Stated choice experiments dominate VOR study. In fact, Bates et al. (2001) argued that there were no adequate real examples at the level of detail required for ascertaining reliability estimates using RP data. They considered stated preference as the best bet. However, they admitted that survey design (i.e., presentation of questions) may affect the outcome of the reliability estimates. This is likely as travel time reliability is difficult to present to subjects without any statistical background unlike travel time savings.

The advantages of SP survey over RP survey data include: ability of predicting responses to new products, robust parameter estimation given sufficient variation in explanatory variables. Hypothetical bias is the major disadvantage of SP survey design, as the hypothetical scenarios presented in SP survey may not reflect actual choices.

One of the concerns related to SP survey is that it may produce biased estimates due to the subtle and nuances of the survey design. Several survey design techniques are available that can be applied in case of VOT and VOR estimation. For example - Db-efficient design, random attribute level generation design, and adaptive random design. However, not all the stated preference survey design techniques are able to estimate VOT and VOR properly. Devarasetty et al. (2012A) improved stated preference survey design techniques to better understand travel behavior of managed lane users.

Travel time variability can be presented to responder in a number of ways and therefore varied considerably across the literature. Each presentation techniques have their own strength and weakness. Major types of presentation techniques have been summarized below.

- Jackson and Jucker (1982) implicitly presented travel time variability as the 'extent' and 'frequency' of delay related to normal travel time. However, the presentation was not convenient for responder to fully understand and interpret specific features of the travel time distribution.
- Senna (1994), Noland and Small (1995), Small et al. (1999), Hollander (2006), Asensio and Matas (2008), and Batley and Ibanez (2012) presented a series of arrival times (5 or 10 levels) in their SP experiments to capture travel time variability.
- Hollander (2006) recommended travel time variability presentation through a series of travel time for each alternative. However, this approach may create cognitive burden for responders.
- Senna (1994) presented travel time reliability, where one route had no travel time variability on five occasions, while the alternative route had different levels of mean travel times and variability, along with cost.

- Batley and Ibanez (2012) presented two train travel options in terms of fare, scheduled journey time, the distribution of journey time and assumed equal probability for the alternatives.

Table 2-3 Summary of Stated Preference (SP) Survey

Study	Data Source
Prashker (1979)	SP survey from Chicago downtown area.
Jackson and Jucker (1982)	SP survey over the employees of Stanford University (214 sample size). The respondents were asked to choose the alternatives based on the information regarding usual time, possible delays, and frequency of delays.
Ghosh (2001)	Both RP and SP data were collected from a congestion pricing project on I-15, California. The panel study conducted five waves of SP surveys between Fall 97 to Fall 99. RP data was collected from loop detectors embedded in the roadway.
Small et al. (2005)	This study used combination of revealed and stated preference data from Los Angeles area.
Brownstone and Small (2005)	Both Stated Preference (SP) and Revealed Preference (RP) survey data were used in this study. Five different data sets were collected from two HOT lane projects of southern California.
Hollander (2006)	An internet based SP survey over bus users in the city of York, England in 2004. Two alternatives are presented to the responder - green bus and red bus, with a different departure and arrival time for different fare structure.
Asensio and Matas (2008)	SP data collected from the commuters of Barcelona (Spain).
Li et al. (2009)	SP survey in Australia
Li et al. (2010)	SP survey in Australia. Based on average travel time experienced, probability of time of arrival, and trip cost; respondents were asked to choose the route they would prefer.
Tilahun and Levinson (2010)	This study used a computer-administered stated preference (SP) survey to collect route preference data. All participants were employee of University of Minnesota's and recruited through email invitation for $15 incentive. To avoid unreasonable choices, tutorials were provided and two control questions were set up in the survey.
Devarasetty et al. (2012B)	SP survey data from pre-opening (2008) and post-opening (2010) of manage lane.
Batley and Ibanez (2012)	SP survey over 2395 rail travelers choosing between a pair of services on the basis of fare, scheduled journey time, and journey time variability.

- Bates et al. (2001) presented two train operators with different fares, different timetables, and different combinations of 10 possible arrivals in terms of the clock-face of cards for each alternative. The clockwise representation reduced cognitive burden for responders.

Tseng (2009) evaluated common travel time variability representation style - verbal description, clock face presentation, and vertical bar in order to investigate what extinct the respondents understood reliability concepts. Based on some key indicators, they found that verbal description presented by Small (1999) as the best practice of travel time reliability presentation. Table 2-3 presents the summary of SP surveys conducted in the context of VOT and/or VOR studies.

2.4.2 Revealed Preference (RP) Survey

Revealed preference (RP) data refers to the choice observed in actual situations. High Occupancy Toll (HOT) lanes are the major source for RP data. Therefore, there are only few revealed preference (RP) based empirical studies for analyzing VOR. Table 2-4 presents the summary of RP surveys conducted in the context of VOT and/or VOR studies.

- He, Liu, and Cao (2012) estimated VOT and VOR using revealed preference data based on a study of I-394 MnPASS program and found VOR is higher than mean VOT.
- Another RP study on Houston Katy Freeway (Devarasetty et al. (2012A)) used to estimate VOT and VOR. Their estimation implies that users put additional value on the reliability offered by managed lane.
- Lam and Small (2001), Small (2005), Brownstone and Small (2005), and Carrion and Levinson (2013) used RP data for VOR study. According to Lam and Small (2001), RP data may lead to statistically biased estimates since cost, travel time, and variability are interrelated.

Table 2-4 Summary of Revealed Preference (RP) Survey

Study	Data Source
Ghosh (2001)	Both RP and SP data were collected from a congestion pricing project on I-15, California. The panel study conducted five waves of SP surveys between Fall 97 to Fall 99. RP data was collected from loop detectors embedded in the roadway. The SP survey collect demographic characteristics - income, home ownership, age, gender, education, number of people working outside house, number of licensed drivers, number of vehicles, and number of people in the household.
Lam and Small (2001)	Loop detector data
Liu et al. (2004)	This study used real-time loop detector data from California State Route 91.
Small et al. (2005)	This study used combination of revealed and stated preference data from Los Angeles area.
Brownstone and Small (2005)	Both Stated Preference (SP) and Revealed Preference (RP) survey data were used in this study. Five different data sets were collected from two HOT lane projects of southern California.
Liu et al. (2007)	This study used loop detector data obtained from California state route 91.
He et al. (2012)	This study used dynamic toll data from I-394, Minnesota. Combined with other data sources, dynamic toll data is reliable, provide drivers route choice information, and no additional equipment installation is required.
Carrion and Levinson (2013)	This study used Revealed Preference (RP) data collected by GPS in Minnesota.
Sheikh et al. (2014)	Revealed preference (RP). State Road and Tollway Authority (SRTA) provided data on transponder account information, toll lane and GP lane trip characteristics etc. Therefore, information on both general purpose lane and express lane is available whether the travelers chose one or another.

- Small, Winston, and Yan (2005) used both RP and SP data for VOT estimation and found that that SP studies underestimate the value of time savings compared to the evidence using RP data. Zheng et al. (2009) attributed this difference to data usage difference in the model.
- RSG (2012) also simultaneously applied SP and RP techniques for estimating value of travel time savings and value of travel time reliability.

2.5 LITERATURE REVIEW FINDINGS

2.5.1 Value of Time and Value of Reliability

VOT and VOR has been the subject of interest for many researchers. As SP based data dominate VOT and VOR studies, mixed logit model has been found as the most popular and powerful modeling techniques in examining user heterogeneity in travel choices.

Various studies have explored how the valuation of travel time and travel time reliability may vary under different circumstances (travel purpose, urgency level, day of week, time of day, gender, income, etc. The literatures suggest that

- Women exhibit higher VOT and VOR than men
- Commuters show higher VOT and VOR than non-commuters
- Morning trips show the highest VOT and VOR than other time period
- Urgent trips have higher VOT and VOR than regular trips
- Fridays experience the highest VOT and VOR than any other weekdays

VOR measurement approach vary substantially from study-to-study in almost every aspect, from the concept (mean-variance, schedule delay, and mean-lateness), data source (SP survey, RP survey, loop-detector and dynamic toll data), and experimental question (presentation of reliability in different scenarios). As a consequence, VOR estimates also exhibit large variation across studies. VOR estimates varied from 0.55 to 3.22 times the VOT estimates. Table 2-5 below presents a quick comparison of VOT and VOR values from different studies.

Table 2-5 VOT and VOR Estimation Comparison

Study	VOT Estimation	VOR Estimation
Noland and Small (1995)	$6.40/hour	$3.90/hour - $15.21/hour
Calfee and Winston (1998)	$3.88/hour (19% of average hourly wage rate)	
Lam and Small (2001)	$22.87/hour(72% of average hourly wage rate)	$15.12/hour, $31.91/hour
Ghosh (2001)	$20.27/hour	$30/hour
Hensher (2001)	$8.69/hour, $9.38/hour, $9.42/hour,	
Liu et al. (2004)	$12.81/hour	$20.63/hour
Small et al. (2005)	$21.46/hour, $11.92/hour	$19.56/hour, $5.40/hour
Brownstone and Small (2005)	$20/hour - $40/hour	
Liu et al. (2007)	$6.82/hour - $27.66/hour	$17.49/hour - $39.24/hour
Asensio and Matas (2008)	$15.93/hour	$68.90/hour– $23.73/hour
Li et al. (2009)	$16.95/hour, $17.95/hour, and $19.08/hour	$16.95/hour, $17.95/hour, and $19.08/hour
Tilahun and Levinson (2007)	$9.54/hour - $25.43/hour	
Li et al. (2010)	$30.04/hour, $28.28/hour	$24.1/hour, $38.86/hour, $40.39/hour
Tilahun and Levinson (2010)	$7.44/hour, $8.07/hour, $7.82/hour	$7.44/hour, $2.31/hour, $6.39/hour
Patil et al. (2011)	$8/hour - $47.5/hour,	
	$7.4/hour - $8.6/hour	
Devarasetty et al. (2012A)	$28/hour ((48% of average hourly wage rate)	$33/hour (56% of average hourly wage rate)
Batley and Ibanez (2012)	$22.17/hour	
	$16.05/hour	
Carrion and Levinson (2013)	$7.30/hour - $9.51/hour	$4.25/hour - $11.31/hour
Sheikh et al. (2014)	$36/hour, $26/hour (greater than average wage rate)	

2.5.2 Attitudinal Aspects of Roadway Pricing

Attitudinal aspects are rarely incorporated into roadway pricing analysis. The existing literature mainly focuses on observed traveler or trip characteristics and is less likely to capture latent preferences of roadway users.

CHAPTER 3

DATA

3.1 INTRODUCTION

This chapter provides a description of the dataset, survey methodology, and preliminary statistics used to identify the market segmentation as well as key variables for the model; the role of additional data sources is also discussed.

3.2 DATA TYPE

The study applied a combined set of stated preference (SP) and revealed preference (RP) data. Stated preference observations were gathered from a survey, while revealed preference observations were obtained from a database. As a consequence of different data sources, the observations did not necessarily represent same individuals.

3.2.1 Stated Preference Survey

Resource Systems Group (RSG) Inc. designed and conducted a stated preference (SP) survey from November 16 to December 15, 2011. The survey was administered online with the help of a computer-assisted self-interview (CASI) technique. A total of 2,300 automobile users from South Florida participated in the survey. The survey was designed in a manner so that the questions would be modified based on previous responses. The final dataset comprised 16,327 SP observations from 2,041 respondents. Each respondent faced eight different scenarios in the stated preference survey.

Respondents were purposefully selected for the survey because they made at least one trip in the previous month on any of the following facilities:

- I-95 between the Golden Glades Interchange and SR 112 (Airport Expressway)

- I-75 between I-595 and SR 826 (Palmetto Expressway)
- SR 826 between SR 836 (Dolphin Expressway) and I-95

Currently only I-95 has an existing managed lanes facility, but new express lanes are proposed for the other corridors. To make I-75 and SR 826's travelers familiar with managed lane programs, a demonstration about managed lanes was provided at the beginning of the survey. The sample was selected so that approximately 50% of the respondents were users of the I-95 facility, because of the presence of the managed lanes, and the remaining 50% was from the two other facilities. Based on an algorithm, if a respondent had used more than one of the corridors, they were randomly assigned to any one of the corridors to balance the sample composition. Table 3-1 provides detailed sample information for each corridor.

Table 3-1 Respondent Share on Each Facility

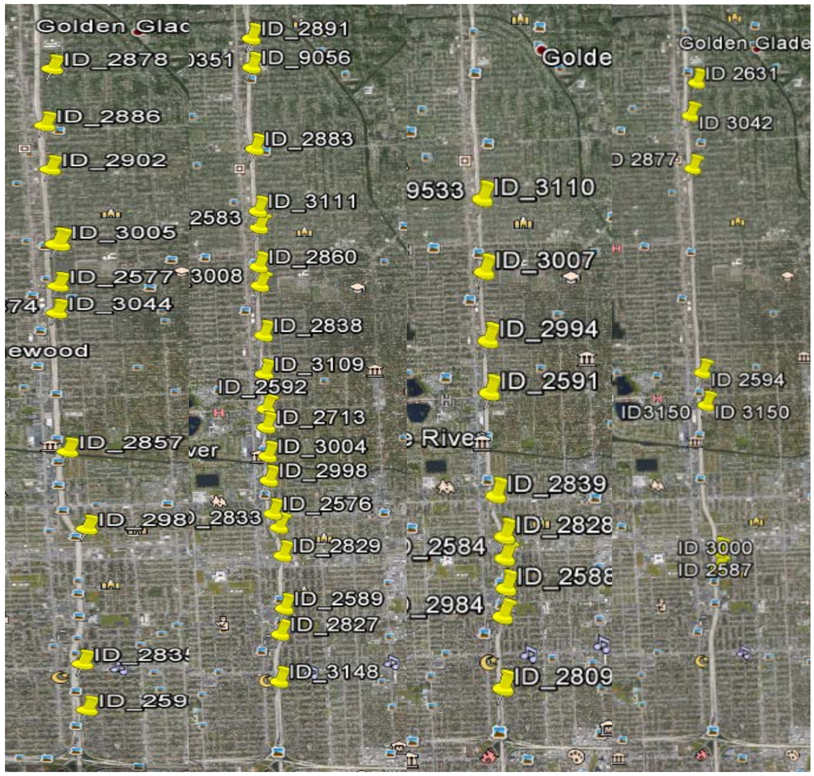
Corridor	Number of Respondents	Percentage of Respondents
I-95	1,060	52%
I-75	521	25.5%
SR 826	460	22.5%
Total	**2,041**	**100%**

3.2.2 Revealed Preference Data

Detector data were gathered from an automated data sharing, dissemination, and archiving system, named regional integrated transportation information system (RITIS). RITIS is operated and maintained by CATT Lab, a user-focused R & D laboratory at the University of Maryland. RITIS was chosen as a detector data source, mainly because of its ability to distinguish between general purpose lanes detector data and managed lanes detector data. Traditionally, transportation agencies develop reliability measures for major road corridors without differentiating managed lanes and general purpose lanes. For example, FDOT District Six prepared travel time index (a reliability measure) by direction for major roads of South Florida including I-95, I-195, I-75, SR 826, but didn't differentiate the measure by general purpose lanes and managed lanes. On the other hand, RITIS provides distinctive data for general purpose and managed lanes by direction. Since our objective was to apply a rich data-set comprised of both SP and RP in order to understand behavioral travel decision making in presence of managed lanes, we found RITIS as the most suitable platform to gather RP data.

To be consistent with the SP survey, which was conducted between November 16th and December 15th of 2011, archived data from RITIS were obtained for the year of 2012. No major infrastructural differences (e.g., ramp metering) were introduced between the year 2011 and 2012 on the I-95 facility which may influence traveler's decision. Four sets of archived data were retrieved from 2012 year: a) I-95 northbound for general purpose lanes b) I-95 northbound for managed lanes c) I-95 southbound for general purpose lanes d) I-95 southbound for managed lanes. The data were collected for the entire segment of the managed lanes facility between golden glades interchange and airport expressway.

Traffic information retrieved from achieved data includes traffic speed, volume, occupancy, and latitude/longitude of detectors. In order to estimate reliability measure, a travel time distribution set is required. Distance was measured using Google Earth. Travel times were calculated based on speed and distance between adjacent detectors by hour of the day. The final travel time distribution data contain a matrix set of 24 by 365 for each facility type by direction. Figure 3-1 below shows the screenshots from Google Earth with locations of the detectors for each facility by direction.



a) I-95 NB GPL b) I-95 NB EL c) I-95 SB GPL d) I-95 SB EL

Figure 3-1 Sample Screenshots from Google Earth – Distance Measurement.

Based on the literature, a set of measures was identified to represent reliability. Finally, 'standard deviation' was selected for this study as it is the most popular and widely used reliability measure, and the travel time distribution pattern suggested reliability is most appropriately captured by the standard deviation measure. Since our study focuses on freeway facilities, the semi-standard deviation measure is employed, which measures the variation in travel time compared to free flow (10 percentile travel time) as the reference instead of average travel time. A semi-standard deviation of 5 minutes indicates that it is not unlikely for it to take 5 minutes more to travel than it would during uncongested conditions.

As a measure of reliability, standard deviation is expected to capture unique benefits offered by the managed lanes. In general, the variations in travel time are expected to be lower in managed lanes facility compared with GP lanes.

Table 3-2 Standard Deviation of Travel Time on I-95

TOD	NBGPL (Northbound General Purpose Lanes)	NBEL (Northbound Express Lanes)	SBGPL (Southbound General Purpose Lanes)	SBEL (Southbound Express Lanes)
0	0.28	0.82	0.58	0.56
1	0.19	0.90	0.22	1.51
2	0.32	0.81	0.11	1.24
3	0.51	0.80	0.16	1.08
4	0.38	0.80	0.11	0.90
5	0.33	0.54	0.34	0.39
6	0.50	0.39	1.53	0.58
7	1.29	0.69	6.42	1.57
8	2.31	1.26	11.91	3.93
9	1.28	1.05	9.41	2.35
10	0.54	0.35	5.47	1.97
11	0.58	0.46	3.81	1.35
12	1.47	0.45	4.00	0.94
13	1.40	0.80	3.60	0.90
14	1.99	1.00	3.28	0.55
15	3.85	2.68	2.75	0.95
16	5.31	5.17	2.65	0.78
17	6.09	5.58	3.00	1.27
18	4.86	4.14	3.17	0.90
19	3.00	2.32	2.21	0.56
20	1.74	1.26	1.37	0.23
21	0.64	0.52	0.78	0.24
22	0.34	0.35	0.92	0.20
23	0.36	0.36	0.61	0.23

A temporal variation is also expected by TOD, as peak periods may have higher variation of travel time compared with off-peak period due to higher traffic volumes. Table 3-2 presented the reliability measures.

Figure 3-2 presented a graphical comparison of standard deviation between general purpose lanes and managed lanes by time of day. As expected, it shows AM peak in the southbound and PM peak in the northbound. In general managed lanes offer lower variation in travel time than the GP lanes, except for the early morning period (between mid-nights to 6 am). The benefits of managed lanes are much more obvious for the southbound traffic, where the semi-standard deviation was approximately 3 times higher in general purpose lanes than the managed lanes in morning peak hours.

