Research Report

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Investigating the Value of Time and Value of Reliability for Managed Lanes

Final Report

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Prepared By

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DISCLAIMER

METRIC CONVERSION CHART

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
AREA				
in^2	squareinches	645.2	square millimeters	mm^2
ft^2	squarefeet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
VOLUME				
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
NOTE: volumes greater than 1000 L shall be shown in m^3				
MASS				
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
TEMPERATURE (exact degrees)				
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
ILLUMINATION				
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
FORCE and PRESSURE or STRESS				
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
AREA				
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
VOLUME				
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
MASS				
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
TEMPERATURE (exact degrees)				
^oC	Celsius	1.8C+32	Fahrenheit	^oF
ILLUMINATION				
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
FORCE and PRESSURE or STRESS				
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

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16. Abstract

This report presents a comprehensive study in Value of Time (VOT) and Value of Reliability (VOR) analysis in the context of managed lane (ML) facilities. Combined Revealed Preference (RP) and Stated Preference (SP) data were used to understand travelers' choice behavior regarding the usage of MLs. 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. Various modeling and analysis approaches were employed to further reveal user heterogeneity in VOT and VOR.

Mixed logit modeling was applied and indicated an average value of $9.41 per hour for VOT and $13.02 per hour for VOR. 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 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 VOT and VOR by incorporating the corresponding interaction effects for specific market segments. 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. These findings can be incorporated into the demand forecasting process and lead to better estimates and enhanced analytical capabilities in various applications, such as toll feasibility studies, pricing strategy and policy evaluations, and impact analysis, etc.

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EXECUTIVE SUMMARY

Managed lanes (MLs) 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 ML strategies in Florida, it is critical to understand the behavior changes and underlying causalities in user responses to MLs 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 report presents a comprehensive study in VOT and VOR analysis in the context of managed lane (ML) facilities. Combined Revealed Preference (RP) and Stated Preference (SP) data were used to understand travelers' choice behavior regarding the usage of MLs. 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. 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 $9.41 per hour for VOT and $13.02 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 MLs with additional options (extra discount for time shifts or for additional passengers), low income (household income < 50 K) people were less likely to use MLs 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 MLs during their regular schedules. Mandatory and weekday trips were more likely to use MLs, which do not seem appealing for short and frequent trips.

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 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. Travelers were likely to exhibit higher willingness to pay when they were female, younger (<35 years), older (>54 years), had higher income (household income > 50 K), driving alone, and travel on weekdays. On the contrary, lower willingness to pay was observed for short/medium length trips (<40 miles), and less frequent trips (< 12 trips/month).

This study provides a robust approach to quantify user heterogeneity in VOT and VOR by incorporating the corresponding interaction effects for specific market segments. 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. 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 strategy and policy evaluations, and impact analysis, etc.

Although this study provides a valid approach in examining user heterogeneity in VOT and VOR, the data used in this study may present certain limitations. Mainly, travel time reliability was not explicitly considered in the SP survey design, where the responses to the alternatives were mainly based on the trade-offs between travel time and cost. Reliability measures were derived based on detector data from I-95 facilities and attached to the alternative sets based on facility type and time of day, with the assumption that reliability benefits were implicitly associated with the choice of ML facility. This method might not be able to reflect the travelers' actual perceived values of reliability improvement. Future study may consider a SP survey design that reflects the trade-offs among all three key attributes: travel time, travel cost, and travel time reliability.

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1 INTRODUCTION

Managed lanes (MLs) 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 ML strategies in Florida, it is critical to understand the behavior changes and underlying causalities in responding to MLs, 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. As most other demand models in practice, the current FSUTMS (Florida Standard Urban Transportation Model Structure) framework does not address VOR, and it only considers VOT as a fixed value of 30 to 40 percent of the average wage rate, which does not reflect sufficient sensitivity among different users to facilitate pricing policy analysis in greater details. The literature has shown evidence that VOT and VOR vary substantially among the users with distinct socioeconomic demographic characteristics (such as by income, household size, gender, etc.), and even the same user would value time and reliability considerably different under different circumstances (such as by trip purpose, time of day, and trip length, etc.).

Although various reliability projects have been initiated at both federal level (such as performance measures, strategy analysis, and data archiving and monitoring,) and state level (such as travel time estimation, and reliability modeling), all efforts focus on the system supply side of reliability. There is still a blank area in quantifying and incorporating the value of reliability from the demand/user perspective.

The I-95 managed lanes program and the associated field data provide a good opportunity to study the VOT and VOR distributions within the ML context. In light of the on-going efforts in enhancing the FSUTMS in handling ML strategies, the proposed study presents a much needed addition to existing projects. As the procedures and modeling structures are currently being tested to model MLs, the detailed behavioral aspects and pricing sensitivities are borrowed from other states or are represented with rough assumptions. This study aims to provide insights to current ML initiatives through a comprehensive investigation of the VOT and VOR for MLs taking into account the heterogeneity in user preferences and travel conditions. Specifically, the objectives of this project are:

1. Quantify VOT and VOR indicators that contribute to the willingness to pay, and explore the dataset needed to understand the behavior changes in responding to MLs;
2. Examine use heterogeneity in VOT and VOR among users and under various circumstances; and
3. Recommend approaches to derive VOT and VOR values for different segments for incorporation into the FSUTMS framework.

This research advances the understanding of travelers' choice behavior in responding to ML adoption, and explores effective approaches to incorporate that into the modeling framework. Incorporating the research results will contribute to better demand forecasting practices through more realistic representation of ML modeling. It leads to capable tools in evaluating and developing ML strategies, which in turn facilitates the decision-making in transportation policy and investment.

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 project, which is focusing on the impacts of MLs, 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 an 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 were 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 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 1 Synthesis of Value of Time Studies

Study	Modeling Approach	Model Structure	Segment	Findings
Jackson and Jucker (1982)	Traveler preferences over alternatives of mode and route choices were analyzed based on mean-variance approach. Weights were developed using linear programming for the attributes that optimizes the model.	Linear programming (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 cost function for morning commuters was optimized 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 had 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 were assumed as $6.40 per hour.

Table 1 Synthesis of Value of Time Studies (continued)

Study	Modeling Approach	Model Structure	Segment	Findings
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		The most trustworthy VOT result obtained from the joint model of transponder, mode, and route choice. Joint model 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.
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 were considered as random parameters. 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.

Table 1 Synthesis of Value of Time Studies (continued)

Study	Modeling Approach	Model Structure	Segment	Findings
Liu et al. (2004)	Route choice utility functions included travel time and toll cost measures	mixed logit model		The median VOT was $12.81. Travelers valued reduction in variability more than in the travel time savings. However, substantial heterogeneity was observed in case of VOT.
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, which were independent from the mode choice of 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.
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 and previous experience (on-time, late), for subscribers and nonsubscribers (MnPass) separately.	VOT varied from $9.54 to $25.43 per hour. Significant differences between on-time and late arrival was observed only for afternoon trips. Those with delay experience would have higher WTP. MnPass users showed Significant differences than non-users.

Table 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.	Multinomial 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 (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.
Patil et al. (2011)	Four travel mode alternatives 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 variable 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.	Six different travel situations, varying by urgency level.	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.	By direction 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.

Table 1 Synthesis of Value of Time Studies (continued)

Study	Modeling Approach	Model Structure	Segment	Findings
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 distance (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.
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 include 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 were performed in this study. The travel time on the corridor was calculated based on the difference between the timestamps of two detection.		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 et al., 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 (75^{th} % - 25^{th} %) of travel time
- 90^{th} % - 50^{th} % travel time
- 80^{th} % - 50^{th} % travel time
- 90^{th} % - 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 model by adding train fare and the mean lateness at the boarding station. Reliability measure 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 Model 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 are 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.

<u>Household Variables</u>: 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 reduces 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 below summarizes the studies in VOR estimation, in terms of reliability measures, modeling approach, model structure, key segments, and major findings.

Table 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.

Table 2 Synthesis of Value of Reliability Studies (continued)

Study	Measures	Modeling Approach	Model Structure	Findings
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.
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 detector data.	Mixed Logit Model	The median VOR was $20.63. This study suggest 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 a 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.	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.	Ordered generalized extreme value (OGEV) and MNL. Final preference was given to MNL.	Based on the scheduling approach; mean earliness was 5.2 pence per minute and mean lateness was 14.4 pence per minute. According to this study, bus users placed a similar penalty on the mean travel time and on early arrival; the penalty on late arrival was much higher. Mean-variance approach seemed inappropriate and underestimated VOR.
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 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)	Moment of inertia (based on the mode travel time), range coupled with lateness probability, and standard deviation.	Total 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 were 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.
He et al. (2012)	Mean-variance measure, 90th % - the instantaneous travel time	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.

Table 2 Synthesis of Value of Reliability Studies (continued)

Study	Measures	Modeling Approach	Model Structure	Findings
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 attribute tastes were modeled in this study.	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.
Carrion and Levinson (2013)	Mean-variance measures - standard deviation, shortened right range, and interquartile range (75^{th} % - 25^{th} %).	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 Data Used in VOT and VOR Study

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

2.3.1 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.

Table 3 below presents the summary of SP surveys conducted in the context of VOT and/or VOR studies.

Table 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 respondent 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) 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 dominates 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.
- 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.

2.3.2 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. A brief summary is presented belw.

- 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.
- 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.

Table 4 presents the summary of RP surveys conducted in the context of VOT and/or VOR studies.

Table 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.

2.4. Literature Review Findings

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 5 below presents a quick comparison of VOT and VOR values from different studies.

Table 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)	14.1€/h	51.4 €/h - 21.0 €/h
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)	25.62 pence/min, 18.55 pence/min	
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)	

3. MODELING APPROACH

3.1 Measurements

3.1.1 Measurement for VOT

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

1. 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.
2. Derived as the ratio of the coefficient of travel time to the coefficient of cost obtained from choice models, when travel time and cost are represented in the utility functions describing the attributes of different alternatives. This method can incorporate market segments and address user heterogeneity with appropriate modeling techniques.