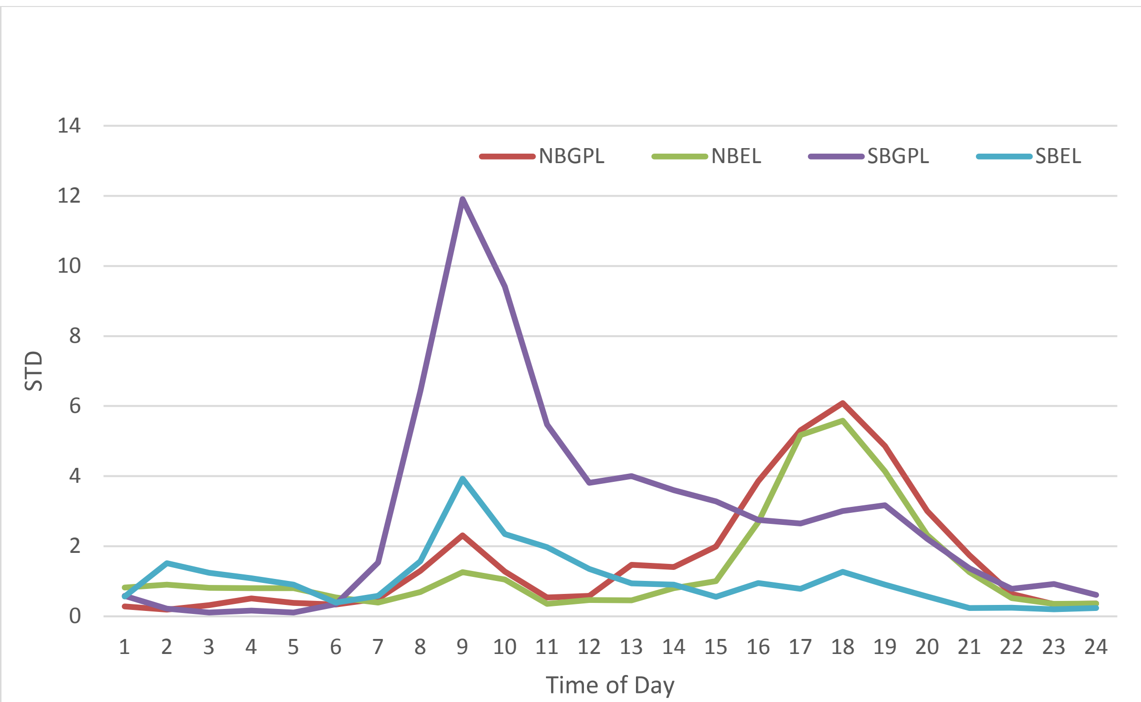


Figure 3-2 Standard Deviation Compariosn by Time of Day.

3.3 DESCRIPTIVE STATISTICS (OBSERVED CHARACTERISTICS)

Stated preference observations were collected from all respondents, regardless of the travel corridor (I-95/I-75/SR-826). During the survey respondents were asked to choose one of the following five travel options: general purpose lanes, managed lanes, managed lanes before the peak period, managed lanes after the peak period, or managed lanes with additional passengers.

Revealed preference observations were collected only for I-95 respondents, since managed lane facility did not exist in other two corridors. I-95 respondents were categorized into three groups: ineligible for express lane, eligible and used express lane, and eligible but did not use the express lane (Table 3-3). The eligibility for express lane was determined based on which on-ramp and off-ramp location a respondent used. In revealed preference observations, respondents had only two travel options: general purpose lanes and managed lanes.

Table 3-3 I-95 User Type

Corridor	Number of Respondents	Percentage of Respondents
Ineligible for express lane	547	51.6%
Eligible for and used express lane	271	25.6%
Eligible for but did not use express lane	242	22.8%
Total	**1060**	**100%**

The descriptive statistics presented in this section represent the stated choice preferences of 2041 respondents and revealed choice preferences of 513 respondents who were eligible for express lane use on I-95.

3.3.1 Trip Purpose

The survey gathered specific purpose of the base trip including work, business, school/college/university, airport, shopping, social/recreational, and other personal trips.

For analysis purpose, trip purposes were grouped into two major purposes – mandatory trips (work, business, and airport trips), and non-mandatory trips (school, shopping, recreational, and other personal trips). Table 3-4 provides frequency and percentage information of both SP and RP respondents by trip purposes.

Table 3-4 Respondent Profiles by Trip Purpose

Trip Purpose	SP Respondents	RP Respondents
Mandatory trips	1051 (51.5%)	990 (48.5%)
Non-Mandatory trips	296 (42.3%)	217 (57.7%)
Total	**2041**	**513**

Figure 3-3 presents an analysis of choice share by trip purpose for both sets of respondents. According to the figure, general purpose lanes (toll-free) were the first choice of the SP respondents irrespective of the trip types, but the RP observations suggested preference level varied with respect to the importance of the trip. More important trips were more likely to be conducted on managed lanes (tolled lanes), perhaps due to time constraints.

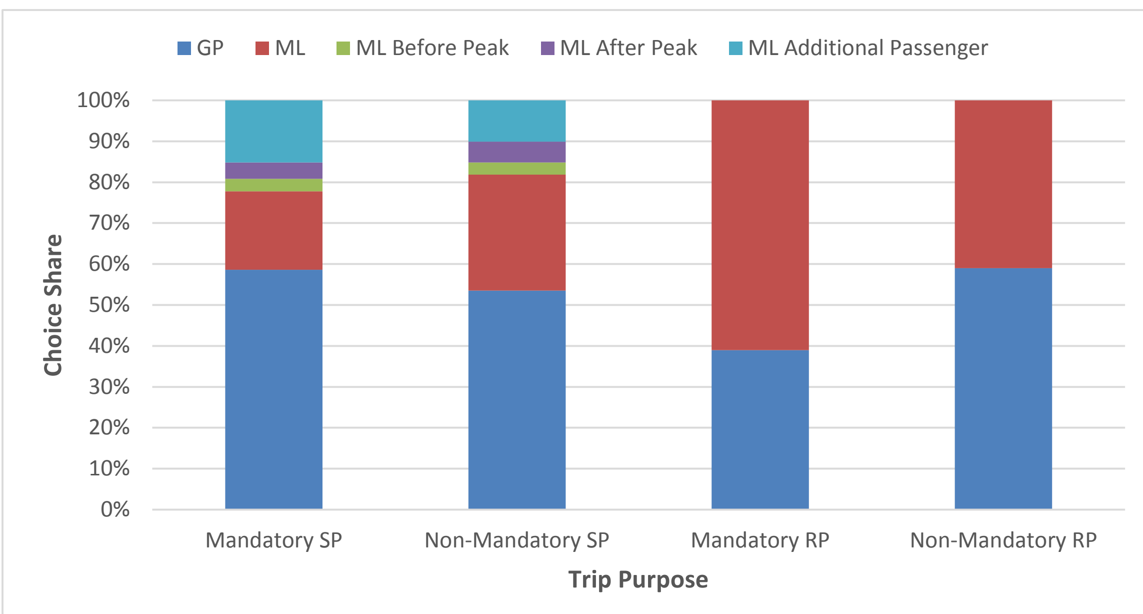


Figure 3-3 Choice Share by Trip Purpose.

3.3.2 Household Income

It was hypothesized that, all things considered, high income travelers are more likely than low income travelers to use managed lanes. Respondents were categorized into three income groups – low, medium, and high (Table 3-5).

Table 3-5 Respondent Profiles by Household Income

Household Income	SP Respondents	RP Respondents
Low Income (<50 K/year)	513 (25.1 %)	107 (20.9 %)
Medium Income (50 k ~ 150 K/year)	1177 (57.7 %)	293 (57.1)
High Income (>150 K/year)	351 (17.2%)	113 (22.0%)
Total	**2041**	**513**

As presented in Figure 3-4, the analysis confirmed the hypothesis. Low income respondents were least interested in traveling on managed lanes whereas high income travelers were the most interested in choosing managed lane travel options. In addition, low and medium income SP respondents were more likely to change departure time or travel with additional passengers in order to reduce travel cost, whereas high income groups were least interested. It suggests that low and medium income traveler's value money more than high income travelers and consequently use managed lanes only when they feel it will be worth their money.

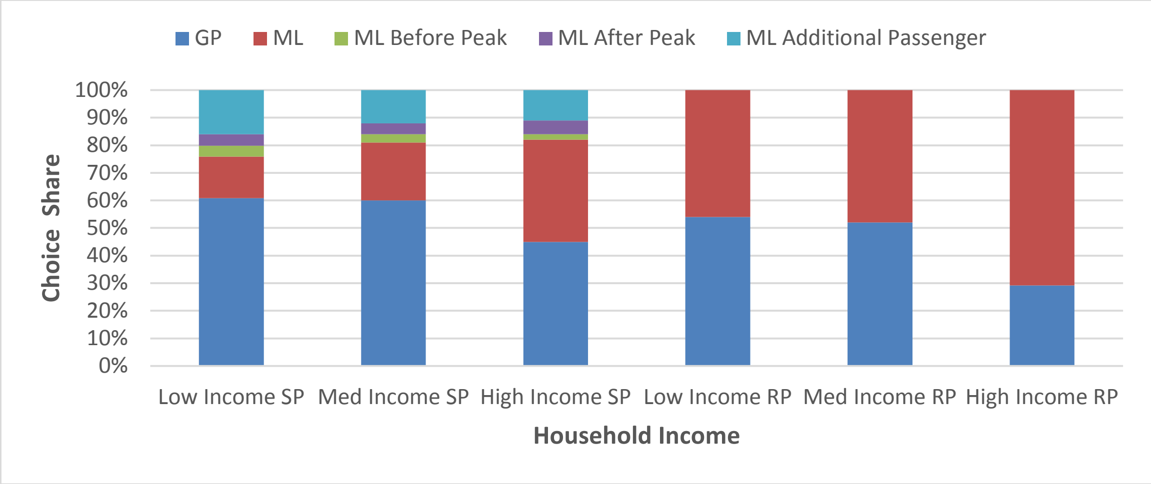


Figure 3-4 Choice Share by Household Income.

3.3.3 Gender

Since men and women have different kinds of household responsibilities, gender is considered an important factor to understand traveler preference between using tolled and toll-free lanes. Table 3-6 provides gender related information including frequency and percentage of respondents.

Table 3-6 Respondent Profiles by Gender

Gender	SP Respondents	RP Respondents
Female	882 (43.2%)	189 (36.8%)
Male	1159 (56.8%)	324 (63.2%)
Total	**2041**	**513**

As suggested in Figure 3-5, males and females exhibited similar choice preferences in the SP observations. Interestingly, the RP observations captured first choice of male drivers was managed lanes while first choice of female drivers was general purpose lanes.

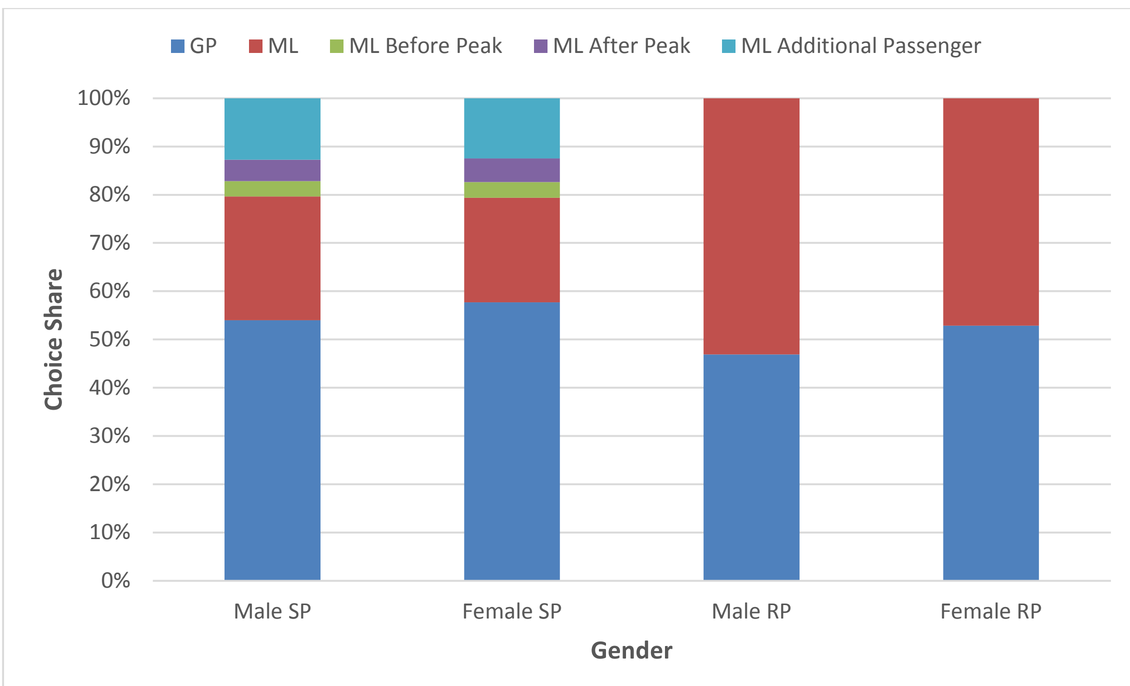


Figure 3-5 Choice Share by Gender.

3.3.4 Day of the Week

The general hypothesis was that, weekday trips have a higher propensity to be conducted on managed lanes compared with weekends. Table 3-7 and Figure 3-6 provides detailed analysis of the impact of days on travel choice share.

Table 3-7 Respondent Profiles by Day of the Week

Day of the Week	SP Respondents	RP Respondents
Weekday	1497 (73.3%)	384 (74.9%)
Weekend	544 (26.7%)	129 (25.1%)
Total	**2041**	**513**

As expected, both of the SP and RP respondents preferred managed lane travel options on weekdays.

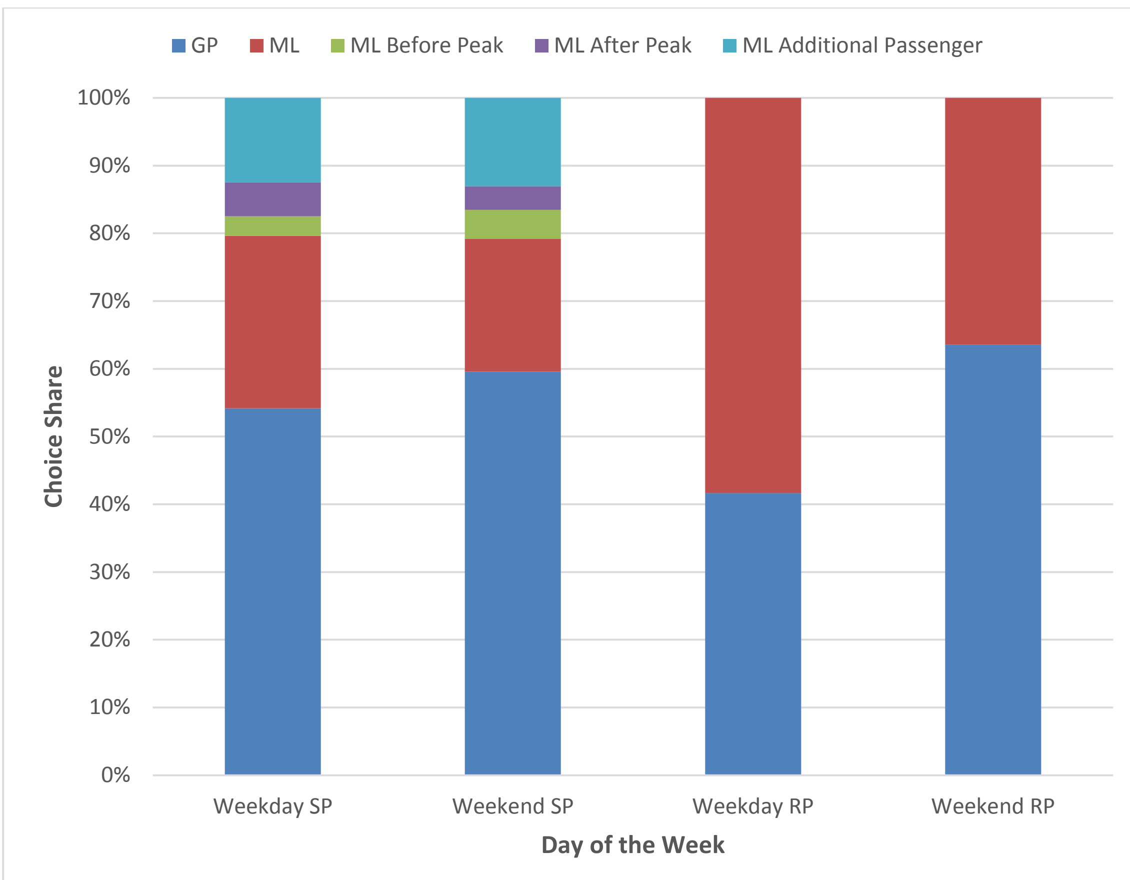


Figure 3-6 Choice Share by Day of the Week.

3.3.5 Time of Day

Peak period trips are expected to prefer managed lane travel options. As shown in Table 3-8, three time periods were considered – morning period in peak direction, evening period in peak direction, and off-peak period (all other time periods). As presented in Figure 3-7, general purpose lanes were always the preferred travel option irrespective of the departure time in case of the SP observations. However, the RP observation captured peak period trips were more likely to be conducted on managed lane facility.

Table 3-8 Respondent Profiles by Time of Day

Time of day	SP Respondents	RP Respondents
AM Peak (7:00 AM ~ 10:00 AM & South bound)	407 (19.9%)	114 (22.2%)
PM Peak (3:00 PM ~ 08:00 PM & North bound)	232 (11.4%)	53 (10.3%)
Off-Peak	1402 (68.7%)	346 (67.4%)
Total	**2041**	**513**

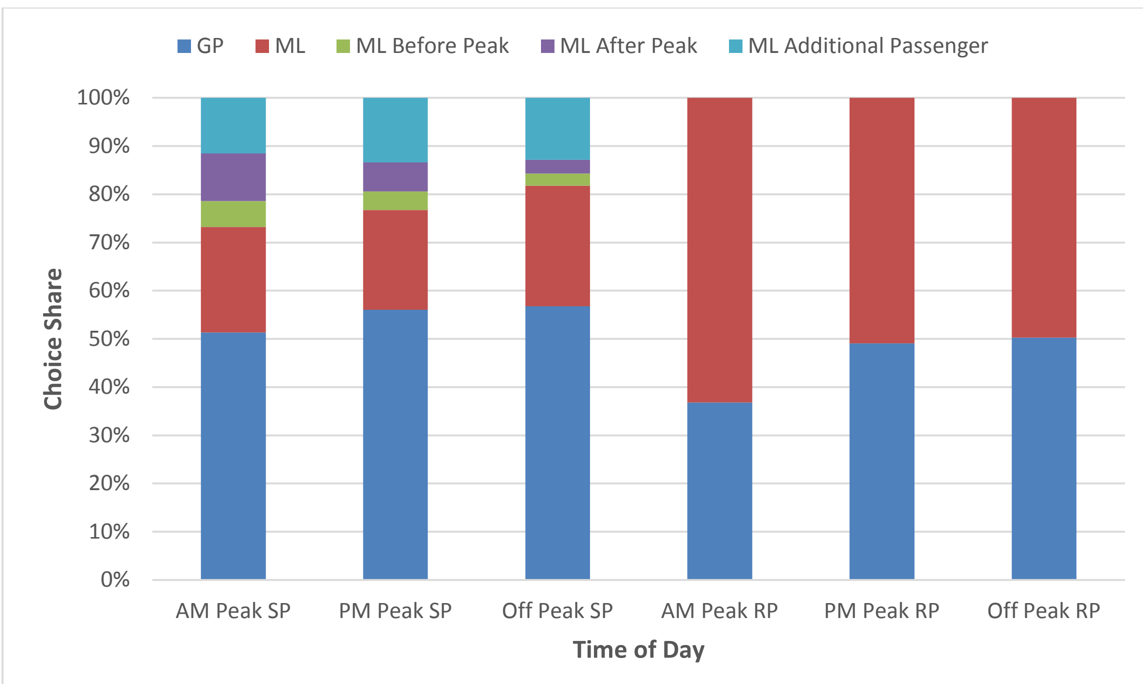


Figure 3-7 Choice Share by Time of Day.

3.3.6 Trip Urgency

The general hypothesis was that, a trip with urgency is more likely to use managed lanes compared to non-urgent trips. For the purpose of this analysis, respondents that reported concern for arriving at their destination on-time were classified as urgent trip makers. As shown in Table 3-9, approximately one-third trips were reported as an urgent trip.

Table 3-9 Respondent Profiles by Trip Urgency

Trip Urgency	SP Respondents	RP Respondents
Urgent Trip	650 (31.8)	175 (34.1%)
Not Urgent Trip	1391 (68.2%)	338 (65.9%)
Total	**2041**	**513**

According to the Figure 3-8, urgent trips were more likely to be conducted on managed lanes compared with unurgent trips. However, the RP observations captured higher percentage of managed lanes share for urgent trips compared with the SP observations where general purpose lanes were preferred choice even for urgent trips.

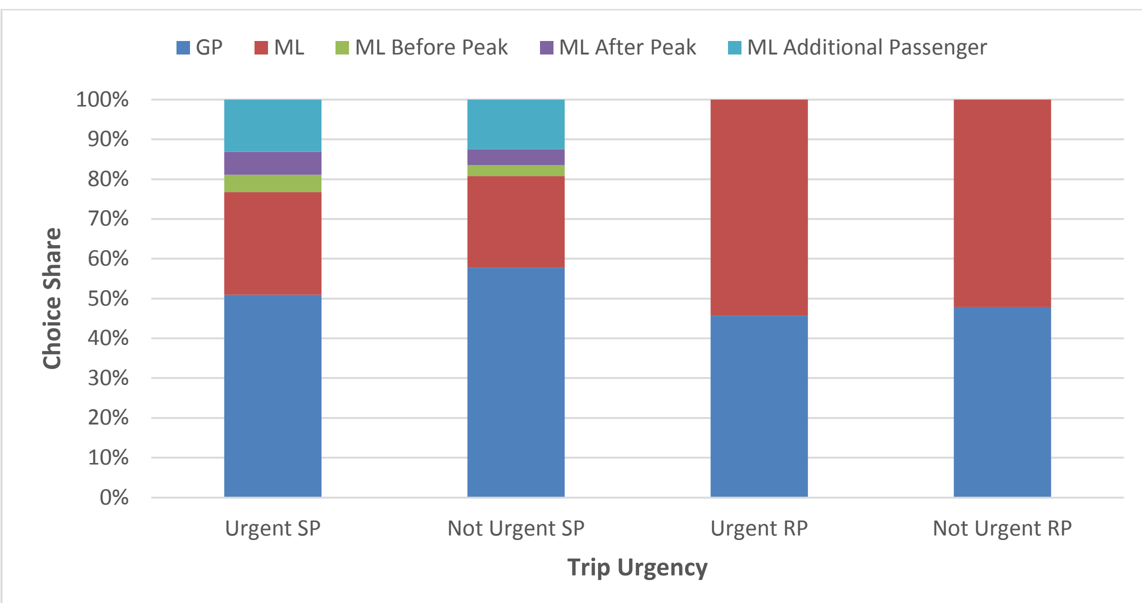


Figure 3-8 Choice Share by Trip Urgency.

3.3.7 Transponder Ownership

In Florida, the most convenient way to pay the tolls associated with managed lanes is through SunPass, an electronic toll collection system. Table 3-10 provides detailed information regarding the number and percentage of respondents for SunPass users.

Table 3-10 Respondent Profiles by Transponder Ownership

Transponder Ownership	SP Respondents	RP Respondents
SunPass Subscriber	1843 (90.3)	475 (92.6)
Not SunPass User	198 (9.7)	38 (7.4)
Total	**2041**	**513**

SunPass subscription implies the intent to use managed lanes, if needed. Similar to the previous attributes, general purpose lanes were preferred over managed lanes by the SP respondents. However, managed lane was found as the preferred travel option for the RP respondents as expected.

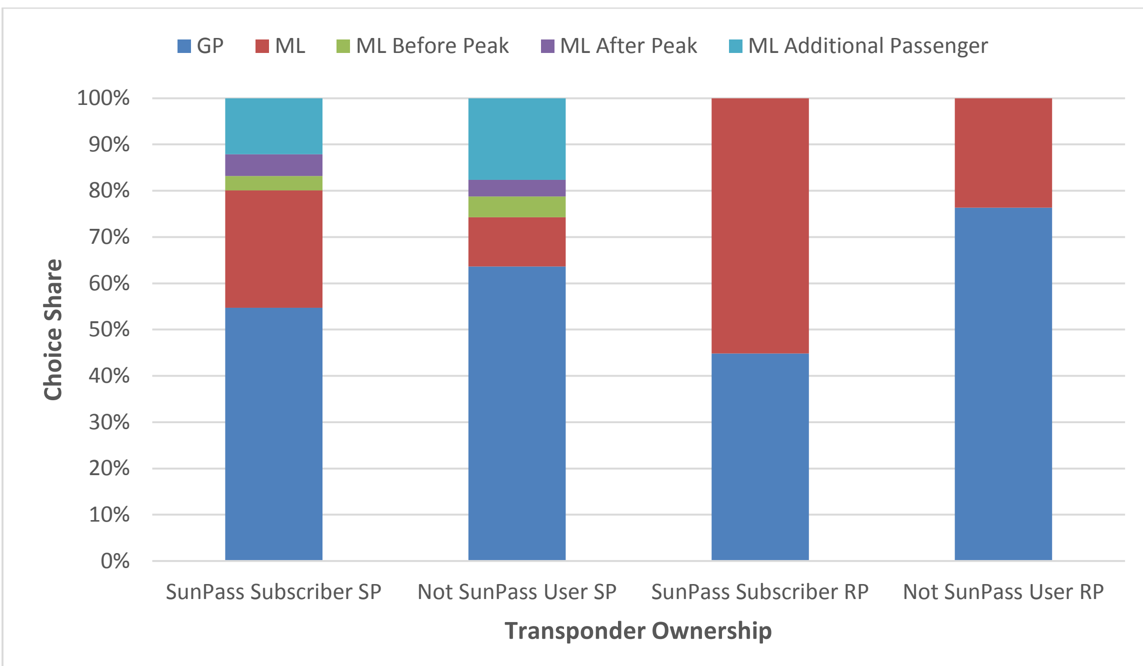


Figure 3-9 Choice Share by Transponder Ownership.

3.3.8 Trip Length

The origin and destination locations of the base trip were gathered during the survey. For analysis purpose, trips were categorized into three types: short trips (up to 20 miles), medium trips (20 miles to 40 miles), and long trips (greater than 40 miles). Detailed profile of each trip category can be found in Table 3-11.

Table 3-11 Respondent Profiles by Trip Length

Trip Length	SP Respondents	RP Respondents
Short Trip	914 (44.8 %)	129 (25.1%)
Medium Trip	886 (43.4%)	306 (59.6%)
Long Trip	241 (11.8%)	78 (15.2%)
Total	**2041**	**513**

Figure 3-10 depicts the influence of trip length on choice preferences. Long trips showed the highest preference for managed lanes, while short trips had the lowest preference. Perhaps the benefits offered by the managed lanes (such as travel time savings, travel time reliability, and driving comfort) were valued enough for long trip makers to accept the additional cost.

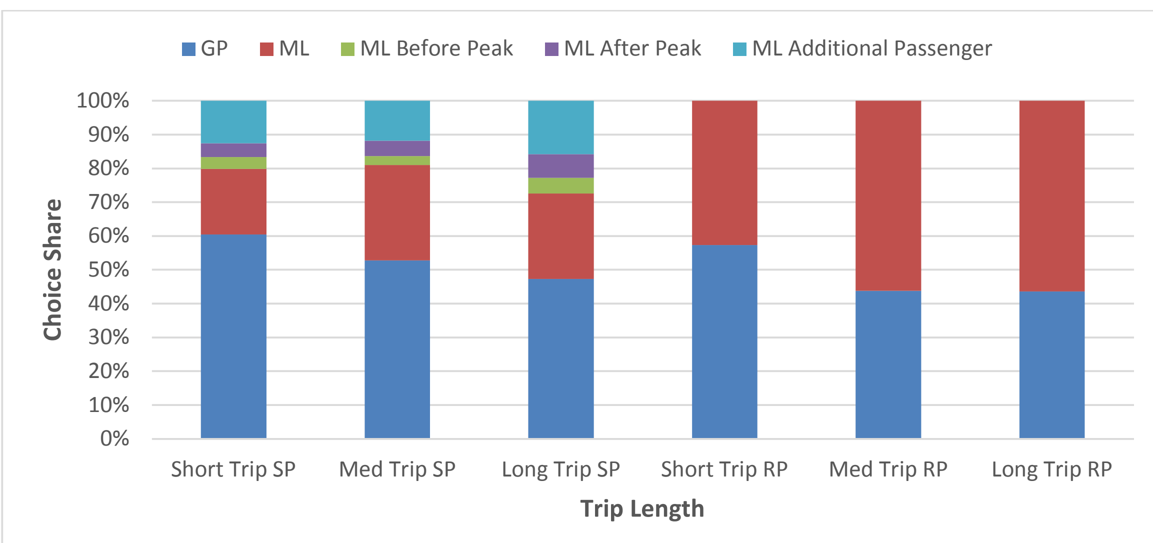


Figure 3-10 Choice Share by Trip Length.

3.3.9 Previous Delay Experience

Respondents were categorized into two types: respondents that experienced delay on their reference trip and respondents that did not experience any delay on reference trip. Following table provides previous congestion experience for the SP and RP respondents.

Table 3-12 Respondent Profiles by Previous Delay Experience

Previous Delay Experience	SP Respondents	RP Respondents
Delay Experienced	860 (42.1%)	208 (40.5%)
No Delay Experienced	1181 (57.9%)	305 (59.5%)
Total	**2041**	**513**

According to stated preference survey, respondents with previous congestion experience preferred managed lane travel options over general purpose lanes. However, the results from revealed preference data showed that respondents with no experience with delay accounted for a higher share of managed lanes usage. Perhaps, because of previous congestion experience, respondents had already made up their minds and decided on travel options accordingly.

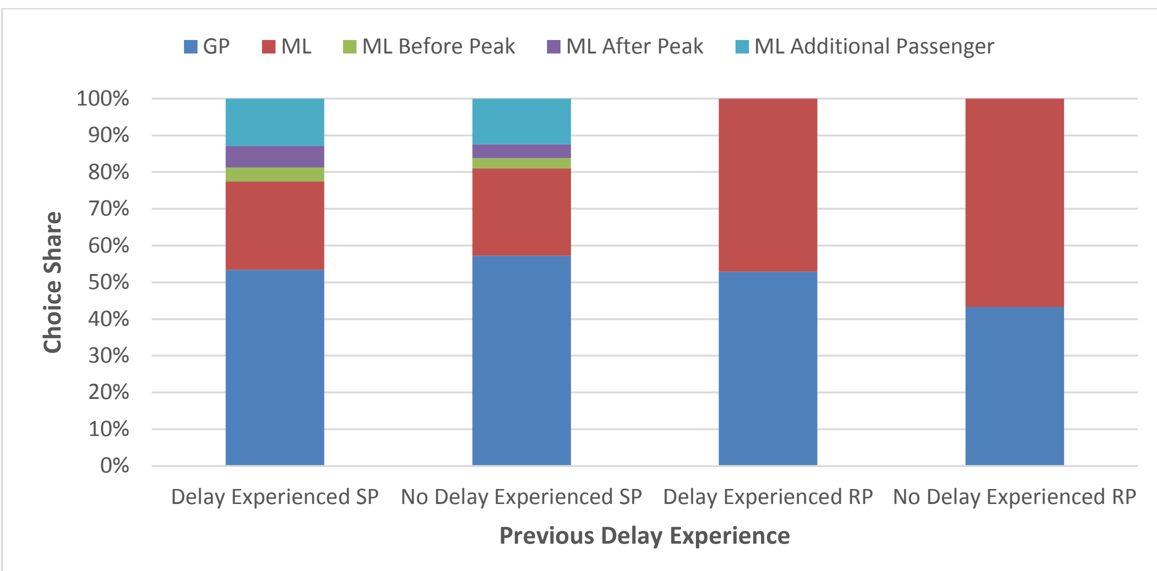


Figure 3-11 Choice Share by Previous Delay Experience.

3.3.10 Trip Frequency

Respondents were assigned to three frequency types based on the number of similar trips made in the past month. The categories were - less frequent users, frequent users, and very frequent users. Table 3-13 provides more information about the respondents profile correspondence with the categories.

Table 3-13 Respondent Profiles by Trip Frequency

User Frequency	SP Respondents	RP Respondents
Less Frequent (> 4 trips/month)	1353 (66.3%)	358 (69.8%)
Medium Frequent (4 ~ 12 trips/month)	229 (11.2%)	56 (10.9%)
Very Frequent (>12 trips/month)	459 (22.5%)	99 (19.3%)
Total	**2041**	**513**

According to Figure 3-12, general purpose lanes were always the preferred travel option irrespective of the trip frequency for the SP respondents. However, the RP observations suggested higher propensity to managed lane with the increase in trip frequency. Perhaps increased frequency lead to a the respondents having a better understanding of the congestion level on managed and general purpose lanes, which prompted respondents to select on managed lanes facilities.

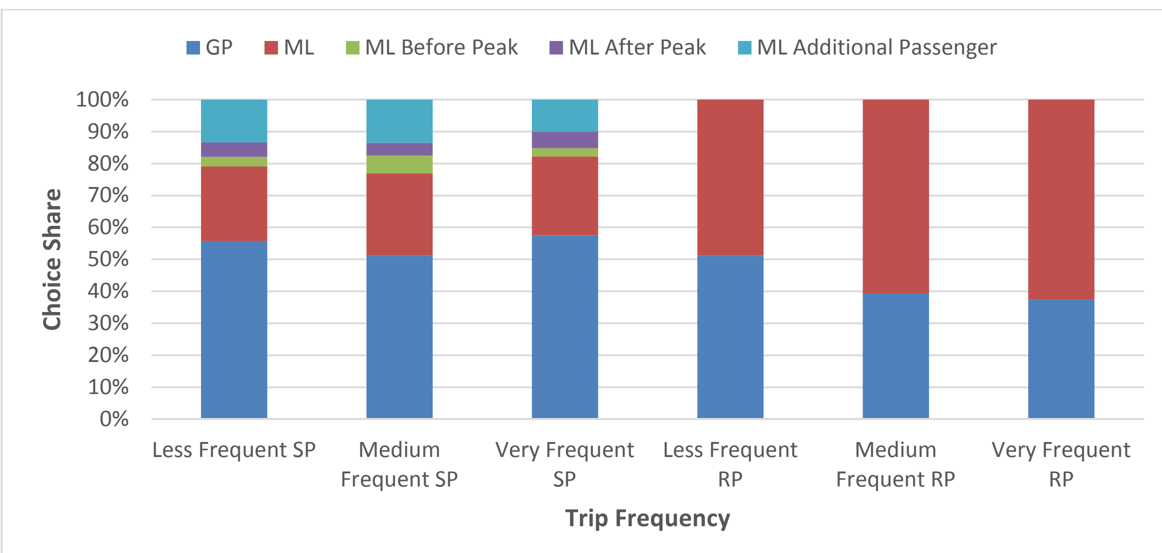


Figure 3-12 Choice Share by Trip Frequency.

3.3.11 Employment Status

The general hypothesis was that employed people are more likely to travel on managed lanes than unemployed people. For the purpose of this analysis, a person was considered employed if he/she had any sort of employment including full-time, part-time, self-employed, and student. According to the Table 3-14, majority of the respondents were employed.

Table 3-14 Respondent Profiles by Employment Status

Employment Status	SP Respondents	RP Respondents
Employed	1709 (83.7%)	445 (86.7%)
Unemployed	332 (16.3%)	68 (13.3%)
Total	**2041**	**513**

From Figure 3-13, it can be seen employed drivers preferred managed lane options and unemployed drivers preferred general purpose option. In addition, unemployed SP respondents were more interested in traveling with additional passengers. This can be explained by the fact that carpooling offers free usage of managed lanes and a reduction in travel cost, both of which may attract an unemployed person.

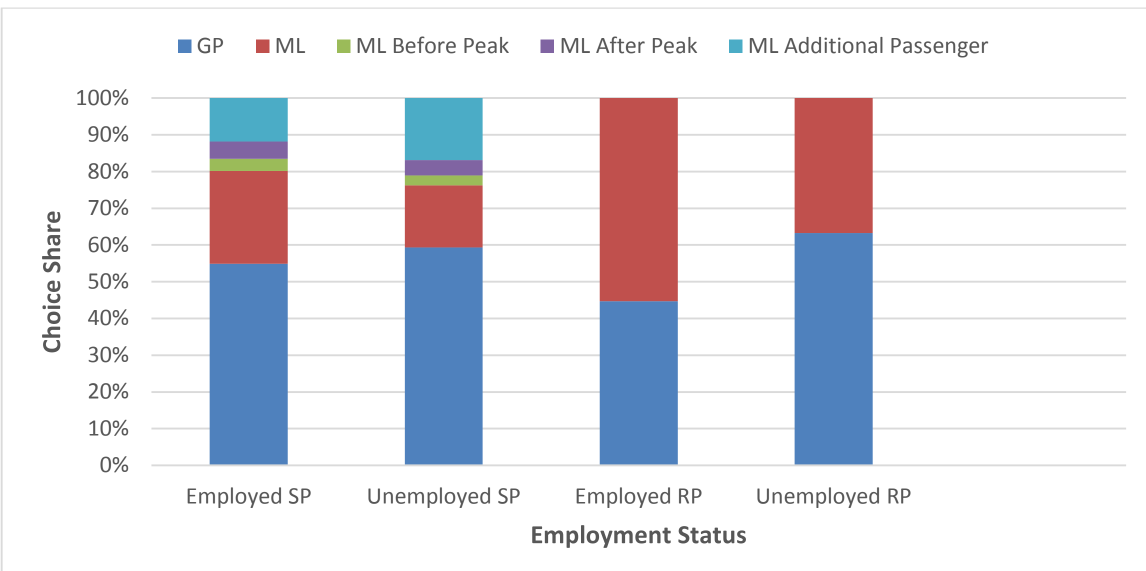


Figure 3-13 Choice Share by Employment Status.

3.3.12 Age

Age can also have influence on travel decisions. For analysis purpose, respondents were categorized into three types – young, mid-age, and old people. Table 3-15 provides detailed information regarding the number and percentage of the respondents for each age category.

Table 3-15 Respondent Profiles by Age

Age	SP Respondents	RP Respondents
Young (<34 years)	480 (23.5%)	112 (21.8%)
Mid-Age (35-54 years)	949 (46.5%)	242 (47.2%)
Old (>55 years)	612 (30.0%)	159 (31.0%)
Total	**2041**	**513**

According to Figure 3-14, young adults were more likely to prefer managed lane travel options. Perhaps respondents within in this category prefer to travel in a faster travel lane, do not like to waste time in congestion, and value their time highly. The lowest managed lane usage was observed for the older age category. Perhaps respondents in this category do not prefer to travel in a faster lane, has more patience for congestion, and has less constraint on arrival time.