This study will explore both methods.

3.1.2 Measurement for VOR

Travel time reliability has been measured using two general approaches:

1. Mean-Variance based, which concerns 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).
2. Scheduling based, which concerns 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; therefore, the scheduling based approach cannot be applied. For this study, the mean-variance approach will be employed. Using detector data from the field, standard deviation and some other measures for general purpose lanes and ML by direction will be derived and explored.

3.2 Market Segmentation

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). This research aims to employ the market segmentation approach that identifies smaller user groups with relative homogeneous behavior or preferences.

Previous literature has explored the following market segmentation attributes: trip purpose, trip distance, trip urgency, previous congestion experience, user frequency, gender, household income, time of day, day of week. A brief description for each attribute is given below.

- VOT and VOR could vary by trip characteristics (e.g., trip purpose, travel distance). For instance, VOT and VOR for airport trips are generally valued much higher than for shopping trips. Batley and Ibanez (2012) measured VOT and VOR for two travel distance levels (short and long) and three purposes (business, commute, and other). The study found higher estimation for long distance business and commute trip category compared with short distance other trip category.
- Time of travel could have influence on VOT and VOR estimation. Morning peak hour trips are usually valued higher than trips made at other times. Several studies found substantial variations over different time of day (e.g., shoulder hour, peak hour, off-peak hour etc.) (Liu et al. (2007), Devarasetty et al. (2012A)).
- Travelers place much higher value on their travel time when facing urgent situations. Patil et al. (2011) investigated the influence of urgency level on VOT and found three times higher estimation for urgent trip.
- Some studies found different VOT and VOR values for different days of the week. He et al. (2012) measured VOT and VOR across different weekdays and found higher estimation on Fridays than any other weekdays.
- Travelers' previous congestion experience can influence subsequent travel decision. Tilahun and Levinson (2007) separated travelers into two categories – early/on time arrival from previous experience and late arrival from previous experience. They found that travelers from the first category placed a higher value on VOT and VOR.
- VOT and VOR estimation may 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.

- Frequency of toll facility usage may also influence VOT and VOR estimation. Sheikh et al. (2014) grouped traveler into three different categories– infrequent user, frequent user, and very frequent user. In the study, infrequent user group showed higher VOT and VOR values compared with the others.
- Household income is considered as an influential attribute in VOT and VOR study. Given everything equal, high income travelers are more likely to prefer reliable and faster travel alternative than travelers from other income groups.

FHWA recommends that any travel demand model intends to analyze travel behavior on managed lane has to incorporate at least three market segmentation - trip purpose, time of day, and household income (Perez et al., 2012). For this study, all the above factors will be explored as potential segmentation variables, the final decision will be based on statistical significance and model performances.

3.3 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.

3.3.1 Multinomial Logit

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

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

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

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

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,

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

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

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).

3.3.2 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)).

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.

3.3.3 Pooled Modeling

VOT and VOR studies commonly employ Stated Preference (SP) and Revealed Preference (RP) survey data. Both data sources have advantages and disadvantages with respect to the estimation of behavioral model parameter of interest.

RP data presents actual travel behavior, but data may only be obtained where actual choice alternatives (such as MLs) are available. On the other hand, SP surveys can be used for hypothetical scenarios, but the data can be biased since hypothetical scenarios may not reflect actual choices. Given the context, researchers are more interested in using both data sources simultaneously to analyze travel behavior (Ghosh (2001), Small, Winston and Yan (2005), Brownstone and Small (2005)) etc.

This study employs both RP and SP data. In order to combine two different data sources (e.g., different years, different geographical locations, different survey designs, etc.), pooled modeling technique is applied to account for the scale difference or variances in different data sources and capture the true impacts of the model parameters on travel behavior.

One common term in combined RP/SP datasets is the scale parameter, which is utilized to address the existing differences between the variations of the error terms from the two subsamples. Accordingly, the scale for the RP dataset is normalized to 1 and a scale parameter is estimated for the SP observations. In other words, in order to capture the true utility of a SP alternative, coefficients should be multiplied by the estimated scale parameter:

$$U_{in,SP} = Scale_{SP} \times U_{in} \tag{8}$$

3.3.4 User Heterogeneity through Interaction Effects

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

$$\boldsymbol{U}_{in} = \beta X_{in} + \beta_{TT} TT_{in} + \beta_{TTR} TTR_{in} + \gamma_{TT}\,(S_{in} * TT_{in}) + \gamma_{TTR}\,(S_{in} * TTR_{in}) + \varepsilon_{in} + \eta_{in} \quad (9)$$

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
$TT_{,in}$	Vector of "Travel Time"
β_{TTR}	Coefficient of "Travel Time Unreliability" as a random parameter
TTR_{in}	Vector of "Travel Time Unreliability"
S_{in}	Segmentation dummy variable
γ_{TT}	Interaction coefficient for travel time
γ_{TTR}	Interaction coefficient for travel time unreliability

Accordingly, two variables of interest including travel time (TT) and travel time unreliability (TTR) are considered as random parameters which are expected to vary across individuals. In order to obtain the underlying factors for preference heterogeneity, interaction terms between the two random coefficients and the individual socioeconomic-demographic variables are tested. Based on the equation (4), if the γ_{TT} (or γ_{TTR}) 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 are expected to reflect disutility (negative β_{TT}, β_{TTR}), positive γ_{TT} (or γ_{TTR}) indicates lesser sensitivity towards the random parameter, while negative interaction coefficients indicate higher sensitivity towards the random parameter.

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

$$\mathrm{VOT_i} = \frac{\partial \mathrm{U_{i,j}} / \partial \mathrm{T_j}}{\partial \mathrm{U_{i,j}} / \partial \mathrm{C_j}} = \frac{\mathrm{\beta_i}^{\mathrm{T}}}{\mathrm{\beta_i}^{\mathrm{C}}} \quad (10)$$

$$\mathrm{VOR_i} = \frac{\partial \mathrm{U_{i,j}} / \partial \mathrm{R_j}}{\partial \mathrm{U_{i,j}} / \partial \mathrm{C_j}} = \frac{\beta_i{}^{R}}{\beta_i{}^{C}} \tag{11}$$

3.3.5 Choice Alternatives

Managed lane programs can influence three main travel choices including route choice, mode choice, and departure time choice. Other travel choices (e.g., destination choice, trip frequency choice, residential location choice) may also be affected by the presence of managed lanes, in a longer term framework. This study only focuses on the three major choices in a daily or short-term framework. This section highlights key features of each of the main travel choices and finalizes the choice alternatives for model development.

3.3.5.1 Route Choice

Route choice represents traveler choice between toll route and toll-free route. Traveler may switch to toll options (managed lane) from existing corridor (general purpose lane) or from a different corridor. Utility functions are specified for each route alternative and the alternatives are distinguished by cost vector. The model hypothesis that, travelers choose the alternative which offer the highest utility. Several studies measured VOT and VOR in context of route choice ((Liu et al., 2004), (Small et al., 2005), (Brownstone and Small, 2005), (Liu et al., 2007), (Asensio and Matas, 2008), (Li et al., 2009, 2010), (Tilahun and Levinson, 2010), (He et al., 2012), (Carrion and Levinson, 2012)).

3.3.5.2 Mode Choice

Mode choice refers to those travel choices where changes in travel mode occurred in presence of managed lanes. Managed lane is free for car-poolers, which may influence individual's decision to travel together. By carpooling, travelers concede the burden of pick-up/drop-off additional passengers and gain better travel environment without paying any additional cost. Another aspect of mode choice could be switching to or from competitive transit mode. Managed lane based transit operation significantly reduced regular travel time. Similar to route choice, utility functions for each mode alternative are specified with unique cost vector and travelers choose the alternative which offers the highest utility. Significant number of studies estimated VOT and VOR in context of mode choice (Prashker (1979), Jackson and Jucker (1982), Ghosh (2001), Devarashetty et al. (2012)).

3.3.5.3 Departure Time Choice

Departure time choice refers to those travel choices where time of travel changes in presence of managed lane. Managed lane offers variable toll price and the least amount of toll is usually charged in off-peak hours. This may attract some of the travelers who usually travel in shoulder hour of peak hour to change travel time and departs in off peak hours. Following studies investigated traveler's departure time choice; Noland and Small (1995), Hollander (2006), Bates et al. (2001), Asensio and Matas (2008).

3.3.5.4 Choice Combination

The presence of managed lanes could influence all three choices simultaneously. This project will include the following choice alternatives in model development. The first two choice alternatives describe route choice options between toll route (managed lane) and toll-free route (general purpose lane). The next two choices are combination of route choice (managed lane) and departure time choice (before/after the peak period). The last choice alternative is a combination of route choice (managed lane) and mode choice (Drive alone/shared ride). However, no transit option was considered in the survey. The alternatives tested in the models are:

- General purpose lane (SP)
- Managed lane (SP)
- Managed lane before the peak period (SP)
- Managed lane after the peak period (SP)
- Managed lane with additional passengers (SP)
- General purpose lane (RP)
- Managed lane (RP)

4. DATA SOURCES AND DESCRIPTIVE ANALYSIS

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.

4.1 Source

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 6 provides detailed sample information for each corridor.

Table 6 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%**

4.2 Descriptive Statistics

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 7). 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 7 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.

4.2.1 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 8 provides frequency and percentage information of both SP and RP respondents by trip purposes.

Table 8 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 1 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 RP observation 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.