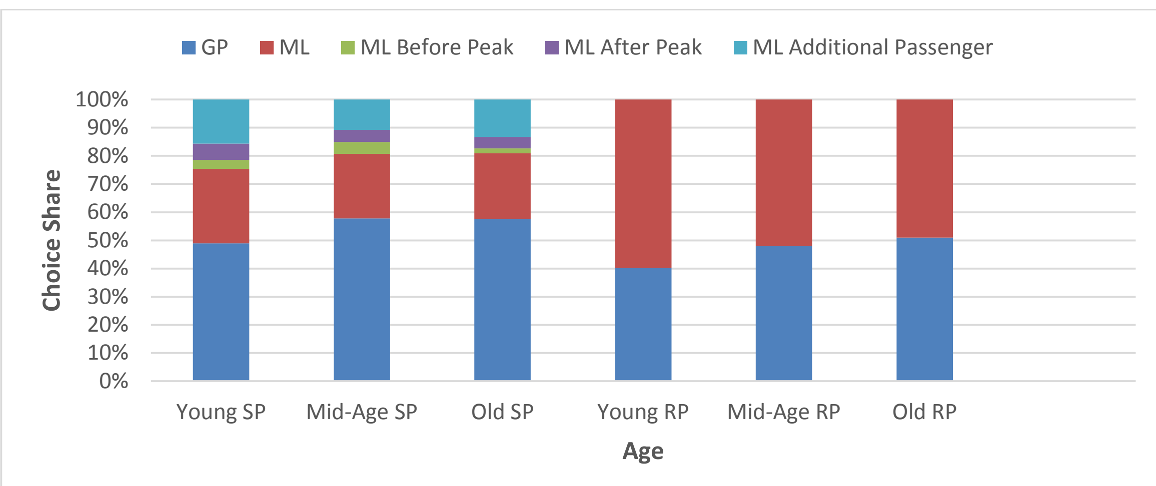


Figure 3-14 Choice Share by Age.

3.3.13 Vehicle Occupancy

Vehicle occupancy has direct influence on preference since managed lanes can be used without paying the toll if a vehicle carries three or more people. For the purpose of this analysis, respondents were categorized into three occupancy categories: drive alone, drive with another passenger, and drive with at least two more passengers (eligible for toll-free).

Table 3-16 Respondent Profiles by Vehicle Occupancy

Vehicle Occupancy	SP Respondents	RP Respondents
Drive Alone	1235 (60.5%)	324 (63.2%)
Drive with Another	474 (23.2%)	109 (21.2%)
HOV 3+	332 (16.3%)	80 (15.6%)
Total	**2041**	**513**

Figure 3-15 describes the influence of vehicle occupancy on travel preference. Interestingly, managed lane travel options were less preferred by the high occupancy vehicle group in the SP observations. They were also uninterested for traveling with additional passengers.

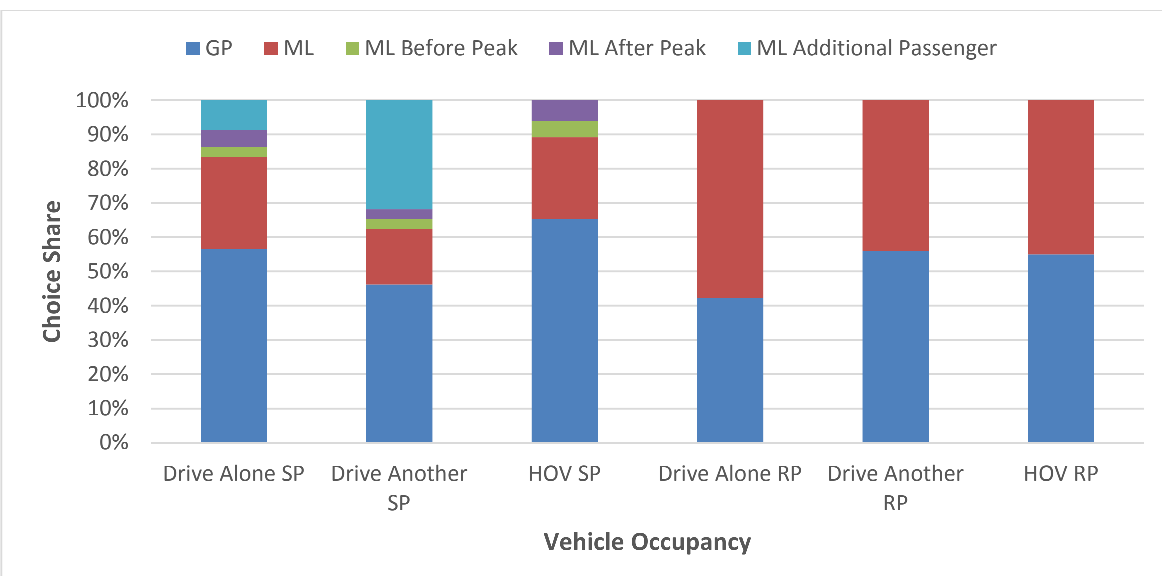


Figure 3-15 Choice Share by Vehicle Occupancy.

Reluctance towards additional passengers is understandable since it does not provide greater benefit in terms of reduction in toll cost. For RP respondents, the drive alone group had the highest share of managed lane usage and both shared ride groups were more likely to prefer general purpose lanes.

3.3.14 Arrival Flexibility

Destination arrival flexibility can influence travel decisions substantially. The general hypothesis was that if a person has no arrival flexibility, he/she is more likely to use managed lanes to ensure on-time arrival. Table 3-17 provides detailed arrival flexibility information for both SP and RP respondents.

Table 3-17 Respondent Profiles by Arrival Flexibility

Arrival Flexibility	SP Respondents	RP Respondents
Flexible	1486 (72.8%)	396 (77.2%)
Not Flexible	555 (27.2%)	117 (22.8%)
Total	**2041**	**513**

According to Figure 3-16, RP respondents with flexibility preferred managed lanes over general purpose lane while SP respondents always preferred general purpose lanes irrespective of arrival flexibility. Interestingly, respondents who had flexibility were more likely to travel on managed lanes compared with those who had no flexibility, which required further investigation.

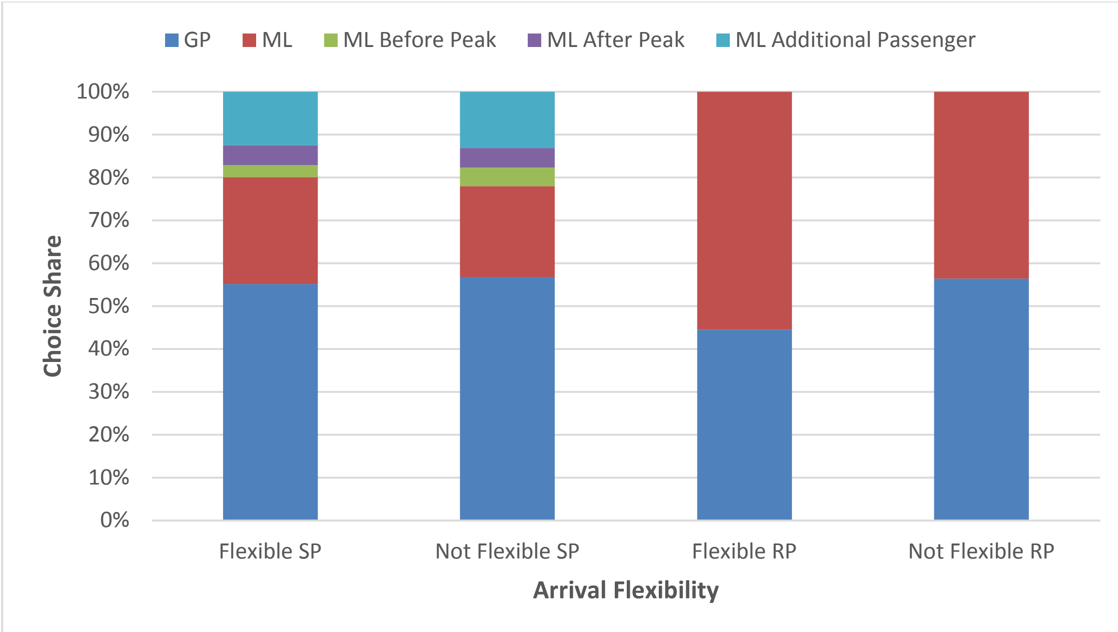
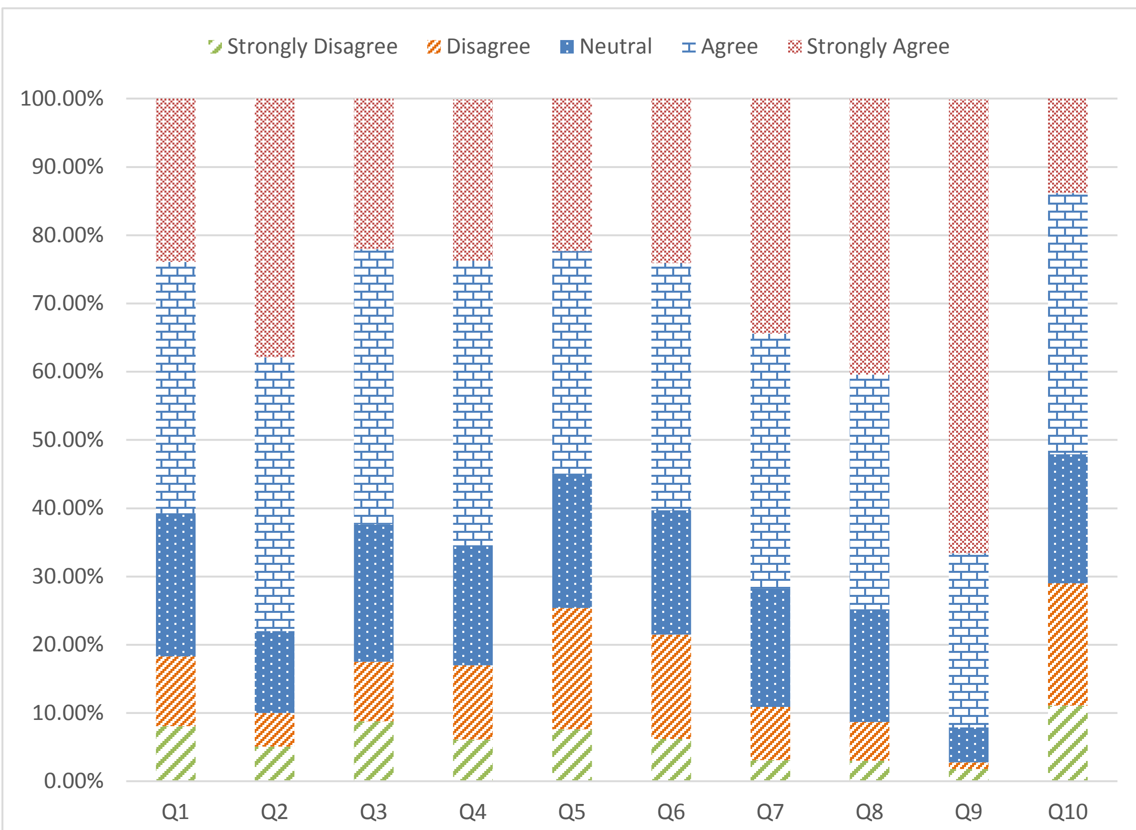


Figure 3-16 Choice Share by Arrival Flexibility.

3.4 Descriptive Statistics (Attitudinal Aspects)

During the SP survey, respondents were presented with a set of questions related to their attitudes including their perspective toward traffic congestion, willingness to pay, and their overall strategies to deal with delays. Figure 3-17 presents the responses' distribution to the attitudinal questions. The answers were coded in a 5 point Likert scale, where 1 represents strongly disagree and 5 represents strongly agree.

As Figure 3-17 shows, a high percentage (71.80%) of the respondents agreed that they were bothered by congestion (Q7). In view of their general perspective, while more than half of the respondents believed that traffic congestion is just a way of life in South Florida (Q10), their answers indicated that they are searching for alternative solutions to avoid congestion. Among the solutions offered, many of them agreed to change either departure time or driving route in order to avoid congestion (Q5, Q6). In general, they can afford to pay toll (Q4), but they always looks for the best deals and try to save money (Q9). It seems that they would be willing to pay toll if the toll amount is reasonable (Q1, Q2). In addition, they usually prefer to be on time (Q8), and supporter of highway improvement through tolling (Q3). The context suggests that implementation of managed lane facilities would be an effective solution. The responses warrant an in-depth attitudinal study of South Florida residents in order to facilitate various operational strategies for managed lane programs.



Q1. I would be willing to pay a toll if it guarantees a travel time for my trip that is reliable every day	Q2. I will use a toll route if the tolls are reasonable and I save time	Q3. I support using tolls to pay for highway improvements that reduce congestion	Q4. I can generally afford to pay tolls	Q5. I regularly change my driving schedule in order to avoid traffic congestion	Q6. I regularly change my route in order to avoid traffic congestion	Q7. It bothers me when congestion adds more than a few minutes to my trips	Q8. I always try to be on time	Q9. I always look for the best deals and try to save money whenever possible	Q10. Traffic congestion is just a way of life in South Florida & something you learn to live with

Figure 3-17 Response of Attitudinal Questions.

3.5 SUMMARY OF DESCRIPTIVE ANALYSIS

The survey gathered information from 2,041 respondents (1,060 from I-95, 521 from I-75, and 460 from SR 826). Among the 1,060 I-95 travelers, 513 were eligible for the ML (the reported on and off ramps were used to determine whether the trips were eligible to use the ML facilities). Each respondent faced eight SP scenarios. The final dataset contains 513 RP responses and 16,327 SP responses.

Table 3-18 below presents the key variables and the corresponding choices by category. A detailed look (Table 3-18) into the survey data suggests that in the SP observations all variable categories reflect higher percentages of GP alternative usage except for high income people.

Based on the RP sample, respondents who are male, employed, young or medium age people, from medium and high income households were more likely to travel on managed lanes compared with their counterparts. In terms of trip characteristics, mandatory trips (work/business/airport), medium and very frequent trips, weekday trips, drive alone trips, medium and long distance trips were more likely to travel on managed lanes compared with non-mandatory (school/ shopping/ recreational/ others), less frequent, weekend, shared, and short trips. Interestingly, trip urgency was not an incentive factor for managed lane usage. As expected, high income users revealed the highest percentage of managed lanes users.

Table 3-18 Choices by Socio-economic, Demographic, And Trip Characteristics

Variables	Category	RP		SP Alternatives				
		GP	ML	GP	ML	ML 2	ML 3	ML 4
Gender	Male	45.00	55.00	57.00	23.00	3.00	4.00	13.00
	Female	51.00	49.00	59.00	21.00	3.00	4.00	13.00
Urgency	Urgent	46.00	54.00	53.00	24.00	5.00	5.00	14.00
	Not Urgent	48.00	52.00	60.00	21.00	2.00	4.00	12.00
Employment	Employed	45.00	55.00	56.00	24.00	3.00	4.00	12.00
	Unemployed	63.00	37.00	64.00	14.00	2.00	4.00	16.00
Age	16-34	40.00	60.00	51.00	24.00	3.00	6.00	16.00
	35-54	48.00	52.00	60.00	22.00	4.00	4.00	11.00
	55 -75+	51.00	49.00	60.00	21.00	2.00	4.00	13.00
Sun Pass	User	45.00	55.00	57.00	23.00	3.00	4.00	12.00
	Not User	76.00	24.00	65.00	10.00	5.00	5.00	15.00
Trip Purpose	Mandatory	39.00	61.00	55.00	26.00	4.00	5.00	10.00
	Voluntary	59.00	41.00	60.00	18.00	3.00	4.00	15.00
Income	Low (<50k)	55.00	45.00	62.00	16.00	3.00	4.00	15.00
	Med (50~150k)	49.00	51.00	59.00	23.00	3.00	4.00	11.00
	High (>150k)	29.00	71.00	45.00	37.00	2.00	5.00	11.00
Trip Frequency (per month)	Less (<4/month)	51.00	49.00	58.00	22.00	3.00	4.00	14.00
	Med (4~12/month)	39.00	61.00	53.00	25.00	5.00	5.00	12.00
	Very (>12/month)	37.00	63.00	60.00	22.00	3.00	5.00	9.00
Day of Week	Week Day	42.00	58.00	57.00	24.00	3.00	5.00	12.00
	Week End	64.00	36.00	61.00	18.00	3.00	3.00	14.00
Occupancy	Drive Alone	42.00	58.00	58.00	25.00	3.00	4.00	9.00
	Drive with Another	56.00	44.00	50.00	14.00	2.00	3.00	31.00
	HOV3	55.00	45.00	66.00	23.00	4.00	7.00	0.00
Trip Length (miles)	Short (<20)	57.00	43.00	62.00	18.00	3.00	4.00	13.00
	Med (20~40)	44.00	56.00	55.00	26.00	3.00	4.00	12.00
	Long (>40)	44.00	56.00	53.00	22.00	4.00	6.00	15.00
Delay Experience	Have Experience	53.00	47.00	55.00	23.00	4.00	5.00	12.00
	No Experience	43.00	57.00	60.00	22.00	2.00	4.00	13.00
Total Sample, N		47.00	53.00	58.00	22.00	3.00	4.00	13.00
		513		**16327**				

CHAPTER 4

METHODOLOGY

4.1 GENERAL ESTIMATION PRINCIPAL

VOT, defined as the marginal rate of substitution between travel time and cost, can be derived in two ways:

- Direct estimation from observed data: recorded toll payments divided by computed travel time savings, usually at aggregate level, can be estimated by group of users, or other segments.
- Derived as the ratio of the coefficient of travel time to the coefficient of cost obtained from choice models: travel time and cost are represented in the utility functions describing the attributes of different alternatives.

The first approach is relatively simple and less representative. It can only be used to get an approximate estimation. The dissertation focused mainly on the second approach, which applies state of the art mathematical models and provide more precise estimation.

On the other hand, VOR, can be measured using two general approaches:

- Mean-Variance approach: concerns about the distribution of travel time. Usually consists of two components, one measures the centrality of travel time distribution (mean, median, etc.), and the other measures the dispersion of travel time distribution (standard deviation).
- Scheduling approach: concerns about the disutility incurred by early or late arrival due to travel time variability. This method requires data on the distribution of travelers' arrival times.

Information on traveler preferred arrival time is not available in the survey; therefore, the scheduling approach cannot be applied. The dissertation employed mean-variance approach to measure VOR.

4.2 MAJOR DIMENSIONS OF ROADWAY PRICING VALUATION

Based on the literature review in chapter 2, two major dimensions of roadway pricing were identified – the user heterogeneity aspect and the attitudinal aspect.

Current practices in VOT and VOR estimation usually focus on single values to represent the whole population, which fails to accommodate user heterogeneity. According to the Priced Managed Lane Guide prepared by the Federal Highway Administration (FHWA), a stratified sample could improve toll prediction accuracy (Perez et al., 2012). Smaller user groups with similar characteristics are expected to exhibit relatively homogeneous behavior or preferences. In order to identify the sources of user heterogeneity, the dissertation explored a series of potential characteristics, including both personal attributes and trip attributes. The following personal attributes were investigated in the models – age, gender, household income, employment status, arrival flexibility, and Sunpass ownership, whereas trip urgency, trip purpose, trip frequency, day of the week, trip occupancy, trip length, previous delay experience were investigated as trip attributes.

Another dimension of roadway pricing is the attitudinal aspect. Although a number of studies were conducted in order to estimate traveler's sensitivity toward travel time, travel time reliability, and toll cost, in most cases the sensitivity was estimated without considering the attitudinal aspects of individuals. Since, previous efforts on addressing attitude were not sufficient, this study aims to incorporate attitudinal variables (as indices of latent preferences) into roadway pricing analysis. The dissertation investigated whether and to what degree the attitudinal factors influence the likelihood of using managed lanes among drivers. Attitudes related to willingness to pay, willingness to shift departure time, utility (travel time/toll) sensitivity, and congestion compliance were explored in this study.

4.3 MODEL STRUCTURE

VOT and VOR are generally estimated using various forms of logit structures including binomial logit, multinomial logit, mixed logit, conditional logit, nested logit, heteroscedastic extreme value (HEV) model etc. Among them, multinomial logit and mixed logit are the two most popular and widely used model structures. A brief discussion for both structures is provided below.