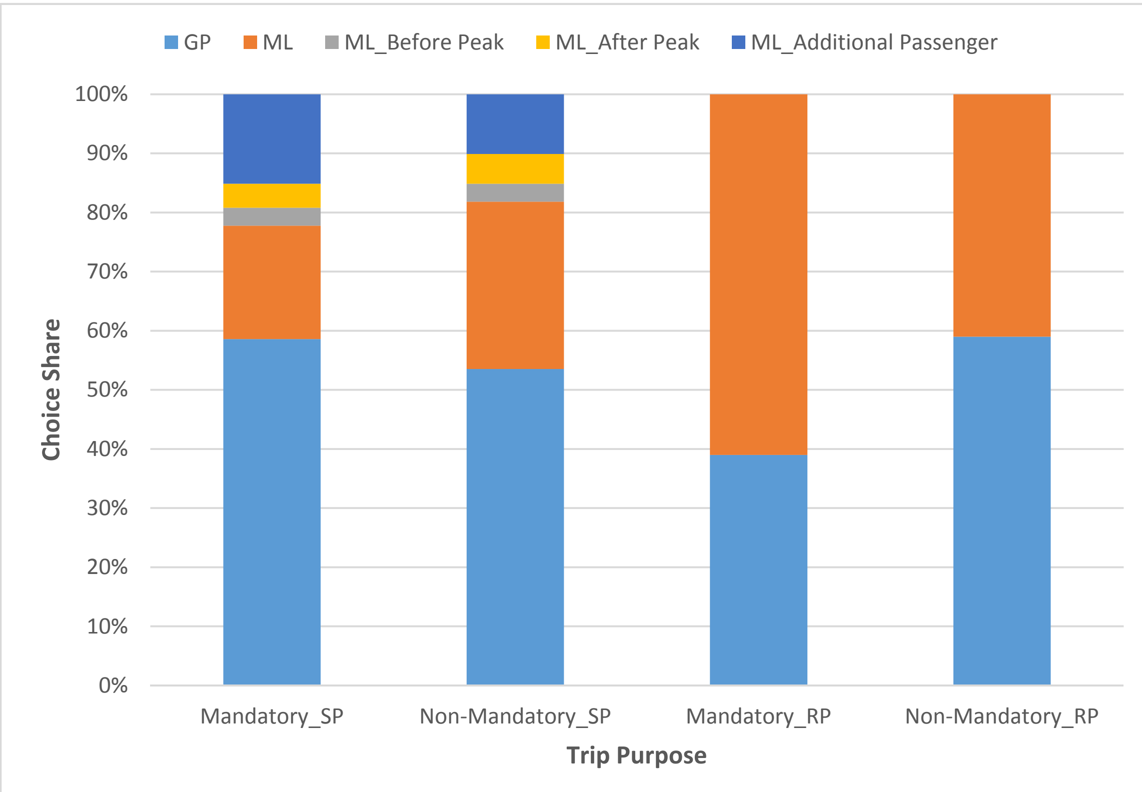


Figure 1 Choice share by trip purpose.

4.2.2 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 9).

Table 9 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 2, 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.

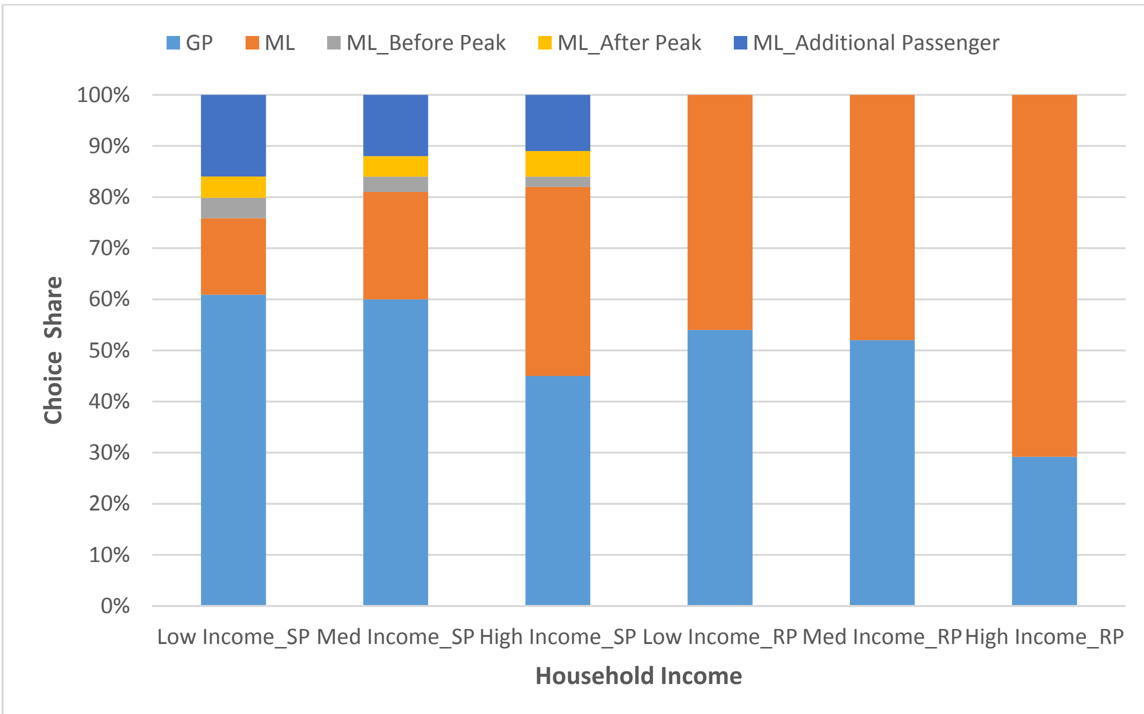


Figure 2 Choice share by household income.

4.2.3 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 10 provides gender related information including frequency and percentage of respondents.

Table 10 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, males and females exhibited similar choice preferences in SP observations. Interestingly, RP observations captured first choice of male drivers was managed lanes while first choice of female drivers was general purpose lanes.

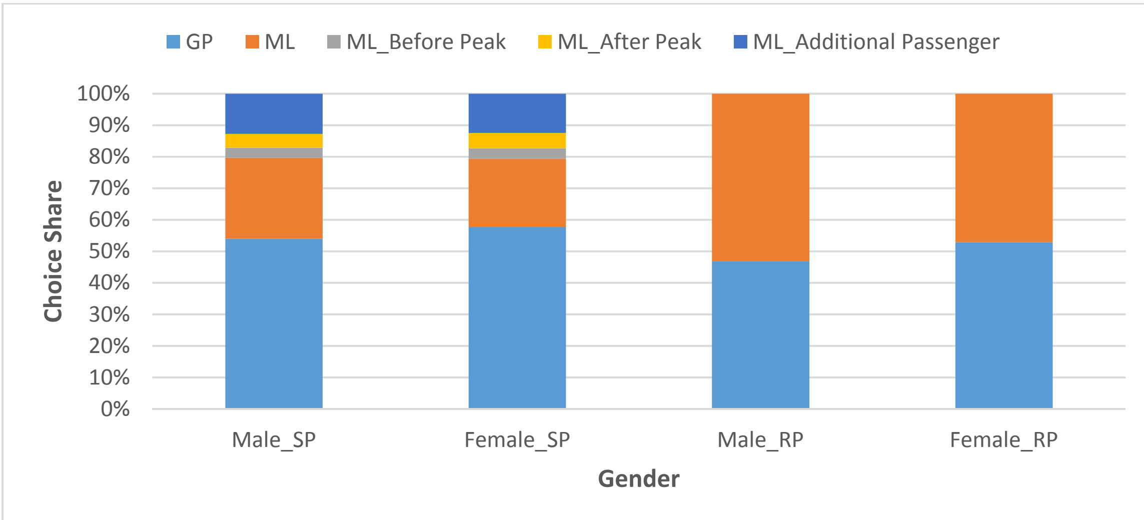


Figure 3 Choice share by gender.

4.2.4 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 11 and figure 4 provides detailed analysis of the impact of days on travel choice share. As expected, both SP and RP respondents preferred managed lane travel options on weekdays.

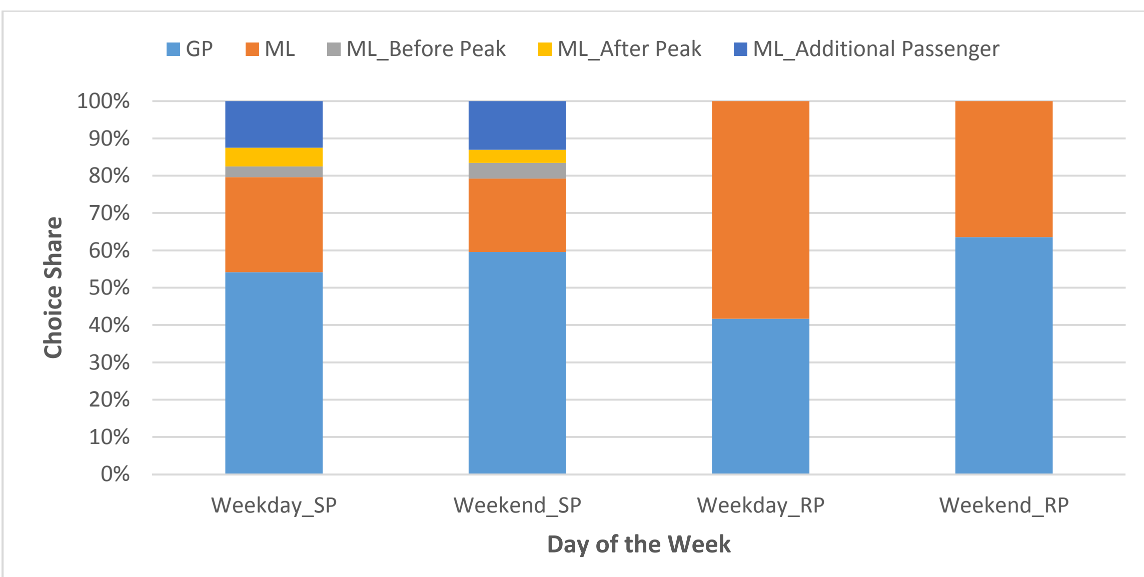


Figure 4 Choice share by day of the week.

Table 11 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**

4.2.5 Time of Day

Peak period trips are expected to prefer managed lane travel options. As shown in table 12, 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 5, general purpose lanes were always the preferred travel option irrespective of the departure time in case of SP observations. However, RP observation captured peak period trips were more likely to be conducted on managed lane facility.