4.3.1 Multinomial Logit

Multinomial logit model structure describes each choice alternative through a utility function. The simplest form of the utility equation is given below:

$$U_1 = \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots\ldots\ldots + \beta_n X_n + \epsilon \quad (1)$$

where, X represents the attributes of the alternatives or the individuals, and any other explanatory variables. β refers to the coefficients corresponding to the attributes. The estimated coefficient value implies relative importance of that attribute (X) in the model. ϵ, the error component accounts for any measurement error, parameter correlation, unobserved individual preferences, and other unobserved characteristics.

The probability of each alternative is estimated using the following equation

$$P(i) = \frac{e^{U_i}}{\sum e^{U_j}} \quad (2)$$

where, P (i) is the probability that any particular alternative (i) will be chosen and U_i is the utility of that alternative (Ben-Akiva and Lerman, 1985).

Multinomial logit model structure has been widely used in several VOT and VOR studies (Li et al., 2010; RSG, 2013; Hollander, 2006; Hensher, 2001; Patil et al., 2011).

In the context of travel choices, travel alternatives differ from each other mainly in three attributes – travel time, travel time reliability, and toll cost. Let's consider following terminology for any travel alternative,

T = The travel time of the alternative

R = The travel time variability of the alternative

C = The out-of-pocket monetary cost of the alternative

According to microeconomic theory, VOT is defined as the marginal rate of disutility between travel time and out-of-pocket toll cost and VOR is defined as the marginal rate of disutility between travel time variability and out-of-pocket toll cost. Therefore,

$$\mathrm{VOT} = \frac{\partial \mathrm{U_i} / \partial \mathrm{T_i}}{\partial \mathrm{U_i} / \partial \mathrm{C_i}} = \frac{\beta^{\mathrm{T}}}{\beta^{\mathrm{C}}} \tag{3}$$

$$\mathrm{VOR} = \frac{\partial \mathrm{U_i} / \partial \mathrm{R_i}}{\partial \mathrm{U_i} / \partial \mathrm{C_i}} = \frac{\beta^{\mathrm{R}}}{\beta^{\mathrm{C}}} \tag{4}$$

Multinomial logit model follows two basic assumptions a) error component needs to be identical and independently distributed (IID) and b) choice alternative needs to follow independence from irrelevant alternatives (IIA) property. The above two assumptions limit MNL's application in managed lane studies. In order to preserve the assumptions, traveler has to be similar to one another in any way and there should not be any repeated observations from the same individual (panel data).

4.3.2 Mixed Logit

Recently, mixed logit models have gained popularity in VOT and VOR studies. Mixed logit is considered as a powerful discrete choice modeling technique as it can incorporate user heterogeneity (travelers need not to be similar to one another) in the models. Several studies applied mixed logit modeling techniques (Liu et al., 2004; Small et al., 2005; Liu et al., 2007; Asensio and Matas, 2008; Li et al., 2010; He et al., 2012; Carrion and Levinson, 2012; Ghosh, 2001; Devarasetty et al., 2012B).

The main assumption of mixed logit model is that the coefficients in the model are realization of random variables. This assumption generalizes the standard multinomial logit model (MNL) and allows the coefficient to vary across decision makers and scenarios. The variable property of coefficients allows mixed logit model to conveniently capture user heterogeneity.

Mixed logit considers that each individual n from the sample faces a choice set of I alternatives in each of the T choice situations (T could be considered as number of time intervals in panel data observations or number of scenarios in a stated-preference survey). Based on the random utility theory, the individual is expected to choose the most appealing alternative (i.e., the one associated with the highest obtained utility). Accordingly, the utility of alternative i evaluated by person n under situation (scenario) t could be expressed as:

$$U_{itn} = \beta'_n X_{itn} + [\eta_{itn} + \varepsilon_{itn}] \tag{5}$$

where X_{itn} is the vector of explanatory variables being observed by the analyst and usually includes socio-economic, demographic and other relevant characteristics of the respondent along with attributes of the alternative itself and the decision context in choice situation t. The component β'_n is the vector of unknown coefficients and needs to be estimated.

Compared to the standard logit models, the fundamental enhancement of the model is observed in the error term. As can be seen, the stochastic error term is divided into two parts: ε_{in} is the random error term with mean zero, being independent and identically distributed (IID) extreme value type I, just as it is in standard logit structures. In other words, it is not correlated among alternatives or individuals. In order to solve this issue, η_{in} is the additional error component added to the structure which is correlated over alternatives and is assumed to follow a certain distribution pattern.

Different assumptions could be made for statistic distribution of η_{in}, including normal, lognormal, or triangular. Regardless, by considering ϕ as the vector of fixed parameters of the distribution, the conditional probability of choosing alternative i can be written a logit format, since the remaining error term follows the IID extreme value distribution. Accordingly,

$$L_{in} = \frac{\exp(\beta'_n X_{in} + \eta_{in})}{\sum_j \exp(\beta'_n X_{jn} + \eta_{jn})} \tag{6}$$

Consequently, one may obtain unconditional probabilities by integrating the above conditional probability across all values of η_{in}:

$$P_{iq} = \int_{\eta_{in}} L_{in}(\beta_n|\phi) f(\beta_n|\phi)\eta_{in} \tag{7}$$

One popular perspective toward mixed logit models is to associate the non-IID error component (η_{in}) with the model coefficients, and therefore considering them to be randomly distributed. In other words, unlike standard logit models where coefficients are theoretically assumed to be fixed across all people in the population, the mixed logit model considers each coefficient to be a random parameter with a mean and a standard deviation across individuals and scenarios. From a conceptual point of view, such variation is usually referred to as “preference heterogeneity”, meaning that there is significant behavioral variation across individuals either in their tastes or their decision making processes.

The VOT and VOR estimation technique for mixed logit is similar to multinomial logit with the only exception of personal heterogeneity incorporation in the model through random variable realization. Therefore,

$$\mathrm{VOT_i} = \frac{\partial \mathrm{U_{i,j}} / \partial \mathrm{T_j}}{\partial \mathrm{U_{i,j}} / \partial \mathrm{C_j}} = \frac{\beta_{\mathrm{i}}^{\mathrm{T}}}{\beta_{\mathrm{i}}^{\mathrm{C}}} \tag{8}$$

$$\mathrm{VOR_i} = \frac{\partial \mathrm{U_{i,j}} / \partial \mathrm{R_j}}{\partial \mathrm{U_{i,j}} / \partial \mathrm{C_j}} = \frac{\beta_{\mathrm{i}}^{\mathrm{R}}}{\beta_{\mathrm{i}}^{\mathrm{C}}} \tag{9}$$

4.4 TREATMENT OF USER HETEROGENEITY

In order to examine whether the taste variation across users can be explained by the observed individual and trip-related attributes, one may use either interaction effects, or divide the population into certain subsamples and develop separate models.

In the first approach, the interaction terms between the random parameters with each of the exogenous variables can be added to the utility function

$$\begin{aligned} \boldsymbol{U}_{in} = {} & \beta X_{in} + \beta_{TT} TT_{in} + \beta_{TTR} TTR_{in} + \beta_{TC} TC_{in} + \gamma_{TT} (S_{in} * TT_{in}) + \\ & \gamma_{TTR} (S_{in} * TTR_{in}) + \gamma_{TC} (S_{in} * TC_{in}) + \varepsilon_{in} + \eta_{in} \end{aligned} \tag{10}$$

where,

β = coefficient vector of non-random parameters,

X_{in} = vector of non-random explanatory variables,

β_{TT} = coefficient of “travel time” as a random parameter,

TT_{in} = “travel time” for individual n in alternative i ,

β_{TTR} = coefficient of "travel time unreliability" as a random parameter,

TTR_{in} = "travel time reliability" for individual n in alternative i,

β_{TC} = coefficient of "travel cost" as a random parameter,

$TC_{,in}$ = "travel cost" for individual n in alternative i,

S_{in} = a subset of X_{in}, which represent potential sources of heterogeneity,

γ_{TT} = interaction coefficient for travel time,

γ_{TTR} = interaction coefficient for travel time unreliability,

γ_{TC} = interaction coefficient for travel cost.

Accordingly, three variables of interest including travel time (TT), travel time unreliability (TTR), and travel cost (TC) were considered as random parameters. In order to obtain the underlying factors for preference heterogeneity, interaction terms between the three random coefficients and the individual socioeconomic-demographic variables were tested. Based on the equation (10), if the γ_{TT} (or γ_{TTR} or γ_{TC}) becomes significant, then the interacted variable S_{in} (which could be any of the non-random variables from X_{in}) is considered as a source of heterogeneity. Therefore, the entire heterogeneity is decomposed into the significant number of covariates.

As the random parameters reflect disutility ($\beta_{\mathrm{TT}}, \beta_{\mathrm{TTR},}$ β_{TC} are expected to be negative), positive γ_{TT} (or γ_{TTR} or γ_{TC}) indicates lower sensitivity, while negative interaction coefficients indicate higher sensitivity toward the random parameter. The sensitivities toward travel time, travel time reliability, and travel cost can then be further interpreted to represent taste variations in VOT and VOR.

In the second approach, a fixed parameter (β) can be obtained through data segmentation (e.g. a different model for each socio-economic stratum such as household income, employment status, age, gender, etc. of each individual in the sample) and/or attribute segmentation (e.g. separate parameter for different trip length ranges for the travel time attribute in a travel choice study), in contrast to treating all as random. The challenge of data segmentation approach is in picking the right segmentation criteria and range cut-offs that account for statistically significant sources of preference heterogeneity (Hensher et al. 2005).

In comparison to the both approach, first approach is mathematically more robust and appropriate to treat user heterogeneity. Therefore, this study prescribes random parameter interaction effect as the preferred treatment for user heterogeneity.

4.5 Incorporation of Attitudinal Aspect

This study employed three steps to incorporate attitudinal preferences into the analysis framework to investigate whether and to what degree the attitudinal factors influence the propensity of using managed lanes, which are – a) factor analysis of attitudinal statements, b) attitudinal model specifications, and c) cluster analysis based on attitudinal factors.

4.5.1 Factor Analysis

Factor analysis is a popular statistical method used to describe variability among a set of observed, correlated variables through lower number of unobserved variables called factors. The assumption is that multiple observed variables have similar patterns of responses because they are all associated with a latent factor. Therefore, the major objective of factor analysis is to reduce the dimension of analysis through extracting latent factors which are capable of explaining an acceptable magnitude of the existing variance in the dataset. Factor analysis identifies joint variations among the observed variables in response to unobserved latent variables (factors).

The factor analysis model could be formulated as follows:

$$(X-\mu)_{ix1} = L_{ixj} F_{jx1} + \varepsilon_{ix1} \tag{11}$$

where, $F's$ are the factors, $L'_{ij}s$ are respective factor loadings, and $\varepsilon_{ij}'s$ are the error terms associated with the observed variables ($X_i^{'}s$). The p random errors and factor loadings are unobserved or latent. Accordingly, a high factor loading value of L_{ij} (>0.7) suggests that variable X_i can be represented by factor F_j.

4.5.2 Attitudinal Model Specifications

Based on the factor analysis, dominant attitudes can be identified and transformed into major attitudinal indicators. These attitudinal indicators are then entered into the econometric models (e.g., multinomial logit) as an independent variable (X_i) to examine their impacts on travelers' decision-making. To capture the actual impacts of attitudes on travel choices, model results are usually compared with and without the attitudinal indicators.

Multinomial logit model structure describes each choice alternative through a utility function. Similar to the equation 1, a simplest form of attitudinal model is given below:

$$U_1 = \beta_1 X_1 + \beta_2 X_2 + \dots\dots\dots\dots\dots\dots + \beta_n X_n + \epsilon \tag{12}$$

where, X represents the attitudinal indicators, and any other explanatory variables. β refers to the coefficients corresponding to the attitudinal indicators and any other explanatory variables. Є, the error component accounts for any measurement error, parameter correlation, unobserved individual preferences, and other unobserved characteristics.

Like any other MNL model, the probability of each alternative of the attitudinal model is estimated using the following equation:

$$P(i) = \frac{e^{U_i}}{\sum e^{U_j}} \qquad (13)$$

where, P (i) is the probability that any particular alternative (i) will be chosen and U_i is the utility of that alternative (Ben-Akiva and Lerman, 1985).

4.5.3 Cluster Analysis

K-means cluster analysis is useful in identifying groups of subjects that share similar features. In this study, we're interested to segment the users into distinct groups based on all four attitudinal factors. These segments then can be further analysed to explore how they behaviour differently to ML policies, and to develop the best pricing strategies. The K-means cluster analysis requires a pre-defined value for K (number of clusters) and initial set of cluster means. Initially, every case (observation) is assigned to a nearest (by distance) cluster mean. Then, cluster means are recomputed and cases are reassigned based on the new cluster means.

4.6 SUMMARY

The core task of this dissertation is to estimate two widely accepted roadway pricing parameters – value of time (VOT) and value of reliability (VOR). VOT and VOR are usually derived from coefficients of travel time, travel time reliability, and travel cost parameters, which can be obtained from discrete choice model structures. In terms of model structure, this dissertation will explore both basic multinomial and more advanced mixed logit structures. The model will consider five choice alternatives for stated preference observations in a combination of route choice, mode choice, and departure time choice, which are: traveling on general purpose lanes, managed lanes, managed lanes before the peak period, managed lanes after the peak periods, and managed lanes with additional passengers; and two choice alternatives for revealed preference observations, which are: traveling on general purpose lanes and managed lanes.

It is recognized that treatment of user heterogeneity and inclusion of attitudinal aspect in travel behavior model has the potential to estimate VOT and VOR in a more accurate, reliable, and credible way. To analyze user heterogeneity, a number of demographic and travel characteristics will be tested as model variables. Using an interaction effects model, potential sources of user heterogeneity will be recognized and quantified. In order to explain the complexity of travel decision making in the presence of managed lanes, a series of relevant attitudinal characteristics will be analyzed. The impact of attitudinal factors on the decision of using managed lanes facility will be captured by comparing an attitudinal model with a reference model (without considering attitudinal factors).

CHAPTER 5

ANALYSIS OF MODEL RESULTS

This chapter presents the results of the estimated models based on the combined RP/SP dataset. The chapter is divided into two major subsections: impact of user heterogeneity on pricing valuation and impact of attitudinal aspect on pricing valuation.

Heterogeneity model is developed using mixed logit modeling framework, whereas attitudinal model is developed using multinomial logit modeling framework.

5.1. IMPACT OF USER HETEROGENEITY ON PRICING VALUATION

In order to identify the impact of user heterogeneity, both MNL and mixed logit base models (without consideration of user heterogeneity) were developed in section 5.1.1. The results can reveal whether there is significant preference heterogeneity in any of the random parameters (time, reliability, and cost). Section 5.2.2 presents the results of the mixed logit model with interaction terms added to help identify and measure different sources of heterogeneity.

5.1.1. Base Models

The RP subsample offered two alternatives only, managed lanes versus general purpose lane, with general purpose lane considered as the base category. The SP subsample expanded managed lane options into 4 separate alternatives: managed lanes with no temporal shift, managed lanes with early shift, managed lanes with late shift, and managed lanes with additional passengers. Respondents in the SP survey who reported a peak period trip were presented two more travel alternatives of travelling on the managed lanes either before or after the peak period, while those who reported a trip with less than three passengers were presented with another alternative of travelling on the managed lanes with additional passengers.

Tables 5-1 and 5-2 presented the model results for MNL and mixed logit models respectively. To account for user heterogeneity, the mixed logit model employed time, reliability, and cost as random parameters instead of fixed parameters as shown in the MNL model. Normal distribution was assumed for the random parameters. Moreover, in order to ensure negativity of time, reliability, and cost coefficients for all observations, a linear constraint was imposed on the mean (μ) and standard deviations (σ) of the normal distributions. Considering that a normally distributed variable has a range of $\pm 3\sigma$ around the mean μ, it was initially assumed that $\frac{\sigma}{\mu} < 0.33$. Furthermore, the normal distribution was truncated for cost coefficient ($|z| < 1.96$), in order to ensure the existence of finite moments (Daly et al., 2011). Non-random parameters were estimated from a discrete distribution rather than a continuous distribution.

In general, the results from the MNL and the mixed logit models were very close, in terms of coefficient values and model performances, as expected. The mixed logit model revealed significant standard deviation values for time, reliability and cost, indicating the taste heterogeneity for these three variables among the users.

The MNL and mixed logit models also showed very close average values for VOT and VOR. Considering that mixed logit model has been proven better than the MNL structure, the average values for VOT was about \$10.68 per hour and \$13.91 per hour for VOR.

Table 5-1 Multinomial Logit (MNL) Base Model

Generic Attributes in utility functions	
Independent Variables	**Parameter**
Time	-0.085 (-24.20)
Reliability	-0.158 (-14.97)
Cost	-0.588 (-41.16)

Alternative Specific Attributes in utility functions					
Independent Variables	**ML (SP)**	**ML2 (SP)**	**ML3 (SP)**	**ML4 (SP)**	**ML (RP)**
ASC	-3.23 (-23.5)	-2.37 (-11.1)	-2.91 (-19.1)	-2.43 (-26.8)	-2.42 (-5.13)
Male	-0.11 (-2.63)	-	-	-	-
Young People (16-34)	0.67 (12.85)	0.30 (2.70)	0.94 (10.18)	0.54 (9.35)	0.56 (2.20)

Med Income (50 ~ 150K)	0.30 (5.35)	-	-	-0.19 (-3.69)	-
High Income (>150k)	1.23 (18.25)	-	0.52 (4.85)	-	0.96 (3.71)
Employed	0.42 (6.30)	-	-	-	-
Sunpass User	0.72 (7.96)	-0.60 (-4.54)	-	-	1.21 (2.77)
Delay Experienced	-	-	-0.32 (-3.76)	-	-
Mandatory	0.50 (10.06)	-	-	-	-
Flexible Trip	-	-0.20 (-1.99)	-	0.10 (1.85)	-
Less Freq. (<4/month)	0.38 (6.49)	0.63 (5.14)	0.49 (4.78)	0.62 (8.90)	-
Med. Freq. (<12/month)	0.47 (6.06)	1.11 (7.41)	0.55 (3.88)	0.42 (4.24)	-
Weekday Trip	0.34 (8.90)	-0.38 (-3.32)	0.28 (2.60)	-	0.88 (3.72)
Urgent Trip	0.21 (4.40)	0.41 (4.19)	-	0.21 (3.71)	-
Short Trip (<20 miles)	-0.40 (-9.19)	-	-0.35 (-4.13)	-	-
Drive Another	0.57 (13.76)	-	-	-	-
VOT	$8.67				
VOR	$16.12				

All variables shown are significant at 5% significance level; t-statistics are shown in parentheses

Table 5-2 shows that for both RP and SP samples, individuals younger than 35, high income people, and sunpass users were more likely to utilize managed lanes. Moreover, mandatory trips and weekday trips also encouraged the usage of MLs.

In view of SP alternatives, a few additional observations could be made based on the model results. Female drivers were more probable to use managed lanes during their regular trip hours (i.e., peak hours without shifts or additional passengers). Avoiding additional passengers might indicate some type of a cultural or attitudinal preference where females prefer to drive-alone compared to other options. Moreover, females are expected to have more complicated trip chain behaviors (e.g., due to escorting kids to school or regular shopping activities) and therefore may not welcome shifting their regular departure times (McGuckin and Nakamoto, 2005).