Table 12 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**

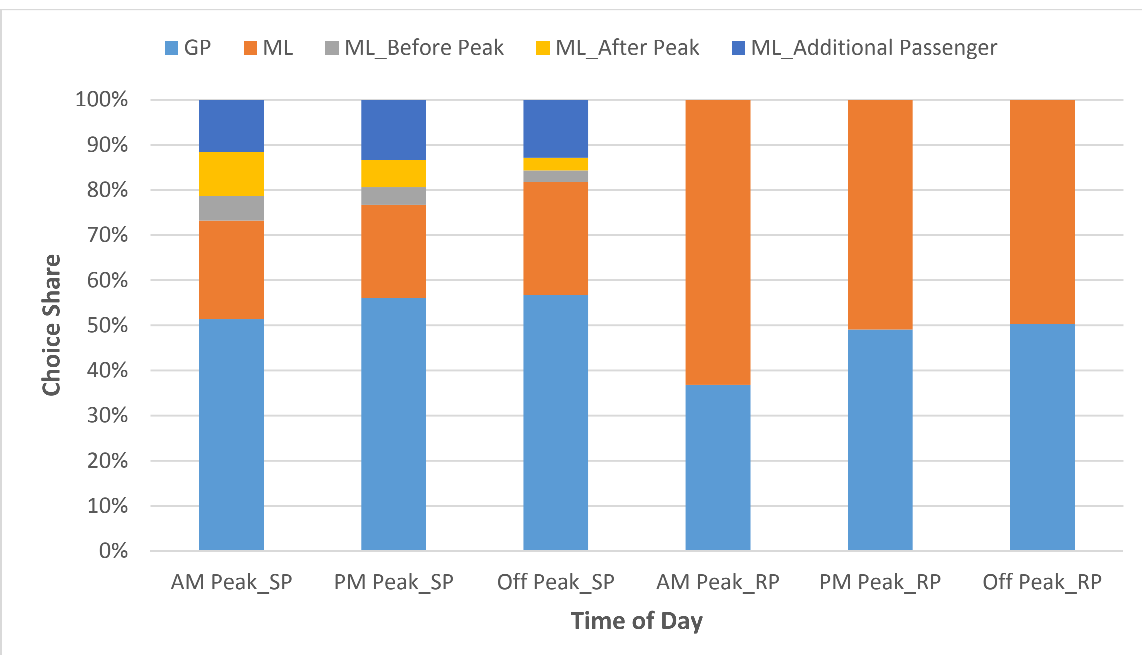


Figure 5 Choice share by time of day.

4.2.6 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 13, approximately one-third trips were reported as an urgent trip.

Table 13 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 6, urgent trips were more likely to be conducted on managed lanes compared with unurgent trips. However, RP observations captured higher percentage of managed lanes share for urgent trips compared with SP observations where general purpose lanes were preferred choice even for urgent trips.

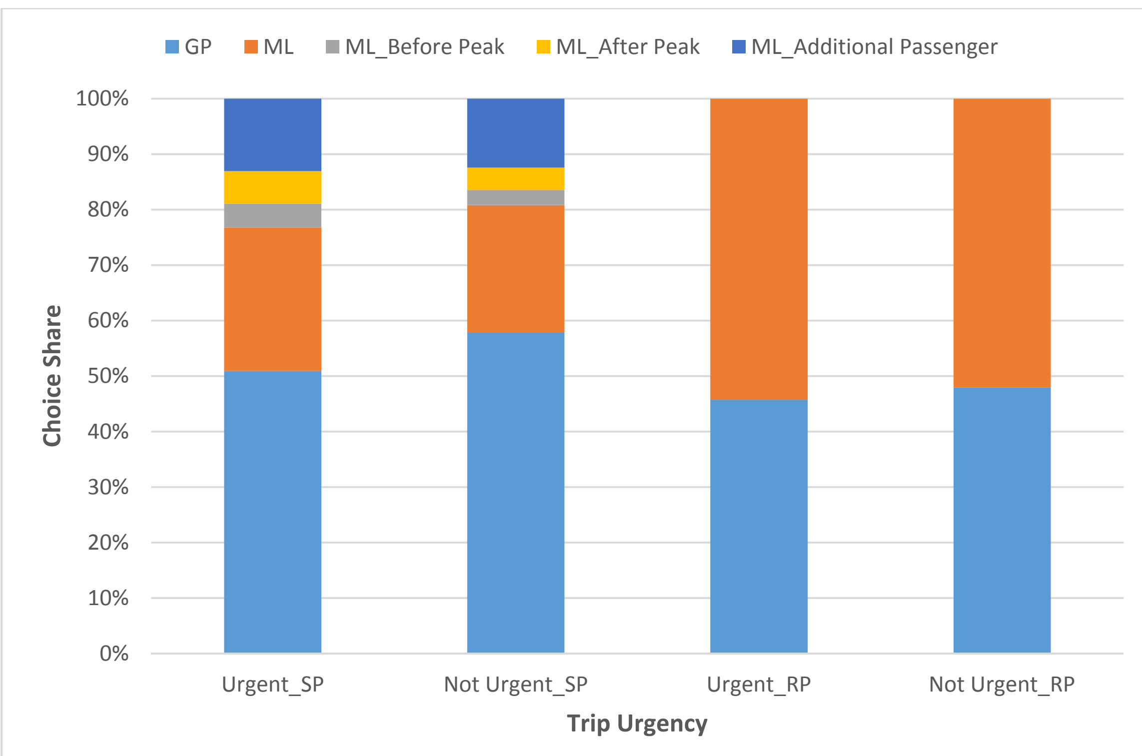


Figure 6 Choice share by trip urgency.

4.2.7 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 14 provides detailed information regarding the number and percentage of respondents for both users and non-users of SunPass.

Table 14 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 RP respondents as expected.

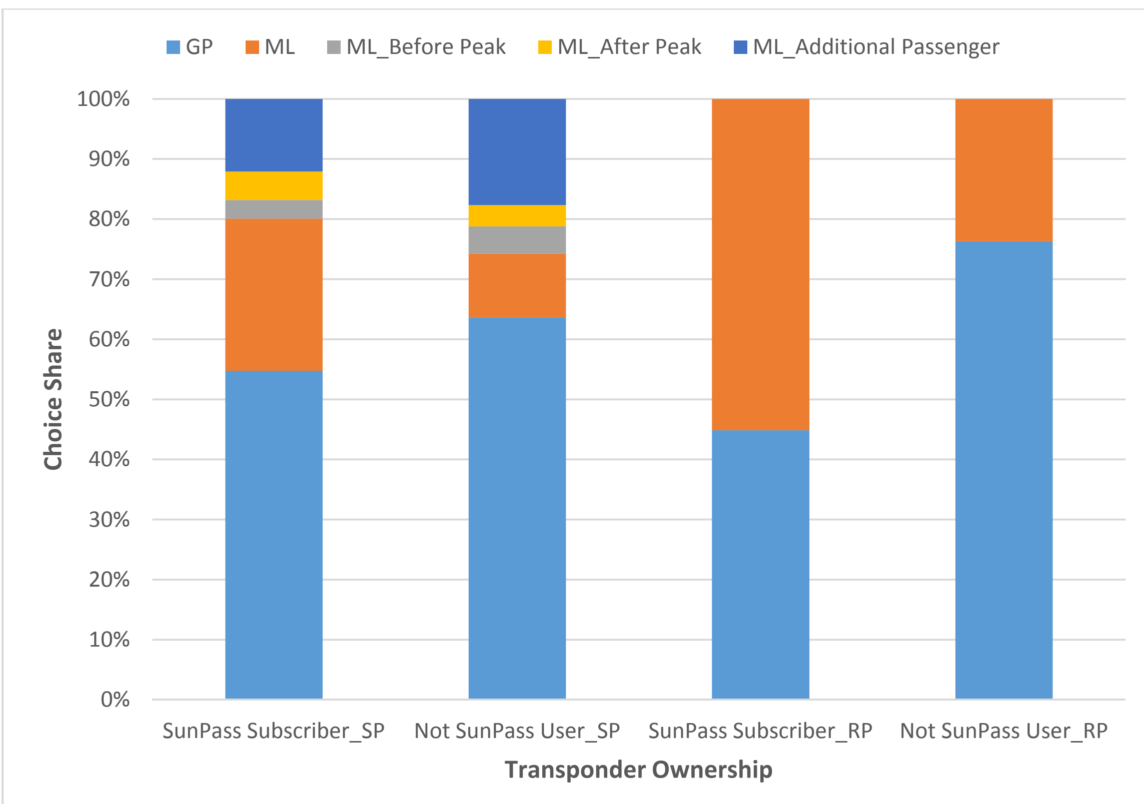


Figure 7 Choice share by transponder ownership.

4.2.8 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 15.

Table 15 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 8 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.

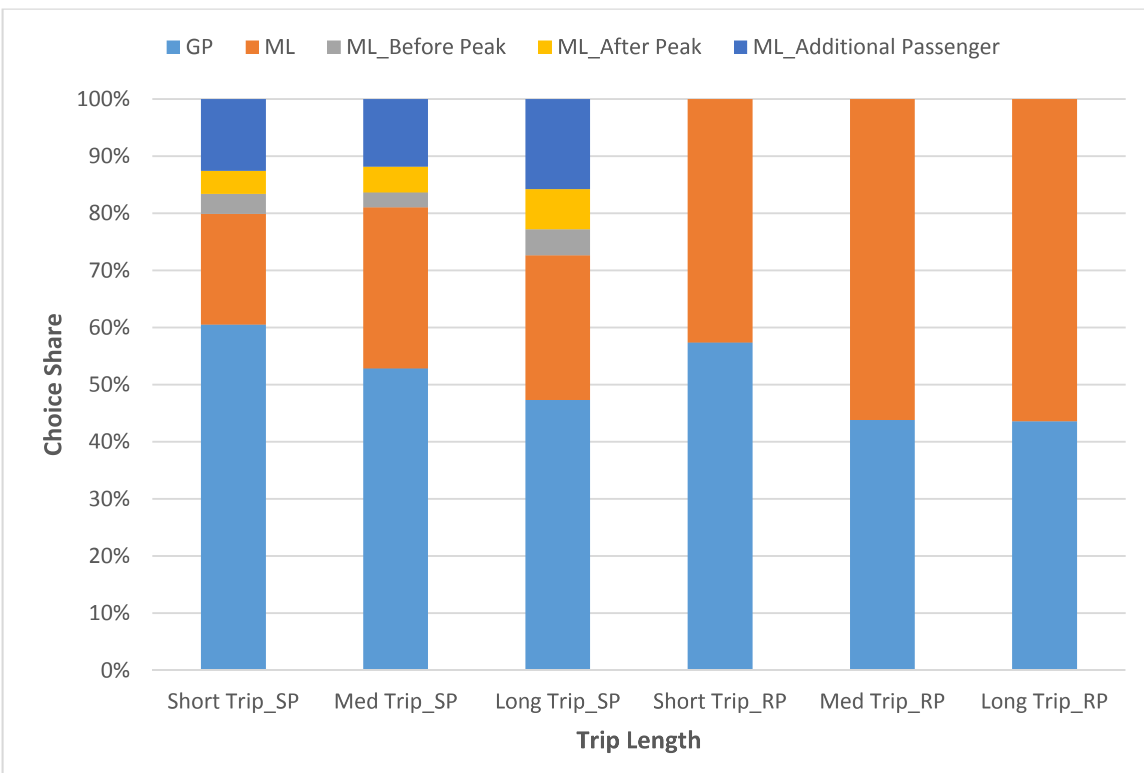


Figure 8 Choice share by trip length.

4.2.9 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 SP and RP respondents.

Table 16 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.

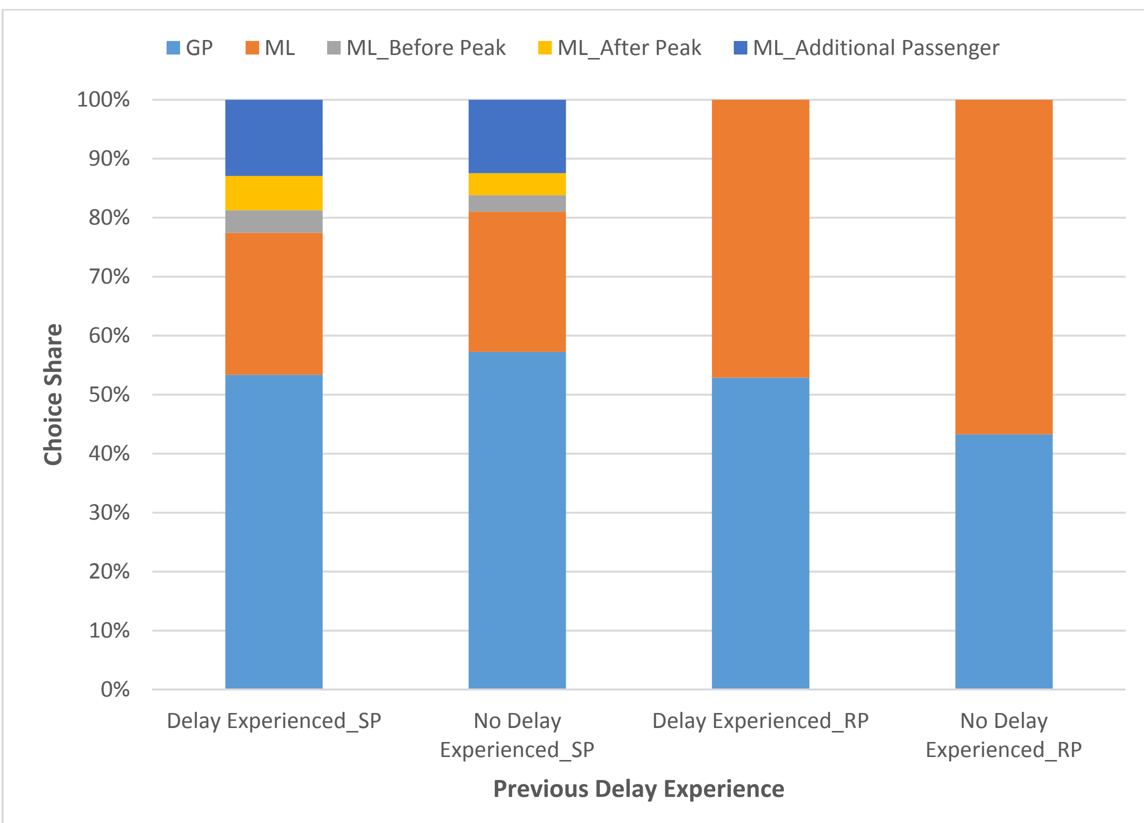


Figure 9 Choice share by previous delay experience.

4.2.10 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 17 provides more information about the respondents profile correspondence with the categories.

Table 17 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 10, general purpose lanes were always the preferred travel option irrespective of the trip frequency for SP respondents. However, 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.

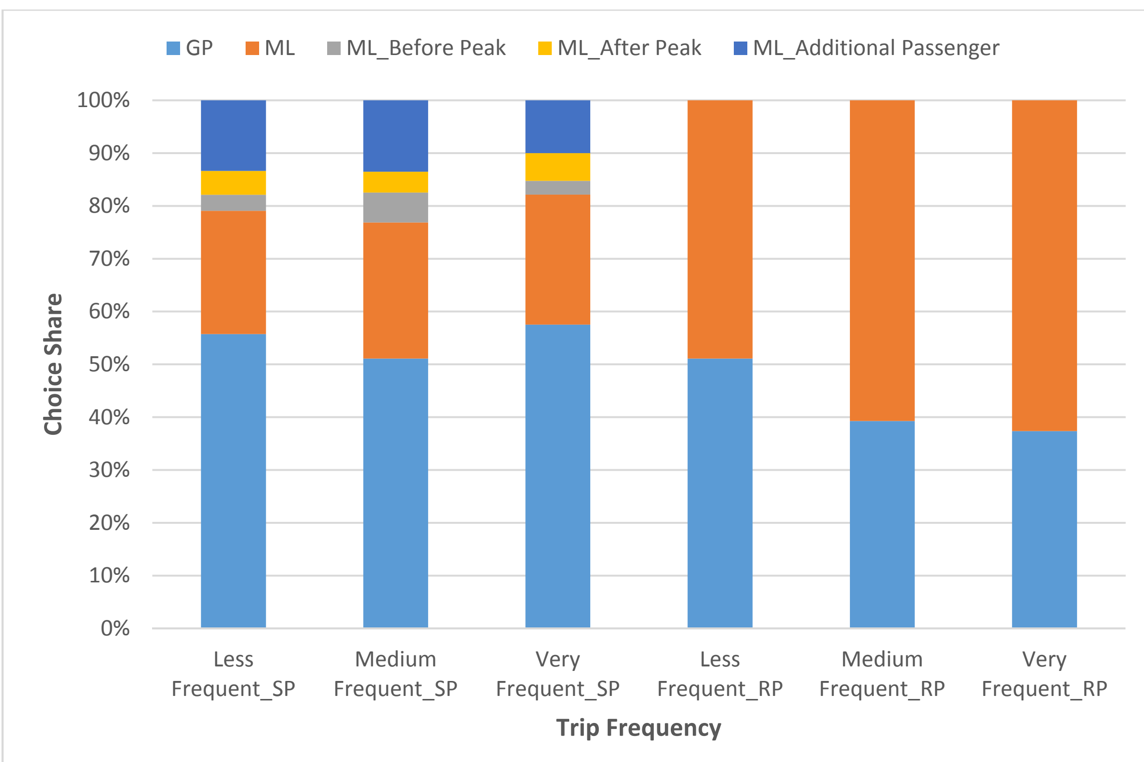


Figure 10 Choice share by trip frequency.

4.2.11 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 18, majority of the respondents were employed.

Table 18 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 11, 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.

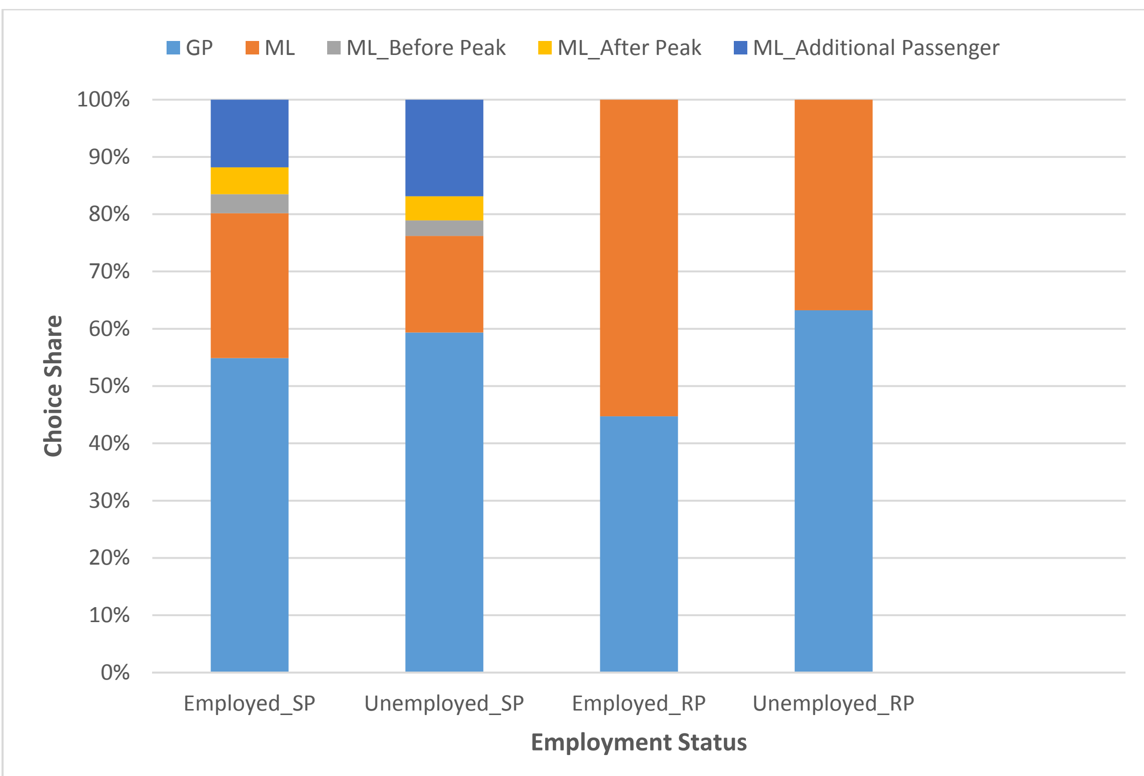


Figure 11 Choice share by employment status.