Table 5-2 Mixed Logit Base Model (1000 draws)

Independent Variables	Parameter	Standard Deviation
Random parameters in utility functions		
Time	-0.20 (-109.31)	0.07 (109.31)
Reliability	-0.26 (-26.22)	0.09 (26.22)

Cost			-1.13 (-65.63)	0.37 (65.63)	

Non-Random parameters in utility functions

Independent Variables	ML (SP)	ML2 (SP)	ML3 (SP)	ML4 (SP)	ML (RP)
ASC	-3.7 (-36.20)	-3.6 (-27.17)	-3.9 (-39.09)	-2.8 (-47.82)	-2.82 (-4.52)
Male	-0.13 (-4.20)	-	-	-	-
Young People (16-34)	0.83 (19.65)	0.43 (5.59)	1.06 (17.02)	0.62 (15.91)	0.56 (1.91)
Med Income (50~150K)	0.34 (8.13)	-	-	-0.21 (-6.47)	-
High Income (>150k)	1.45 (28.54)	-	0.57 (8.54)	-	1.03 (3.41)
Employed	0.47 (8.59)	-	-	-	-
Sunpass User	0.76 (11.19)	-0.55 (-7.06)	-	-	1.17 (2.01)
Delay Experienced	-	-	-0.50 (-9.10)	-	-
Mandatory Trip	0.41 (10.74)	-	-	-	-
Arrival Flexibility	-	-0.17 (-2.75)	-	0.07 (2.00)	-
Less Freq. (<4/month)	0.60 (12.62)	0.83 (9.82)	0.73 (10.62)	0.84 (18.43)	-
Med. Freq. (<12/month)	0.61 (9.99)	1.44 (14.02)	0.87 (9.07)	0.57 (8.61)	-
Weekday Trip	0.25 (5.94)	-0.36 (-4.49)	0.23 (3.45)	-	1.28 (4.49)
Urgent Trip	0.14 (3.82)	0.39 (6.09)	-	0.11 (3.24)	-
Short Trip (<20 miles)	-0.30 (-9.16)	-	-0.21 (-4.06)	-	-
Drive Another	-0.78 (-19.3)	-	-	-	-
VOT	$10.68				
VOR	$13.91				

Model Performance: Log Likelihood Function = -16270.68, McFadden Pseudo R-squared = 0.546
All variables shown are significant at 5% significance level; t-statistics are shown in parentheses

In general, medium and high income people were more likely to use managed lanes compared with low income people who may consider managed lanes options only when they were offered discount options such as additional passengers. This seems reasonable, considering their monetary budget constraints. High income people, on the other hand, were less prone toward early departures. In case of work trips, this might stem from their usually high-ranked positions where strict work timetables are not enforced.

Arrival flexibility encouraged the option of additional passengers and discouraged early shifts. This sounds reasonable as flexible trips might have procured the additional time required for carpooling (e.g., imposed by the increased waiting time, etc.). As expected, individuals who had experienced delays were not willing to shift to after peak travel. The model suggested that Sunpass users were more prone to keeping their regular departure times rather than accepting departure shifts. This may signify an attitudinal aspect where using electronic payment options would increase the expectations of drivers, as they were not willing to incur any changes in their daily travel patterns.

Trip attributes were also important contributors to the model. Accordingly, mandatory trips were less prone toward temporal shift. Results also indicated that managed lanes were not an appealing option for short trips. In fact, they were even less desirable than general purpose lanes in case of no temporal shift/or with early shifts. However, they were more desired for urgent trips mainly accompanied by an early shift. In terms of trip frequency, less frequent and medium frequent trips had positive contributions to SP managed lanes alternatives, with highest impacts on early shifts. It might suggest that very frequent trips were likely to reduce the probability of managed lanes utilization, perhaps because of the high total payment in an extended period of time. In addition, early departures may not have been perceived as an acceptable option for frequent trips.

A review of mode attributes revealed that those who drive alone were more prone toward a late departure shift while drivers with only one passenger had higher tendency to use managed lanes in the peak period.

As can be seen in the model results, the standard deviation values were high and statistically significant for time, reliability, and cost. This provided solid evidence for the presence of heterogeneity among system users in their valuation of travel time and travel time reliability. The next subsection will further investigate the potential sources of heterogeneity and the magnitude of their impacts on VOT and VOR.

5.1.2. Interaction Effects Model

In this section, interaction effects were added to the base model to further identify the potential sources of heterogeneity for travel time, reliability, and cost in the dataset. Various socioeconomic demographic characteristics and trip attributes were tested in the model, such as age, gender, income, trip purpose, trip urgency and trip length, etc.

Table 5-3 presents the results of the mixed logit model with interaction effects. All variables shown are significant at 5% significance level. The main effects were fairly comparable with the results from the mixed logit model without interaction effects, in terms of coefficient signs and values. The interaction model reflected a slightly better goodness-of-fit in terms of likelihood and rho squared values, which showed that taking heterogeneity into account improves the predictive power of the model.

The interaction effects were expected to provide more accurate estimates of the random variables by taking into account the potential sources of heterogeneity. Accordingly, instead of approximating random parameters with their mean values for all observations, they help the analyst develop a theoretical formula for each of the random parameters based on its loading on each source of heterogeneity. In this case, for each of the observations, the random coefficients for time, reliability, and cost could be written as follows:

Time Coefficient = -0.38 + 0.02(Urgent trip) + 0.04(Employed) - 0.05(Age<34) + 0.02(Age>54) + 0.07(Drive alone) + 0.14(Drive another) +0.03(Freq<4/month) +0.06(Sunpass user) + 0.03(Delay experienced) (14)

Reliability Coefficient = -1.94 - 0.19 (High Income) + 0.25(Urgent trip) + 0.80(Distance<20 miles) + 0.70(Distance<20~40 miles) + 0.24(Age<34) + 0.18(Age>54) + 0.18(male) -0.27(Drive another) + 0.59(Freq. <4/month) + 0.33(Freq. 4~12/month) + 0.24(Delay experienced) - 0.16(Arrival Flexibility) (15)

Cost Coefficient= -2.74 + 0.47(High income) + 0.13(Med income) +0.23 (Urgent trip) +0.26 (Employed) +0.30 (Age<34) + 0.28(Age>54) + 0.22(Drive alone) – 0.18(Drive another) + 0.28(Freq. <4/month) + 0.19 (Freq. 4~12/month) + 0.21(Sunpass user) +0.23 (Weekday) + 0.22 (Delay experienced) (16)

Due to the linear formulation for each of the variables, the interaction effects actually imply the sensitivity towards each of the random parameters. Given the negative sign for the base values of the random parameters, a negative interaction effect means higher sensitivity while a positive interaction coefficient bodes for lower sensitivity. For instance, one might infer that high income individuals showed the lowest sensitivity to cost, and young people were the most sensitive toward travel time.

As the purpose of this study is to examine the impacts of heterogeneity on values of travel time, and travel time reliability, partial derivatives could be employed in order to obtain VOT and VOR sensitivities for each of the potential heterogeneity sources. By considering the existing heterogeneity in the three variables of time, reliability, and cost, one could provide a full analysis of VOT and VOR heterogeneity.

Table 5-3 Mixed Logit Model with Interaction Effects (1000 draws)

Independent Variables	Parameter	Standard Deviation
Random parameters in utility functions		
Time	-0.38 (-79.34)	0.13 (79.34)
Reliability	-1.94 (-36.94)	0.64 (36.94)
Cost	-2.74 (-70.42)	0.90 (70.42)

Non-Random parameters in utility functions

Independent Variables	ML (SP)	ML2 (SP)	ML3 (SP)	ML4 (SP)	ML (RP)
ASC	-3.32 (-16.7)	-2.93 (-10.8)	-3.45 (-15.4)	-2.63 (-21.7)	-2.91 (-4.20)
Male	-0.18 (-2.46)	-	-	-	-
Young People (16-34)	-	-0.38 (-2.8)	0.29 (2.43)	0.22 (3.15)	-
Med Income (50~150K)	0.28 (3.00)	-	-	-0.17 (-2.65)	-
High Income (>150k)	1.09 (8.93)	-	0.45 (3.17)	-	-
Employed	0.56 (5.17)	-	-	-	-
Sunpass User	0.92 (6.89)	-0.39 (-2.43)	-	-	1.55 (2.35)
Mandatory Trip	0.59 (7.08)	-	-	-	-
Less Freq. (<4/month)	-	0.87 (4.36)	0.62 (3.32)	0.56 (5.11)	-

Med. Freq. (<12/month)	0.66 (3.03)	1.82 (6.59)	1.09 (4.05)	0.65 (4.08)	-
Weekday Trip	0.24 (2.32)	-0.48 (-2.97)	0.34 (2.23)	-	1.27 (3.84)
Urgent Trip	0.33 (3.62)	0.77 (6.15)	-	0.48 (6.49)	-
Short Trip (<20 miles)	-0.40 (-5.27)	-	-0.37 (-3.47)	-	-
Drive Alone	-	-	0.24 (2.24)	-	-
Drive Another	1.65 (19.80)	-	-	-	-

Heterogeneity	**Time**	**Reliability**	**Cost**
High Income (>150K)	-	-0.19 (-1.66)	0.47 (5.70)
Med Income (50~150K)	-	-	0.13 (2.09)
Urgent Trip	0.02 (2.21)	0.25 (3.07)	0.23 (4.16)
Employed	0.04 (3.01)	-	0.26 (3.42)
Short Trip (<20 miles)	-	0.80 (7.26)	-
Med. Trip (20~40 miles)	-	0.70 (6.52)	-
Young People (<34)	-0.05 (-4.46)	0.24 (2.57)	0.30 (4.78)
Old People (>54)	0.02 (2.31)	0.18 (2.27)	0.28 (5.00)
Male	-	0.18 (2.25)	-
Drive Alone	0.07 (6.06)	-	0.22 (3.08)
Drive Another	0.14 (9.95)	-0.27 (-2.25)	-0.18 (-2.27)
Mandatory Trip	-	-	-
Less Freq. (<4/month)	0.03 (2.19)	0.59 (6.40)	0.28 (4.65)
Med. Freq. (<12/month)	-	0.33 (2.18)	0.19 (2.26)
Sunpass User	0.06 (4.75)	-	0.21 (2.35)
Weekday Trip	-	-	0.23 (3.47)
Delay Experienced	.03 (3.74)	0.24 (2.98)	0.22 (4.27)
Arrival Flexibility	-	-0.16 (-1.96)	-

Model Performance: Log Likelihood Function = -14021.82, McFadden Pseudo R-squared = 0.572
All variables shown are significant at 5% significance level; t-statistics are shown in parentheses.

Accordingly,

$$\frac{\partial VOT}{\partial s} = \frac{\left(\frac{\partial TT}{\partial s}\right)\times TC - \left(\frac{\partial TC}{\partial s}\right)\times TT}{TC^2} = \frac{\gamma_{TT}\times TC - \gamma_{TC}\times TT}{TC^2} \tag{17}$$

$$\frac{\partial VOR}{\partial s} = \frac{\left(\frac{\partial TR}{\partial s}\right)\times TC - \left(\frac{\partial TC}{\partial s}\right)\times TR}{TC^2} = \frac{\gamma_{TR}\times TC - \gamma_{TC}\times TR}{TC^2} \tag{18}$$

where, s denotes any of the segment variables indicating potential heterogeneity sources.

It should be noted that the partial derivatives also depend on the values of travel time, travel time reliability and travel cost coefficients (TT, TTR, and TC, respectively). To obtain a general understanding of the effects and to make it simple, base values are applied. As an example, the sensitivity of VOT and VOR with respect to high income category is calculated as:

$$\frac{\partial VOT}{\partial(High\ income)} = (\frac{0.00\times(-2.74)+0.47\times0.38}{(-2.74)^2}) \times 60 = 1.42 \text{ \$/hour}$$

$$\frac{\partial VOR}{\partial(High\ income)} = (\frac{(-0.19)\times(-2.74)+0.47\times1.94}{(-2.74)^2}) \times 60 = 11.34 \text{ \$/hour}$$

This can be interpreted as, when all other conditions keep constant, being in the high income category is expected to increase the values of VOT and VOR by $1.42 and $11.34 per hour, respectively. Similar calculations could be done for all other interaction segments. Results are presented in the Table 5-4.

The VOT and VOR sensitivity values are further illustrated in Figures 5-1 and Figure 5-2 in order to provide a more informative schematic view of the impacts of user heterogeneity on VOT and VOR.

Table 5-4 Heterogeneity in VOT and VOR Based on Partial Derivatives

Heterogeneity Sources	ΔVOT	ΔVOR
High Income (>150K)	1.42	11.34
Med Income (50~150K)	0.40	2.05
Urgent Trip	0.25	-1.96
Employed	0.03	4.09
Short Trip (<20 miles)	0.00	-17.43
Med. Trip (20~40 miles)	0.00	-15.40
Young People (<34)	1.93	-0.54
Old People (>54)	0.38	0.34
Male	0.00	-3.86
Drive Alone	-0.92	3.47
Drive Another	-3.58	3.16
Less Freq. (<4/month)	0.26	-8.58
Med. Freq. (<12/month)	0.59	-4.19
Sunpass User	-0.75	3.24
Weekday Trip	0.71	3.60
Delay Experienced	-0.06	-1.76

Flexible Trip	0.00	3.50

As shown in Figure 5-1, high income people (household income larger than 150K) along with individuals younger than 35 years old had the highest positive impacts on VOT. It is reasonable to assume that high income people perceive higher VOT due to their profitable work/business hours, and therefore are likely to pay to get time savings. Younger individuals, on the other hand, are expected to have more complicated responsibilities including a variety of time-sensitive activities such as work, school, and social errands. Their high values of time stemmed from both high sensitivity to time and low sensitivity to cost.

Weekdays were associated with higher VOT, perhaps because activity types and trip purposes on weekdays are different from weekends and mainly follow a fixed/rigid schedule. Medium income travelers (household income between 50K and150K) and older people (54 years old or older) also revealed considerable contributions to higher VOT, followed by medium and less frequent trips.

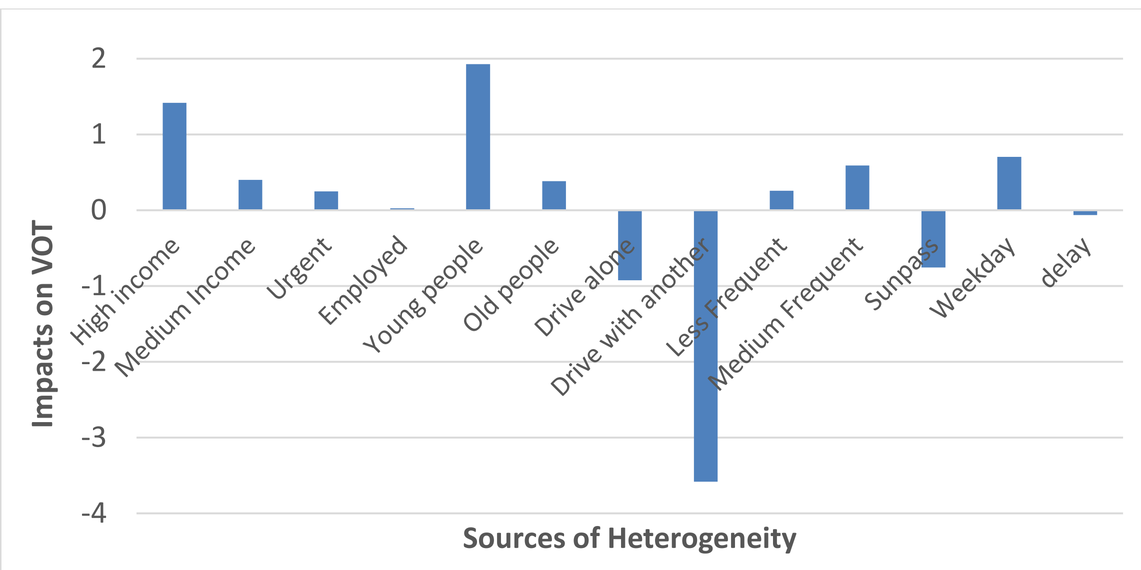


Figure 5-1 Heterogeneity in VOT.

As expected, urgent trips revealed higher VOT. The model also reflected slightly higher values of VOT for employed people, which conforms to common sense. No matter it's a work trip or non-work travel, employed people are probably affected by work-related temporal constraints, and are expected to show higher VOTs.

It was interesting to see that sunpass users were associated with lower VOT. A deeper look into sunpass users revealed that these drivers had lower sensitivity to travel time, perhaps because of their tendency to maintain their peak hour period travel, no matter what other options are. In addition, results also showed that drive alone and drive another modes were accompanied with lower VOT than driving with two or more passengers. This might be due to the reason that driving with additional passengers received toll discount or cost sharing, that would lead to higher usage of MLs and higher willingness to pay.

Delay experienced travelers also showed slightly lower VOT than those without delay experiences. This may be a little bit complicated, as these travelers may have taken delay as expected and had lower willingness to pay, or they generally preferred not to pay so they're more likely to experience delays.

In view of VOR, Figure 5-2 illustrates that high income individuals and employed travelers showed the highest positive impacts. As expected, weekdays also contributed to higher VOR values. Female travelers, sunpass users and medium income travelers also exhibited considerable contributions to higher VOR values.

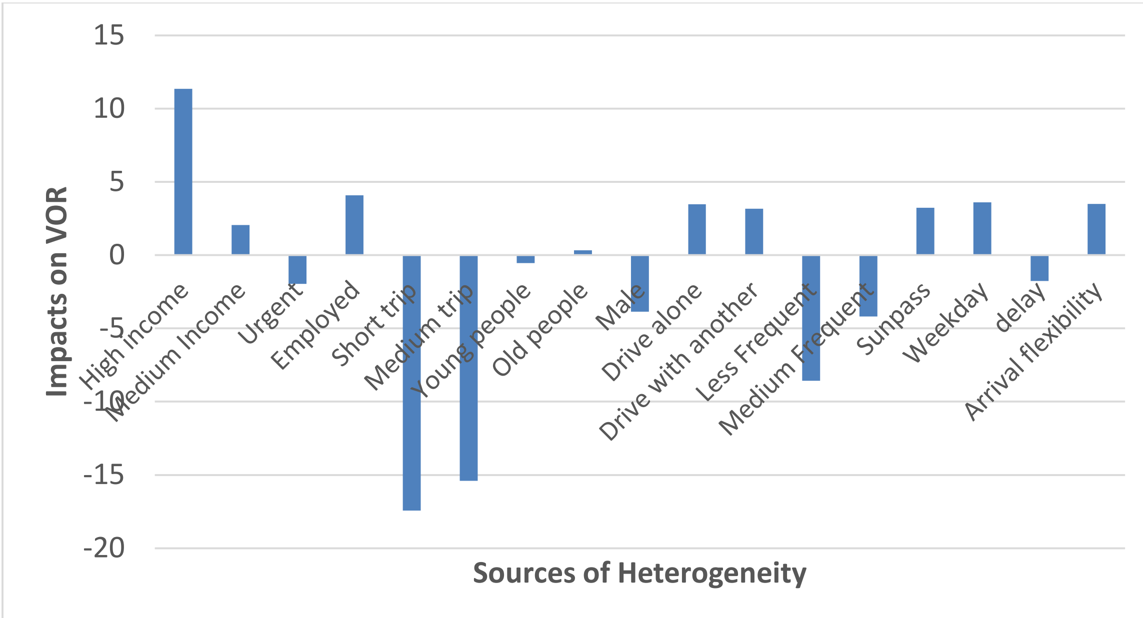


Figure 5-2 Heterogeneity in VOR.

Travelers older than 54 showed slightly higher VOR while younger travelers (younger than 35) showed slightly lower VOR compared with middle aged travelers. Driving with two or more additional passengers (HOV3+) would lead to lower VOR, while long trips (longer than 40 miles) and very frequent trips (more than 12 times a month) seemed to contribute to higher VOR.