4.2.12 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 19 provides detailed information regarding the number and percentage of the respondents for each age category.

Table 19 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 12, 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 older age category. Perhaps this category does not prefer to travel in a faster lane, has more patience for congestion, and has less constraint on arrival time.

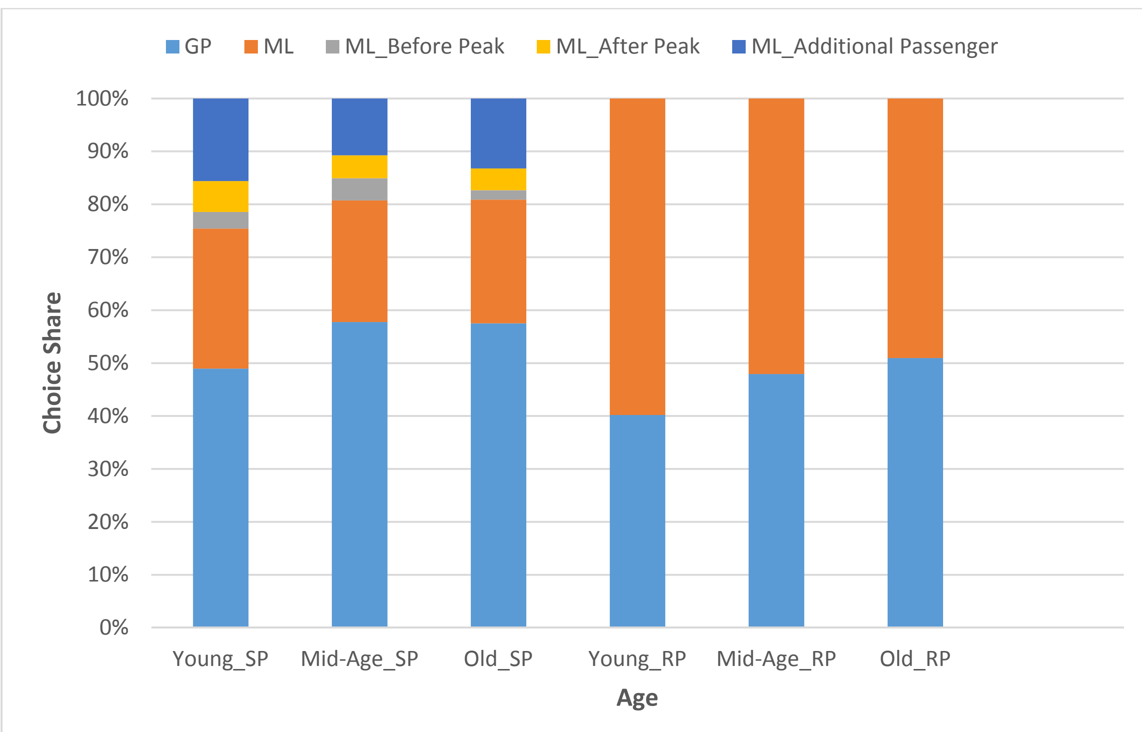


Figure 12 Choice share by age.

4.2.13 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 2 more passengers (eligible for toll-free).

Table 20 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 14 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. 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.

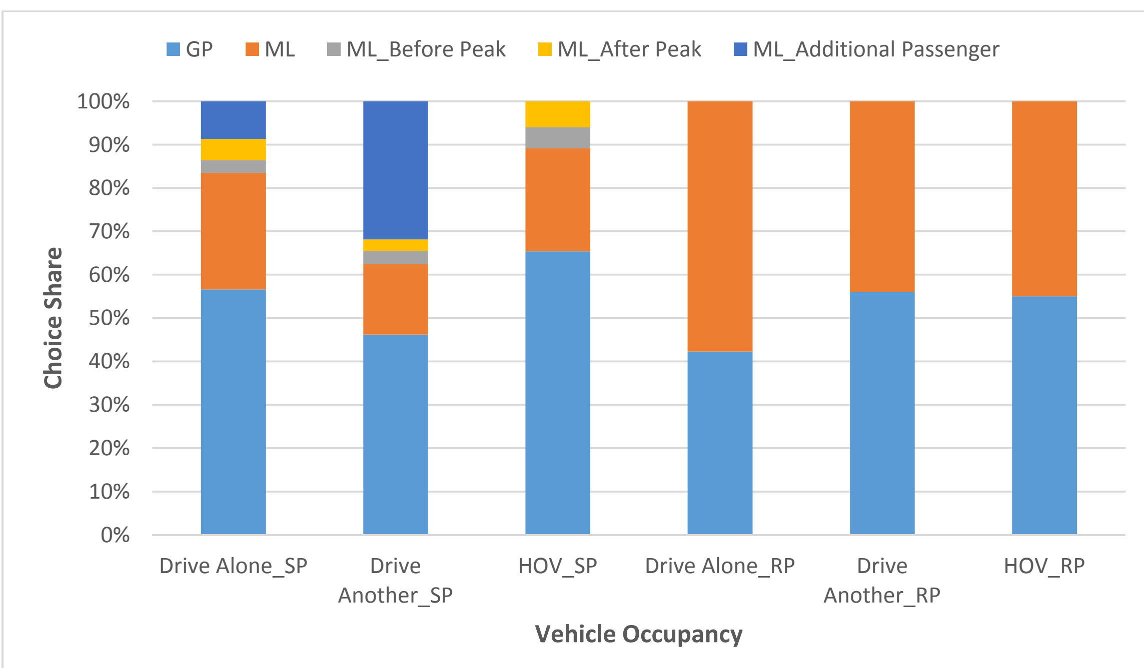


Figure 13 Choice share by vehicle occupancy.

4.2.14 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 21 provides detailed arrival flexibility information for both SP and RP respondents.

Table 21 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 14, 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.

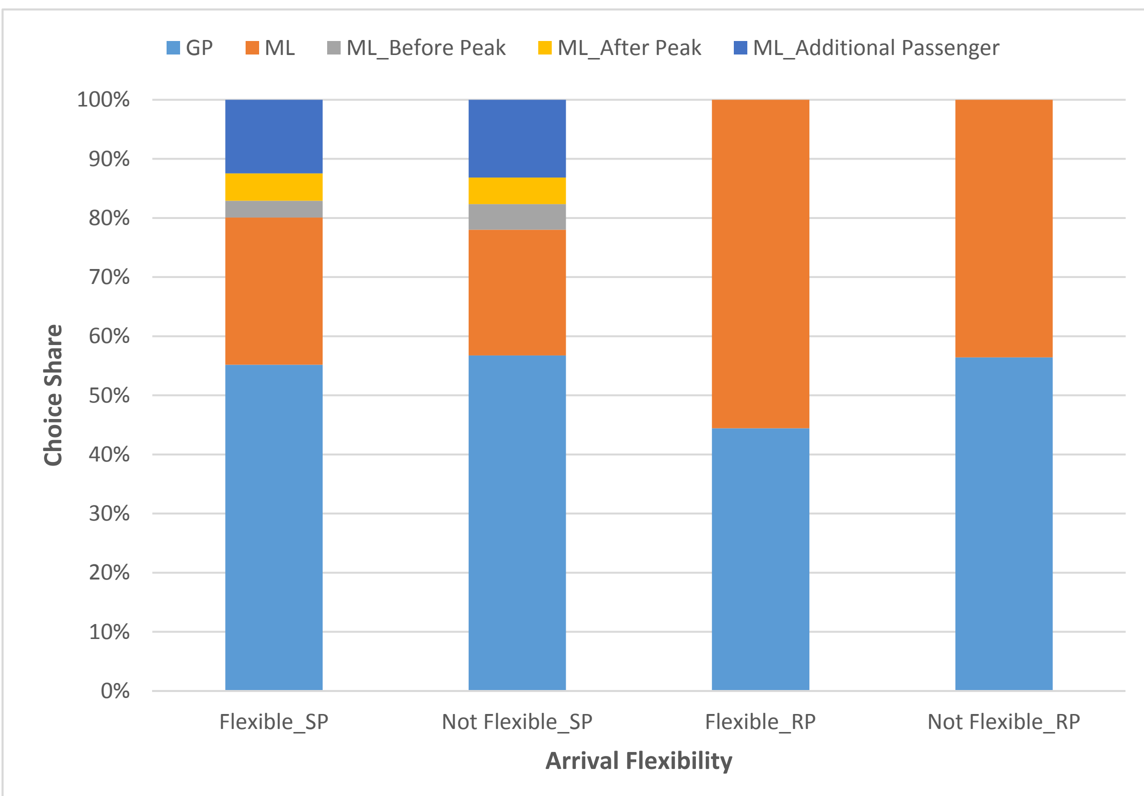


Figure 14 Choice share by arrival flexibility.

4.3 Summary of Descriptive Analysis

Based on the SP data, the following observations are summarized.