Lower reliability values for urgent trips might signify that in public belief, urgency and delay are usually interpreted based on the need for shorter travel time and not reliability. The lower values of both VOT and VOR for delay experienced travelers indicated that people who are less willingness to pay, will probably experience higher delays, or those with higher tolerance for delays exhibited less willingness to pay.

Some of the results, however, may need further investigation. For instance, higher reliability values for trips with flexible arrival schedules did not seem reasonable. However this was consistent with the observations, where travelers with arrival flexibility from both RP and SP subsamples showed higher usage of MLs than those without arrival flexibility.

Also, the interaction model still reflected significant standard deviations for all three random parameters. This indicates that probably there are unaddressed sources of heterogeneity in the model. This probably happened due to several factors. First, the perceptions of travel time, cost, and reliability are probably a simultaneous process and therefore the interaction effects may well be correlated. Secondly, it is probable that single variable interactions do not completely address the user heterogeneity. In this regard, a more sophisticated approach which founds meaningful clusters of users based on variable combinations may be required. Thirdly, user attitudinal factors, which usually play important role in travel behavior studies, were not accounted for. Adding attitudinal factors could possibly address the remaining heterogeneity in the model.

5.1.3. Summary of Findings in User Heterogeneity

Mixed logit model results indicated an average value of \$10.68 per hour for VOT and \$13.91 per hour for VOR, with significant heterogeneity among the travelers. Among the choices between GP lanes and MLs with additional options (time shift or travel with additional passengers), the model showed that in general:

- Individuals younger than 35, high income people (annual household income larger than \$150K), and Sunpass users were more likely to utilize MLs.
- Low income people (annual household income less than \$50K) were less likely to use managed lanes unless they were being offered discount options such as additional passengers. This seems reasonable considering their

monetary budget constraints. High income people were less prone toward early departures.

- Female drivers were more probable to use managed lanes during their regular trip hours (i.e., peak hours without shifts or additional passengers).
- As expected, individuals who had experienced delays were not willing to late shifts.
- Sunpass users were more prone to using MLs and keeping their regular departure times rather than accepting departure shifts.
- Arrival flexibility seemed to encourage the option of additional passengers and discourage early shifts. This sounds reasonable as arrival flexibility procured the additional time required for carpooling (e.g., imposed by the increased waiting time, etc.).
- Weekday trips showed positive contribution to the usage of MLs, but with reduced probability of early shifts.
- Mandatory trips were less prone toward temporal shift.
- MLs were not an appealing option for short trips. However, they were more desirable for urgent trips mainly accompanied by an early shift.
- Less and medium frequent trips (less than 12 trips per month) had positive contributions to ML alternatives, with the highest impacts on early shifts. It might suggest that very frequent trips tended to reduce the probability of ML utilization, perhaps because of the high total payment in an extended period of time, or perhaps they had adjusted to delay through modal, residential, workplace choices or other arrangements.

In view of sensitivity to time, reliability, and cost, the interaction effects revealed significant user heterogeneity among the users. Taking all the sensitivities into account, a full analysis of user heterogeneity on VOT and VOR indicated that, everything else being equal:

- High and medium income groups (annual household income larger than $50K), employed travelers, older individuals (54 years or older), and weekday trips would lead to higher values for both VOT and VOR.
- Urgent trips, less and medium frequent trips (12 times or less per month), and young individuals (34 years old or younger) perceived higher values of time and lower values of reliability, which may indicate that travel time savings might be more important for these trips/travelers.
- Female travelers showed considerably higher VOR than males, possibly because females are expected to have more complicated trip chain behavior or other activities that require on-time arrivals (e.g., escorting kids from/to schools).
- Sunpass users and drive-alone travelers showed lower VOT and higher VOR, which mainly stemmed from their lower sensitivity to cost and time.
- Delay experienced travelers showed lower values for both VOT and VOR, which may indicate that people who were less willing to pay, would probably experience higher delays, or those with higher tolerance for delays exhibited less willingness to pay.
- Short and medium trips (less than 40 miles) only affected VOR, both of which had significantly lower VOR values compared to long trips.

5.2. IMPACT OF ATTITUDINAL ASPECT ON PRICING VALUATION

Inclusion of attitudinal aspects in the behavioral model requires careful attention to several issues. First, the influence of attitudes towards actual decision making needs to be determined, which intends to establish a meaningful relationship between attitudes and choice preferences. Moreover, the study may contain multiple sets of attitudes. Not all the attitudes would have the same level of influence on decision making. Therefore, attitudes need to be regrouped based on their influence levels.

This dissertation employed the following steps to address the aforementioned issues, as follows:

- Factor analysis was conducted to regroup homogeneous attitudes into major attitudinal indicators.
- The attitudinal indicators were incorporated into the model specifications, to examine the influence of attitudes on the choice to use managed lanes.
- The factors were further used in a cluster analysis which identifies major segments of roadway users. Such segmentation is expected to provide valuable insights on distinguishing travelers' behavior, which could enhance transportation planning efforts and policy making procedures.

5.2.1. Analysis of Attitudinal Factors

As discussed previously, factor analysis was applied to identify the underlying factors that could represent the ten attitudinal statements. Factors are derived based on the values of factor loading (L_{ij}), which represents the correlation between a variable and the underlying factors that has been extracted from the data. Factor loadings are usually estimated from two popular methods – the principal component method and the maximum likelihood method. We applied the principal component method, which was able to account for larger cumulative proportion of the sample variance than the maximum likelihood method.

The "Varimax Rotation" method was adopted so that each variable shows a high factor loading on a single factor and has small to moderate loadings on the remaining factors. This methods (high/low factor loadings) helps to identify which variables (attitudinal statements) can be represented by which latent variables (factors).

The results of the factor analysis are presented in Table 5-5. Four meaningful factors were identified. The values in the table represent the corresponding factor loadings. As expected, every attitudinal statements were heavily loaded (loadings >0.5) on a single factor and small to moderately loaded on the remaining factors (loadings sum <0.5). The shaded cells represent the heavily loaded factor for each attitudinal question. For instance, Q1, Q2, Q3, and Q4 had higher loadings for factor 1 and small to moderate loadings for other factors. Therefore, these statements were assigned to factor 1. Similarly, Q5 and Q6 belonged to factor 2; Q7, Q8, and Q9 pertained to factor 3; and Q 10 by itself was attributed to factor 4.

To make sense of the extracted latent variables, the factors were named based on the inherent meaning of the associated attitudinal statements.

- Factor 1 willingness to pay: the general attitudes toward paying tolls.
- Factor 2 willingness to shift: an indicator of the tendency to adopt time/route changes as a strategy to avoid traffic congestion.
- Factor 3 utility sensitivity: reflects the user's sensitivity to the total cost of the trip, including both travel time and toll.

- Factor 4 congestion tolerance: the acceptance level of traffic congestion.

Table 5-5 Factor Loadings on Attitudinal Statements

Attitudinal Attributes	Factor 1 (Willingness to Pay)	Factor 2 (Willingness to Shift)	Factor 3 (Utility Sensitivity)	Factor 4 (Congestion Tolerance)
Q1. I would be willing to pay a toll if it guarantees a travel time for my trip that is reliable every day	**0.857**	0.107	0.039	-0.069
Q2. I will use a toll route if the tolls are reasonable and I save time	**0.821**	0.091	0.150	-0.069
Q3. I support using tolls to pay for highway improvements that reduce congestion	**0.827**	0.002	0.056	0.009
Q4. I can generally afford to pay tolls	**0.699**	-0.026	-0.079	0.065
Q5. I regularly change my driving schedule in order to avoid traffic congestion	0.045	**0.875**	0.081	0.052
Q6. I regularly change my route in order to avoid traffic congestion	0.058	**0.863**	0.127	-0.046
Q7. It bothers me when traffic congestion adds more than a few minutes to my trips	0.199	0.187	**0.583**	-0.379
Q8. I always try to be on time	-0.222	0.130	**0.713**	0.234
Q9. I always look for the best deals and try to save money whenever possible	0.151	0.023	**0.751**	0.032
Q10. Traffic congestion is just a way of life in South Florida & something you learn to live with	0.035	0.031	0.090	**0.928**

The factor analysis produced four factor scores for each respondent based on his/her responses to the attitudinal questions, each factor score corresponds to one of the four derived factors. Based on these factor scores, the respondents were further clustered into two categories (high or low) for each latent factor, indicating whether they have high or low willingness to pay, or high or low willingness to shift departure time, and so on.

Table 5-6 shows the SP choice shares among the respondents by category. The choice shares were compared between the two categories within each factor using a

Bonferroni proportion z test. The results of the test were indicated by letter a or b as shown in the parentheses. If the two groups show the same letter, it rejects the hypothesis that there is statistically significant difference between the choices of the two groups at 95% confidence interval. For instances, utility sensitivity did not show significant influence in terms of the preference to use general purpose lane (a, a); on the other hand, high and low willingness to pay groups exhibitted statistically different preference for using the general purpose lanes (a, b).

Figure 5-3 provides a graphical visual of Table 5-6 to aid with the analysis. It shows that individuals with high willingness to pay (WTP-H) showed significantly lower percentages of GP lane usage (51.30% versus 80.50%). Among different ML alternatives, individuals with high willingness to pay also prefered to maintain their regular schedule, which may signify their reluctance to incur any time shift.

Table 5-6 Sample Composition of Respondents' Attitude across SP Choices

Attitudes	GP	ML	ML 2	ML 3	ML 4	Total
Willingness to Pay - High	6531 51.30% (a)	3389 26.60% (a)	432 3.40% (a)	644 5.10% (a)	1739 13.70% (a)	12375 100%
Willingness to Pay-Low	2892 80.50% (b)	216 6.00% (b)	84 2.30% (b)	65 1.80% (b)	335 9.30% (b)	3592 100%
Willingness to Shift - High	5726 55.90% (a)	2238 21.80% (a)	389 3.80% (a)	447 4.40% (a)	1447 14.10% (a)	10247 100%
Willingness to Shift - Low	3697 60.80% (b)	1367 22.50% (a)	127 2.10% (b)	262 4.30% (a)	627 10.30% (b)	6080 100%
Utility Sensitivity - High	8891 57.70% (a)	3382 22.00% (a)	477 3.10% (a)	679 4.40% (a)	1978 12.80% (a)	15407 100%
Utility Sensitivity - Low	532 57.80% (a)	223 24.20% (a)	39 4.20% (a)	30 3.30% (a)	96 10.40% (b)	920 100%
Congestion Tolerance - High	5962 61.60% (a)	1791 18.50% (a)	271 2.80% (a)	384 4.00% (a)	1271 13.10% (a)	9679 100%
Congestion Tolerance - Low	3461 52.10% (b)	1814 27.30% (b)	245 3.70% (b)	325 4.90% (b)	803 12.10% (b)	6648 100%

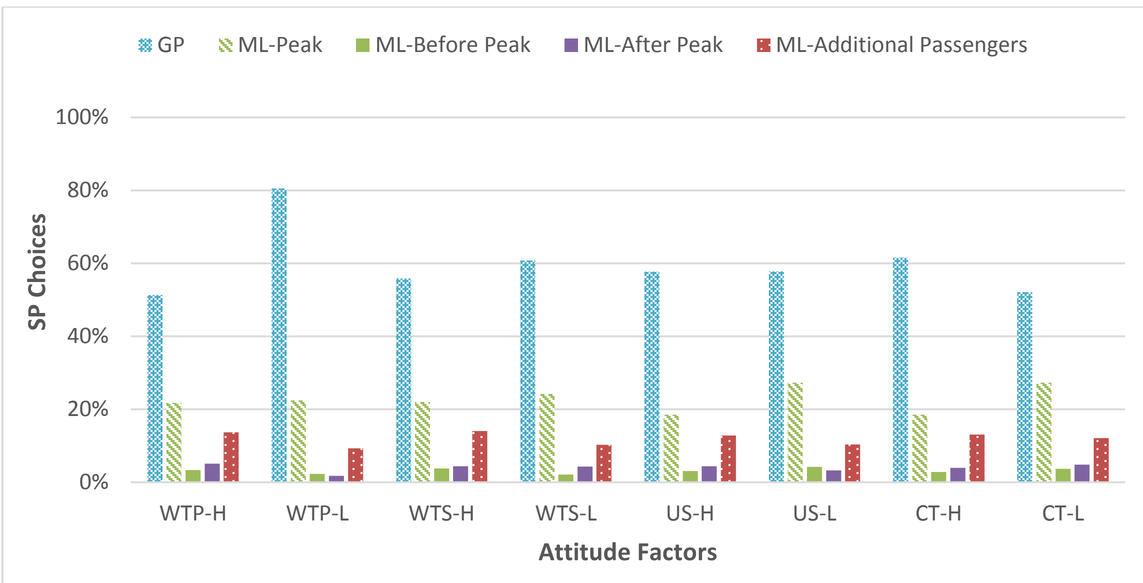


Figure 5-3 SP Choice Share across Respondents' Attitudes.

Users with high willingness to shift (WTS-H) were still more likely to use MLs (44.10% versus 39.20%). The values also indicated higher tendency toward early shift. Utility sensitivity (US-H and US-L) did not show any significant impact on individuals' decisions, perhaps because approximately 95% of the sample was considered to be high utility sensitive users. The only exception is for the traveling with additional passenger alternative, which was significantly preferred by users with high utility sensitivity. Finally, users with high congestion tolerance (CT-H) showed higher tendencies for GP lanes. In particular, they were less likely to use ML during peak or before peak hours.

Table 5-7 shows the choice shares by attitudinal factor category for the RP data. Accordingly, high willingness to pay increased the probability of ML usage by 29%, which is the highest impact among the attitudinal factors. High Utility sensitivity and high congestion tolerance reduced the likelihood of ML usage by 23% and 17%, respectively. Interestingly, the willingness to shift did not have significant influence on the choice of using MLs. Figure 5-4 presents RP choice shares by respondents' attitude category.

Table 5-7 Sample Composition of Respondents' Attitude across RP Choices

Attitudes	GP	ML	Total
Willingness to Pay - High	187 42.90% (a)	249 57.10%	436 100%
Willingness to Pay-Low	55 71.40% (b)	22 28.60%	77 100%
Willingness to Shift - High	149 45.20% (a)	181 54.80%	330 100%
Willingness to Shift - Low	93 50.80% (a)	90 49.20%	183 100%
Utility Sensitivity - High	236 48.30% (a)	253 51.70%	489 100%
Utility Sensitivity - Low	6 25.00% (b)	18 75.00%	24 100%
Congestion Tolerance - High	160 54.40% (a)	134 45.60%	294 100%
Congestion Tolerance - Low	82 37.40% (b)	137 62.60%	219 100%

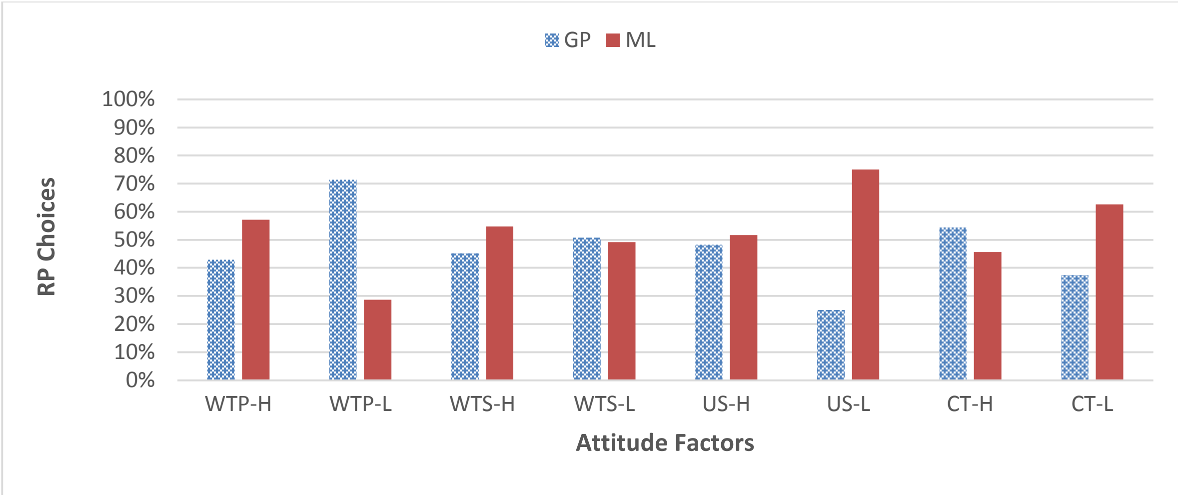


Figure 5-4 RP Choice Share across Respondents' Attitudes.

5.2.2. Attitudinal Model Results

Two multinomial logit models were prepared; a reference model without considering attitudinal factors and an attitudinal model, to capture the impact of attitudinal factors on the decision of using ML facility. Table 5-8 presents the results of the reference model and Table 5-9 provide attitudinal model estimation results.

As the main focus of this paper is to capture the impacts of attitudinal variables on the propensity to use ML facility, detailed discussion of the reference model is not provided here. In general, the impacts of personal and trip characteristics seem to be very much compatible with general expectation based on previous literature and common sense. As expected, travelers were likely to prefer ML alternatives when they were younger (<35 years), female, employed, sunpass user, had high income (household income >150K), and were traveling on mandatory, urgent, or weekday trips. On the contrary, ML did not seem to be an appealing option for respondents who had previous delay experience or arrival flexibility, and for short (less than 20 miles in length) or very frequent trips (more than 12 trips per month).

Table 5-8 Multinomial logit (MNL) Model – Without Attitudinal Variables.

Independent Variables	ML (SP)	ML2 (SP)	ML3 (SP)	ML4 (SP)	ML (RP)
Time			-0.08713***		
Reliability			-0.47637***		
Cost			-0.59688***		
ASC	-2.44***	-2.41***	-2.24***	-3.03***	-2.16***
Male	-0.15***	-	-	-	-
Age (<34 years)	0.74***	0.30***	0.93***	0.53***	0.56**
Age (>55 years)	0.14***	-	-	-	-
Income (>150K)	0.82***	-	0.54***	0.31***	0.97***
Income (<75K)	-0.46***	-	-	0.21***	-
Employed	0.38***	-	-	-	-
Sunpass User	0.66***	-0.59***	-	-	1.22***
Delay Experienced	-	-	-0.31***	-	-
Mandatory Trip	0.35***	-	-	-	0.70***
Low Freq. (<4/Month)	0.42***	0.64***	0.50***	0.35***	
Med Freq. (4~12/Month)	0.43***	1.11***	0.55***	0.30***	-
Weekday	0.26***	-0.36***	0.34***	0.19***	0.87***
Urgent Trip	0.27***	0.48***	-	0.28***	-
Short Trip (<20 miles)	-0.42***	-	-0.34***	-	-
Drive Alone	-	-	-0.72***	-	-
Drive with Another	-0.26***	-	-0.90***	1.62***	-
Arrival Flexibility	-	-0.20**	-	-	-
Log Likelihood			-15789.08063		
R^2			0.41		

***, **,* represents significance level at 1%, 5%, 10%, respectively; RP/SP scale parameter was insignificant

Table 5-9 shows the results of the model when attitudinal factors were added. Among different attitudes, willingness to pay had the highest impact on the likelihood of using MLs for all available options of SP and RP samples. Furthermore, individuals with higher WTP showed higher probabilities of maintaining their regular peak hour trips rather than shifting the schedule. Willingness to shift also showed positive contribution to ML usage. However, as expected, it was more likely to result in a schedule shift to off-peak hours. Holding high utility sensitive attitude, which means using any opportunity to save both money and time, showed a negative impact on ML utilization. A detailed review of the coefficients revealed that this attitude signifies unwillingness to pay for express lanes unless it is a very good and economical deal. Congestion tolerance, which shows individuals attitude toward traffic congestion, also showed significant contribution to the model. In view of that, high congestion tolerance individuals, who accept traffic delays as part of life, were less likely to be express lane users. They did not view congestion as an acute problem therefore, may not see any point in using MLs. Hence, it was not surprising why they showed the highest negative impacts on ML utilization.