- Generally, respondents preferred general purpose lanes alternative over managed lanes alternatives, except for the respondents who were from age group 25-34 years. Preference was determined if an alternative received more than half of the observations on its favor.
- In terms of preference to managed lanes alternatives, no significant differences were observed among the categories of variables including gender, previous delay experience, user frequency, household size, household vehicle, and arrival flexibility.
- Respondents, who were employed, used SunPass transponder, and lived in a household with annual income more than 200 thousand dollars, exhibited significant preference for managed lane facility.
- Trips, which were urgent and performed in weekdays, were more likely to be conducted in managed lanes.
- Short trips, which lengths were less than 20 miles, were less likely to be conducted in managed lanes.
- Among the trip purpose category, business trips were most likely to be conducted on managed lanes, whereas shopping trips were least likely to be conducted on managed lanes.
- Among the age category, respondents from age group 25-34 showed highest preferences for managed lanes alternatives, whereas older respondents (75+ age) displayed least interest for managed lanes alternatives.
- Surprisingly, respondents with 2 or more passenger preferred general purpose lanes alternative instead of managed alternatives.

The summary based on RP observations are presented below.

- Unlike SP survey, RP survey found mixed responses in terms of respondent preference to general purpose lanes alternative and managed lanes alternative.
- Regarding preference to managed lane facility, no significant differences were observed in the categories of following variables, including household vehicle, trip urgency, and household size.
- I-95 users, who were employed, male, used SunPass, and conducted trips in weekdays, preferred managed lane facility whereas their counterparts preferred general purpose lanes alternative.

- Regarding trip purpose, work trips were more likely to be conducted on managed lane facility, whereas school trips were more likely to be conducted on general purpose lanes.
- As expected, high income (>200K) household respondents preferred to travel on managed lane facility.
- Similar to SP, short trips, with less than 20 miles length, were more likely to be conducted on managed lane facility.
- Furthermore, respondents, who were more frequent user of I-95, were more likely to travel on managed lane facility. A linear relationship was observed between user frequency and managed lane preference level.
- Similar to SP, younger respondents were more inclined towards managed lane facility, whereas older respondents were less likely to travel on it.
- Surprisingly, respondents who, had previous delay experience, travelled with additional passengers, and without flexibility in arrival time preferred general purpose travel lanes alternative instead of managed lanes alternative.

4.4 Additional Data Source for Reliability Measures

4.4.1 Data Source

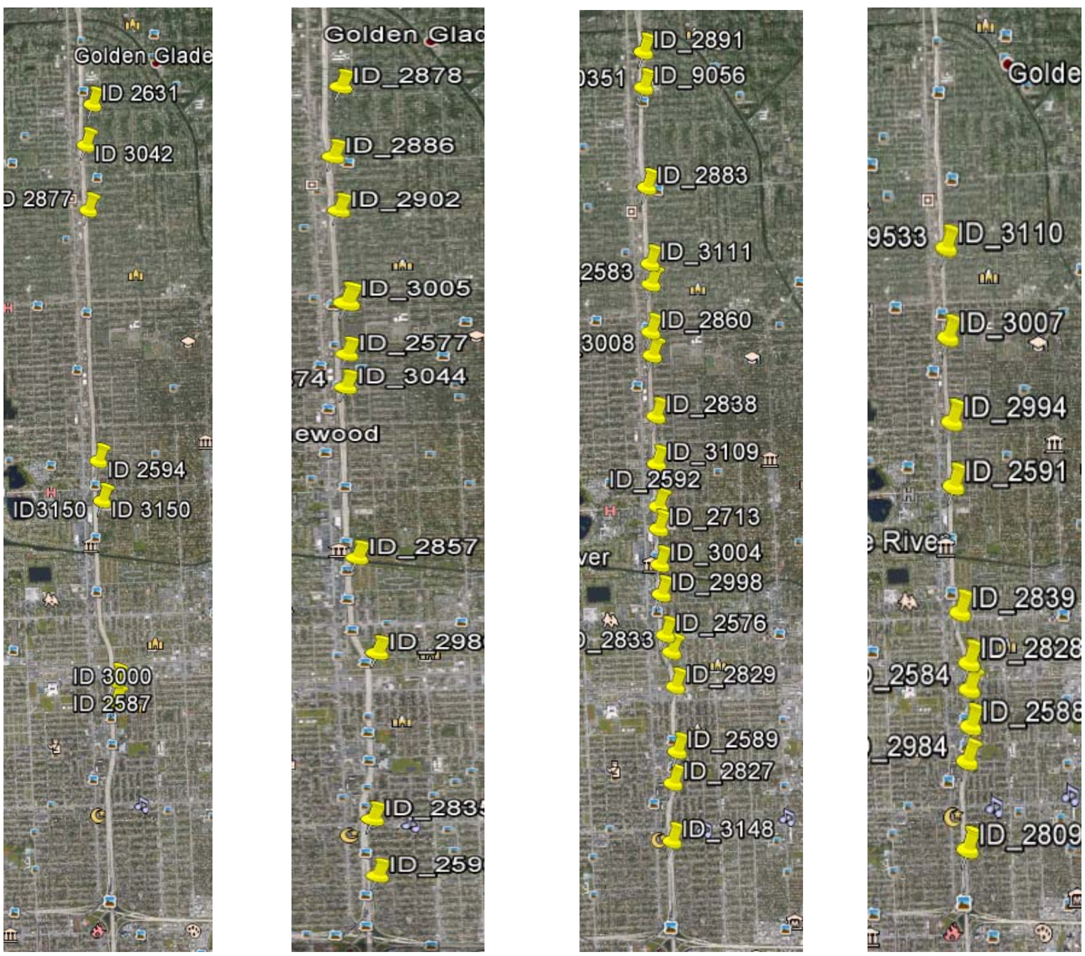
Detector data were gathered from an automated data sharing, dissemination, and archiving system, named regional integrated transportation information system (RITIS). RITIS is operated and maintained by CATT Lab, a user-focused R & D laboratory at the University of Maryland. RITIS was chosen as a detector 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. 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 ML facility between golden glades interchange and airport expressway.

4.4.2 Data Processing

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 15 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 15 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 uses the free flow travel time (10 percentile travel time) as the reference instead of average travel time.

4.4.3 Reliability Measures Used in the Study

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

Table 22 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 22 presented the reliability measures.

Figure 16 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 MLs 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 MLs are much more obvious for the southbound traffic, where the semi-standard deviation was approximately 3 times higher in general purpose lanes than the ML lanes in morning peak hours.

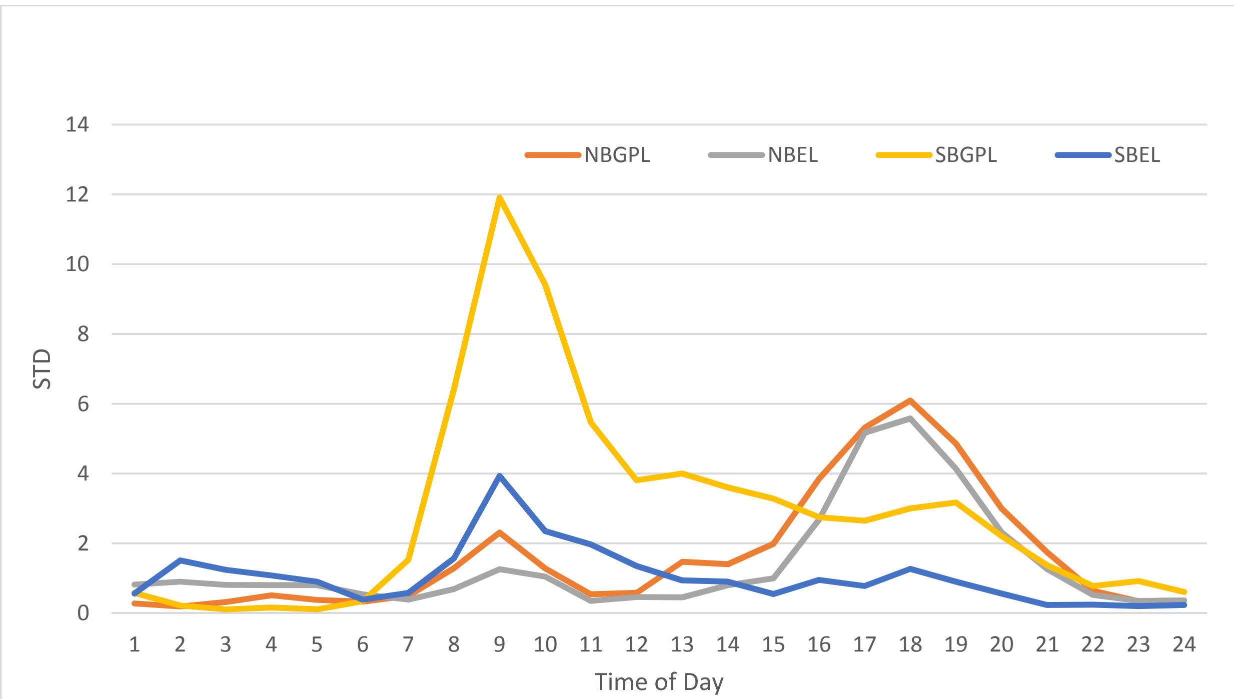


Figure 16 Standard deviation comparison by time of day.

5. MODEL RESULTS

This chapter presents the results of the estimated models based on the combined RP and SP dataset. Section 5.1 presents the MNL and mixed logit models without consideration of user heterogeneity. The results can reveal whether there is significant preference heterogeneity in any of the random parameters (time, reliability, and cost). Section 5.2 presents the results of the mixed logit model with interaction terms added to help identify and measure different sources of heterogeneity.

5.1 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: ML with no temporal shift, ML with early shift, ML with late shift, and ML 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 23 and 24 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 $\frac{\sigma}{\mu} < 0.33$.

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 \$9.41 per hour and \$13.02 per hour for VOR.

Table 23 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	SP – ML Peak	SP – ML Before Peak	SP – ML After Peak	SP-ML Ad. Passenger	RP-ML
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

Table 24 shows that for both RP and SP samples, individuals younger than 35, high income people, and sunpass users were more likely to utilize MLs. Mandatory and weekday trips also encouraged using 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 MLs 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. Moreover, females are expected to have more complicated trip chains (e.g., escorting kids and maintenance activities) and may not able to shift their regular departure times (McGuckin and Nakamoto, 2005).