Table 5-9 Multinomial logit (MNL) Model – With Attitudinal Variables

Independent Variables	**ML (SP)**	**ML2 (SP)**	**ML3 (SP)**	**ML4 (SP)**	**ML (RP)**
Time			-0.09854***		
Reliability			-0.44647***		
Cost			-0.63261***		
ASC	-3.30***	-3.06***	-3.79***	-3.82***	-1.04
Male	-0.16***	-	-	-	-
Age (<34 years)	0.73***	0.33***	0.94***	0.53***	0.53**
Age (>55 years)	0.16***	-	-	-	-
Income (>150K)	0.66***	-	0.36***	0.21***	0.85***
Income (<75K)	-0.36***	-	-	0.30***	-
Employed	0.39***	-	-	-	-
Sunpass User	0.53***	-0.76***	-	-	1.06**
Delay Experienced	-	-	-0.36***	-	-
Mandatory Trip	0.29***	-	-	-	0.69***
Low Freq. (<4/Month)	0.33***	0.58***	0.43***	0.26***	
Med Freq. (4~12/Month)	0.33***	1.06***	0.55***	0.20***	-
Weekday	0.30***	-0.28**	0.41***	0.19***	0.90***
Urgent Trip	0.25***	0.41***	-	0.27***	-
Short Trip (<20 miles)	-0.36***	-	-0.26***	-	-
Drive Alone	-	-	-0.75***	-	-
Drive with Another	-0.20***	-	-0.86***	1.68***	-
Arrival Flexibility	-	-0.35**	-	-	
Willingness to Pay	2.02***	1.33***	1.74***	1.09***	1.19***
Willingness to Shift	0.10**	0.97***	0.41***	0.37***	-
Utility Sensitivity	-0.50***	-0.67***	-	-0.21*	-1.76***
Congestion Tolerance	-0.60***	-0.41***	-0.36***	-0.21***	-0.59***
Log Likelihood			-14408.20901		
R^2			0.44		

***, **,* represents significance level at 1%, 5%, 10%, respectively; RP/SP scale parameter was insignificant

The comparison of the two models in terms of statistical performance also shed light on some invaluable insights. Accordingly, the attitudinal model increased the log likelihood parameter by 1381 (difference between attitude model log likelihood 14408.2

and reference model log likelihood 15789.1), leading to a chi-square statistic of 31.4, which was statistically significant at 5%. In other words, incorporating attitudinal factors in the model significantly improved the model's performance.

VOT and VOR estimated from the reference model were \$8.76/hour and \$47.89/hour, respectively. While the attitudinal model showed VOT as \$9.49/hour and VOR as \$34.8/hour. It implies that traditional models (without considering attitudinal effect) may undervalue VOT slightly and overestimate VOR.

5.2.3. Cluster Analysis Based on Attitudinal Factors

The factor analysis discussed earlier helped to identify each respondent's attitudes toward the four factors, separately. This cluster analysis aims to identify distinct segments based on all factors (represented by certain combinations of the four aforementioned attitudinal factors). Each segment represents one group of roadway users that share similar attitudes. Then these segments can be further explored in terms of how their behaviour toward the usage of MLs may differ.

K-means cluster analysis results are presented in Table 5-10. An optimum number of four clusters were defined through trial and error. The values in the table represent cluster centers, which were obtained after assigning and optimizing each of the observations to the nearest cluster mean. The table also provides results of ANOVA in order to show whether and to what extent the attitudinal differences were significant among the cluster segments. Results indicated that all attitudinal factors were statistically different across the four market segments.

Table 5-10 also showed the distribution of the respondents to the cluster segments as follows; 176 respondents belonged to segment 1, 1186 individuals were allocated to segment 2, 499 fell into segment 3, and 180 travelers were assigned to segment 4.

Table 5-10 ANOVA Results for Differences in Attitudinal Factors among the Segments.

Attitudinal Factors	Segments				ANOVA	
	Segment 1 (176)	Segment 2 (1186)	Segment 3 (499)	Segment 4 (180)	F	Sig.
Willingness to pay	0.00	1.00	0.79	0.07	1847.968	0.0
Willingness to shift	1.00	0.51	1.00	0.00	413.883	0.0
Utility sensitivity	0.85	0.96	0.97	0.83	30.912	0.0
Congestion Tolerance	0.89	0.81	0.00	0.49	700.206	0.0

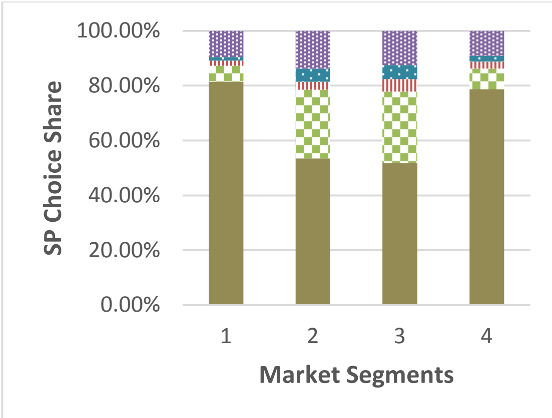
By reviewing the cluster centre values in Table 5-10, reasonable inferences can be made about the overall characteristics of each segment. Generally, segment1 displayed the highest mean for willingness to shift, along with the lowest mean value for willingness to pay. Segment 2 differed from segment 1, as it had high score for willingness to pay but moderate level of willingness to shift. Similar to segment 1, segment 3 showed high willingness to shift, but minimum level for congestion tolerance. Finally, segment 4 exhibited minimum scores for both willingness to pay and shift.

Taking these characteristics into account, the four segments were respectively labelled as follows: shift prone, toll prone, congestion avoider, and congestion adapters. The characteristics of the users in each segment can be summarized as below.

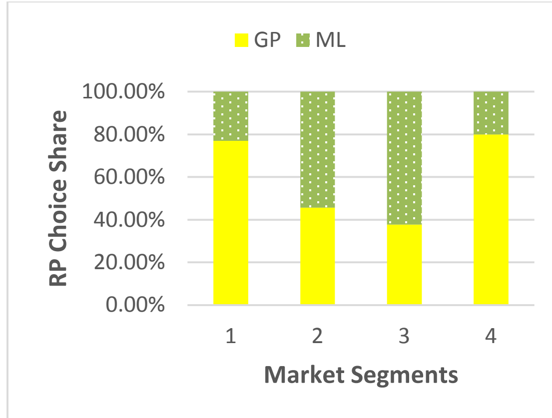
- Segment 1 (Shift Prone Individuals): This category includes users who view traffic as a way of life. They were not willing to pay tolls unless there was a very good and economical deal. Instead, they highly welcomed time shift in their trip schedules in order to tackle traffic congestions. Congestion compliant individuals were better prepared to tackle congestion; they either changed departure time or driving route.

- Segment 2 (Toll Prone Individuals): Like the first category, these drivers hold the same perspective towards traffic congestion. However, they had different priority to tackle this problem. They were more likely to pay tolls as long as they received the desired level of service. Shifting their schedules was a less appealing strategy. These users are very likely to use ML facilities.
- Segment 3 (Congestion Avoiders): Unlike the previous two groups, this group of users had very low tolerance for congestion who view traffic as an acute problem which needs to be tackled by any means. Therefore, they showed both high willingness to shift and high willingness to pay. Being intolerant to traffic congestion and with high willingness to pay, these individuals are the most suitable candidates for ML facilities.
- Segment 4 (Congestion Adapters): This category consists of people who were neither willing to pay tolls nor willing to shift schedules. They were more likely to use the GP lanes and showed little interest in MLs.

Given these distinct segments, further analysis was conducted to examine their corresponding choice preferences. As seen in Figure 5-5, shift prone individuals and congestion adapters were more likely to use GP lanes, whereas toll prone individuals and congestion avoiders were more likely to prefer ML facility. The choice preferences showed similar patterns between the SP and RP data. The patterns also supported the application of attitudinal characteristics to derive market segments, which reflected their actual choice preferences.



(a) SP Choice Share across the Segments



(b) RP Choice Share across the Segments

Figure 5-5 Choice Preferences among the Users by Segment.

5.2.4. Summary of Findings in Attitudinal Aspects

This dissertation examined the effect of attitudinal factors on the choice of using MLs. Combined RP and SP dataset were used to support the analysis. The survey included ten questions that measured the users' attitudes toward tolls and traffic congestion, and their strategies in dealing with congestion. Through factor analysis, four underlying attitudinal factors (willingness to pay, willingness to shift, utility sensitivity, and congestion tolerance) were identified based on the users' attitudinal statements.

Two multinomial logit models were developed, a reference model and an attitudinal model to capture the impacts of attitudinal factors on the usage of ML facilities. Model results indicated the significant roles of attitudes in explaining ML usage. As expected, high willingness to pay and shift increased the propensity of using MLs, whereas travellers with high sensitivity to utility (using any opportunity to save both money and time) and high tolerance of congestion showed negative impacts on ML utilization. The results point to the needs to incorporate attitudinal factors in the analysis of ML strategies.

The findings of the factor analysis and model exploration were further supported by a k-means cluster analysis. Based on the underlying attitudinal factors, the study identified four user groups, which were shift prone individuals, toll prone individuals, congestion avoiders, and congestion adapters. These segments can be well defined by the corresponding combinations of attitudinal factors, and showed consistent choice preferences. Particularly, shift prone travelers and congestion adapters were more likely to stay with GP lanes, while toll prone users and congestion avoiders showed significantly higher usage of MLs.

Both descriptive statistical and model results identified attitudes as important explanatory factors in traevlers' choice behavior. It suggests the need to consider attitudinal aspects in tolling analysis. More than half of the respondents (52.20%) accepted congestion as a way of life and were not optimistic on any improvement in current situation (Fig 3-17), which might imply that current demand management efforts had not been adequate. In addition, almost one quarter of the respondents (segment 3) considered congestion as an acute problem and showed high willingness to pay or shift schedule to avoid congestion, and a majority of the respondents (83%) had high willingness to pay. These attitudes may imply that an immediate solution is required and people would consider extra payment to save time or ensure reliability. However, the large group of users with high sensitive to cost and time also suggests the needs for more innovative pricing strategies in order to attract users. The higher value of VOR (compared to VOT) may suggest that reliability feature of ML facility plays an important role in attracting users; therefore, particular consideration should be given to ensure reliability from the operational perspective of ML facilities.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1. SUMMARY AND CONCLUSIONS

Managed lanes refer to the application of various operational and design strategies on highway facilities to improve system efficiency and mobility by proactively allocating traffic capacity to different lanes. With increasing emphasis on managed lanes strategies, it is critical to understand the behavior changes and underlying causalities in user responses to managed lanes in order to evaluate the program impacts and effectiveness, especially when facing demand and other system changes. One of the key elements is to examine the value of time (VOT) and value of reliability (VOR) distributions or variations across different users and under different circumstances.

VOT and VOR represent the users' willingness to pay to reduce travel time and the variability in travel time, respectively. This dissertation presents a comprehensive study in VOT and VOR analysis in the context of managed lane facilities. Combined Revealed Preference (RP) and Stated Preference (SP) data were used to understand travelers' choice behavior regarding the usage of managed lanes. The data were obtained from the South Florida Expressway Stated Preference Survey conducted by the Resource Systems Group, Inc. (RSG), which gathered information from automobile drivers of South Florida who had recently made a trip on I-75, I-95, or SR 826 corridors. Revealed preference data were gathered from an automated data sharing, dissemination, and archiving system, named regional integrated transportation information system (RITIS). To be consistent with the SP survey, which was conducted between November 16th and December 15th of 2011, archived data from RITIS were obtained for the year of 2012. Four sets of archived data were retrieved: a) I-95 northbound for general purpose lanes b) I-95 northbound for managed lanes c) I-95 southbound for general purpose lanes d) I-95 southbound for managed lanes. The data were collected for the entire segment of the managed lanes facility between the golden glades interchange and airport expressway.

Various modeling and analysis approaches were employed to further reveal the user heterogeneity in VOT and VOR. Mixed logit modeling was applied as the state of the art methodology to capture heterogeneity in users' choice behavior. The model revealed an average value of $10.68 per hour for VOT and $13.91 per hour for VOR, which are reasonable considering the average household income in the region, and are well within the ranges found in the literature. Among the choices between general purpose (GP) lanes and managed lanes with additional options (extra discount for time shifts or for additional passengers), low income (household income < 50 K) people were less likely to use managed lanes unless they were offered discount options, such as additional passengers. Arrival flexibility seemed to encourage the option of additional passengers and discourage early shifts. Individuals who have experienced delays were less willing to prefer late shifts. Sunpass users and female travelers were more prone to use managed lanes during their regular schedules. Individuals taking mandatory and weekday trips were more likely to use MLs, which do not seem appealing for short and frequent trips.

This study also hypothesizes that attitudes can play an important role in travel behavior analysis. In the context of managed lanes facility, the study examined the effect of attitudinal variables on a mode choice setting with the general purpose lane and different kinds of managed lane travel options, and found that attitude can explain the complexity of travel decision making in the presence of managed lanes. The study analyzed ten attitudinal questions, mainly focusing on drivers' sensitivity toward traffic and their strategies to avoid congestion delays. By administering a factor analysis technique, four meaningful factors (willingness to pay, willingness to shift, utility sensitivity, and congestion compliance) were identified that can be included in the traditional managed lane models.

Two multinomial logit models were developed: a reference model without considering attitudinal factors and an attitudinal model to capture the impact of attitudinal factors on the decision of using managed lanes facility. VOT and VOR estimated from reference models are $8.76/hour and $47.89/hour, whereas the values derived from attitudinal models are $9.49/hour and $34.8/hour. Thus, traditional models (without attitude) are more likely to underestimate VOT, and overestimate VOR. Model results implied that attitudinal variables are important and statistically significant in explaining managed lane usage propensity.

Based on the attitudinal model, willingness to pay and willingness to shift attitude increases the utility of all kind of managed lane travel options, whereas utility sensitivity and congestion compliance tendency decreases the utilities. As well as conforming to common sense expectations, results imply that attitudinal variables are significant contributors to the model, and they could be applied to explain any kind of intriguing travel behavior on managed lanes facility. In terms of model performance, the likelihood ratio test indicated that model explanatory power improved significantly when attitudinal variables are included in the models. Therefore, attitudinal variables need to be included to explain travel behavior in managed lanes facility, in addition to the socio economic and demographic variables. The results are supported by a previous study conducted by Kuppam et al. (1999), where attitudinal impacts were measured in a mode choice study.

6.2. RESEARCH CONTRIBUTIONS

The topics explored in this dissertation are expected to improve the current planning framework from a variety of perspectives, beginning with estimation. This study identified possible reasons for the large variation of VOT and VOR estimates, and proposed two major treatments for consistent VOT and VOR estimation: user heterogeneity and attitudinal aspects. The study hypothesizes that inclusion of attitudinal indicators into the model specifications and disaggregates VOT and VOR estimation for appropriate markets has the potential to forecast travel demand in a more accurate, reliable, and credible way.

Unlike many other studies, the study goes beyond providing a single estimate of VOT and VOR to represent the entire population. The dissertation employed a robust approach to quantify VOT and VOR, both in terms of data quality and model structure. The study applied a rich data-set, which includes combined stated and revealed preference observations from a representative sample consisting of 2041 respondents. As part of the robust approach, this dissertation developed mixed logit models, which is considered as a powerful discrete choice modeling technique as it can incorporate user heterogeneity (travelers need not to be similar to one another) in the models. Unlike standard logit models where coefficients are theoretically assumed to be fixed across all people in the population, the mixed logit model considers each coefficient to be a random parameter with a mean and a standard deviation across individuals and scenarios. From a conceptual point of view, such variation is usually referred to as "preference heterogeneity," meaning that there is significant behavior variation across individuals, either in their tastes or their decision-making processes.

The model was further enhanced by adding interaction effects of variables, which helped recognize and quantify potential sources of heterogeneity in user sensitivities to time, reliability, and cost. The sensitivities were further employed to capture the user heterogeneity in VOT and VOR. The findings indicated that various socioeconomic-demographic characteristics and trip attributes contributed to the variations in VOT and VOR at different magnitudes. This study provides a robust approach to quantify user heterogeneity in the values of VOT and VOR by incorporating the corresponding interaction effects for specific market segments. The results of this study contributed to a better understanding on what attributes led to higher or lower VOT and VOR and to what extent. These findings can be incorporated into the demand forecasting process and lead to better estimates and analytical capabilities in various applications, such as toll feasibility studies, pricing strategies, policy evaluations, impact analysis, etc.

In terms of attitudinal perspectives, this study is one of the few which focuses on evaluation of attitudinal parameters in the context of managed lanes' utility for roadway users. The existing literature mainly focuses on observed travelers or trip characteristics and is less likely to capture latent preferences or heterogeneity of roadway users. Motivated to address this knowledge gap, the study herein made an effort to explore the role of attitudinal factors in drivers' propensity toward using managed lanes. The dissertation presents an approach which can capture whether and to what extent the choice of using or not using a tolled facility can be attributed to the travelers' attitudinal preferences. In order to measure the influence of attitudinal aspects, two set of models (with and without the attitudinal indicators) were developed and compared. Both descriptive statistics and model results identified attitudes as important model explanatory factors in drivers' decisions. Therefore, it could be recommended that future survey designs should consider a more detailed focus on attitudinal perspectives.

6.3. STUDY LIMITATIONS

Like any other research effort, the results of this study are subject to a few limitations, including the following:

1. Lack of reliability data. Travel time reliability was not considered in the SP survey design, where the respondents were only asked to consider the trade-offs between time and cost. Instead, reliability was measured based on travel time variability derived from detector data. Hence, travelers' responses to the alternatives might not have reflected their perceived values of reliability improvement.
2. Reliability measure. The study considered semi-standard deviation as the reliability measure (mean-variance approach). VOR could have been derived and compared using few other popular reliability measure, including travel time index, buffer index, 90th % - 50th % travel time, etc. Since the survey did not obtain preferred arrival time (PAT) information, none of the scheduling approach reliability measure could have been applied to the study.
3. Nature of attitude data. From the theoretical perspective, one major limitation of this study is that it neglects the endogenous nature of attitudes and considers them as being exogenous. Endogeneity can be fully addressed, if attitudinal model is developed in hybrid choice model platform.

4. Simple market segmentation. The study adopted simple cluster analysis approach to segment travelers into homogeneous user groups. A more representative segmentation would have been obtained through latent class model structure, a more robust approach compared to the cluster analysis. Latent class model can employ attitudinal attributes as a criterion to determine number of segments and segment characteristics are reflected by the corresponding attitudinal profile.

6.4. RECOMMENDATIONS FOR FUTURE RESEARCH

Future study can extend this analysis in the context of:

1. Modal shifts as managed lanes programs also bring new opportunities for transit service, making it a viable choice by providing express lane benefits without additional costs to the passengers. Given that these benefits may be more attractive to certain users than the others, further study can be performed to provide insights in this regard and contribute to the integration of transit with managed lanes programs.
2. Another aspect for future study can be developed along the lines of automated/connected vehicle research. As these technologies become available, they may bring transformative shifts in how people live and travel, and have great impacts on the values people place on travel time and reliability.
3. In future research, the authors plan to develop a hybrid choice model to capture attitudinal impacts in a more precise manner. Construction of hybrid choice model would reveal the relationship between attitude and socio-economic-trip variables, and provide joint estimation of choice and latent variables.

DISCLAIMER

The study used data only from residents of South Florida. No other cross-validation was conducted. Therefore, the findings of this dissertation may not be directly applied to any other regions or demographics.

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