Table 24 Mixed Logit Base Model (1000 draws)

Independent Variables	Parameter	Standard Deviation
Random parameters in utility functions		
Time	-0.193 (-94.23)	0.064 (94.23)
Reliability	-0.267 (-27.16)	0.088 (27.16))
Cost	-1.23 (-84.66)	0.407 (84.66)

Non-Random parameters in utility functions

Independent Variables	SP – ML Peak	SP – ML Before Peak	SP – ML After Peak	SP-ML Ad. Passenger	RP-ML
ASC	-4.1 (-40.22)	-3.3 (-24.96)	-3.9 (-39.07)	-2.9 (-46.78)	-2.96 (-4.71)
Male	-0.13 (-3.95)	-	-	-	-
Young People (16-34)	0.88 (20.59)	0.43 (5.60)	1.09 (17.51)	0.63 (15.52)	0.64 (2.17)
Med Income (50~150K)	0.34 (7.90)	-	-	-0.21 (-6.19)	-
High Income (>150k)	1.44 (28.36)	-	0.58 (8.75)	-	1.01 (3.38)
Employed	0.53 (9.75)	-	-	-	-
Sunpass User	0.79 (11.53)	-0.58 (-7.33)	-	-	1.24 (2.11)
Delay Experienced	-	-	-0.47 (-8.59)	-	-
Mandatory	0.60 (15.68)	-	-	-	-
Flexible Trip	-	-0.17 (-2.67)	-	0.07 (1.95)	-
Less Freq. (<4/month)	0.42 (8.74)	0.78 (9.21)	0.59 (8.54)	0.66 (13.73)	-
Med. Freq. (<12/month)	0.60 (9.65)	1.44 (13.93)	0.83 (8.66)	0.51 (7.42)	-
Weekday Trip	0.38 (8.90)	-0.42 (-5.26)	0.27 (4.08)	-	1.06 (3.71)
Urgent Trip	0.16 (4.19)	0.40 (6.15)	-	0.16 (4.34)	-
Short Trip (<20 miles)	-0.33 (-9.92)	-	-0.26 (-5.05)	-	-
Drive Alone	-	-	0.20 (3.40)	-	-
Drive Another	0.89 (27.26)	-	-	-	-
VOT	$9.41				
VOR	$13.02				

Model Performance: Log Likelihood Function = -14883.77, McFadden Pseudo R-squared = 0.546
All variables shown are significant at 5% significance level

In general, medium and high income people were more likely to use MLs compared with low income people who may consider ML 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.

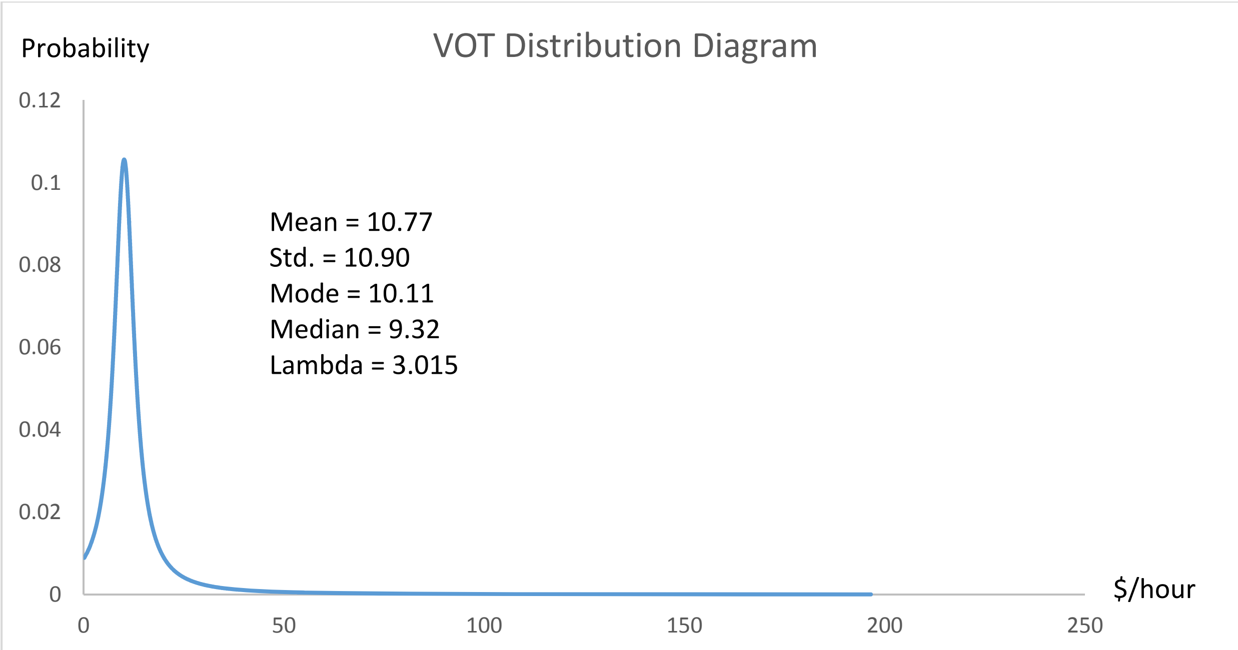
Trip attributes were also important contributors to the model. Accordingly, mandatory trips were less prone toward temporal shift. Results also indicated that managed lanes were not an appealing option for short trips. In fact, they were even less desirable than general purpose lanes in case of no temporal 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 towards a late departure shift while drivers with only one passenger had higher tendency to use managed lanes in the peak period.

Based on the results from the base mixed logit model, the distribution diagrams for VOT and VOR could be drawn. It should be noticed that either of the two parameters (VOT or VOR) is the division of two normal variables, which would result in a *Cauchy* distribution. In other words, any change in either the numerator (time/reliability) or denominator (cost) will result in a shift in VOT (VOR) magnitudes.

In order to draw the distributions of VOT and VOR, a random sample of 2000 was drawn from the observations and values for time, reliability, and cost were generated based on their mean and standard deviations in a normal distribution. The 2000 draw sample of VOT and VOR values are presented in Figure 17.

The mean values of VOT and VOR in the diagrams were slightly different from the values derived from the average coefficients of time, reliability and cost given by the model, as the values were based on a random draw of only 2000 observations. Nonetheless, the diagrams show the distribution patterns of VOT and VOR.



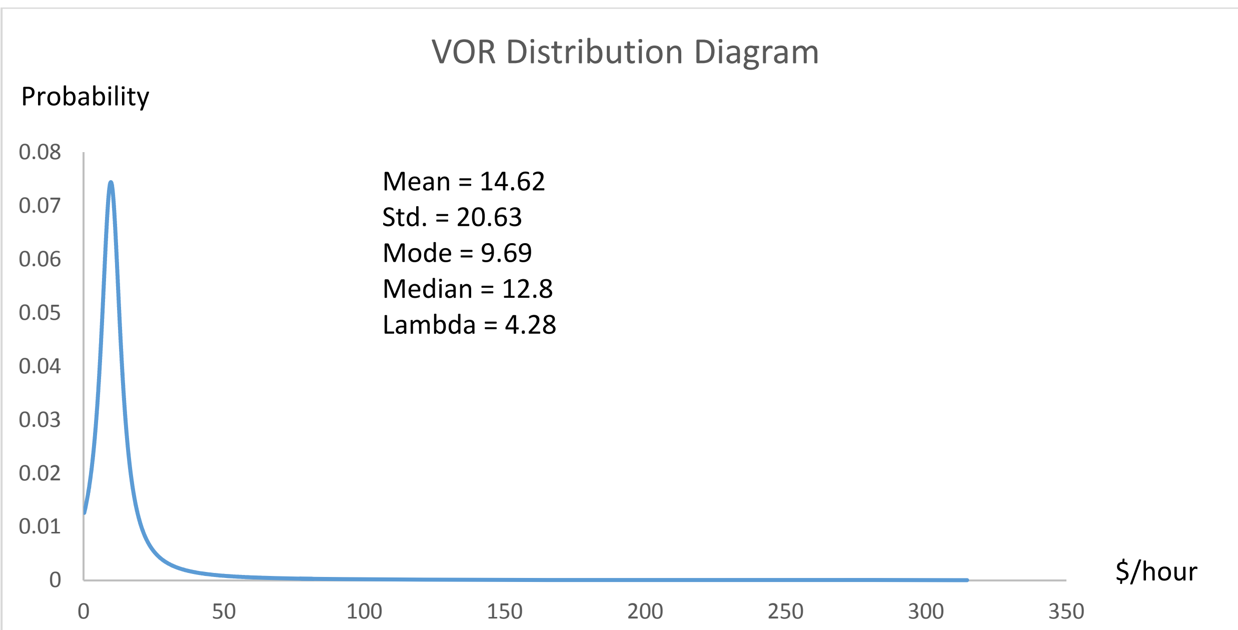


Figure 17 VOT and VOR distribution based on 2000 random draws.

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.

5.2 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 25 presents the results of the mixed logit model with interaction effects. 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, the random coefficients for time, reliability, and cost could be written as follows:

Time Coefficient = -0.38 + 0.02 (Urgent trip) + 0.03(Employed) - 0.04(Age<35) + 0.02(Age>54) + 0.07(Drive alone) + 0.14(Drive another) + 0.03(Freq<4/month) + 0.04(Freq 4~12/month) + 0.06(Sunpass user) + 0.03(Delay experienced)

Reliability Coefficient = -2.05 - 0.21 (High income) + 0.27(Urgent trip) + 0.19(Employed) + 0.85(Distance<20 miles) + 0.74(20~40 miles) + 0.26(Age<34) + 0.19(Age>54) + 0.20(male) - 0.29(Drive another) + 0.64(Freq<4/month) + 0.36(Freq 4~12/month) + 0.26(Delay experienced) - 0.18(Flexible trip)

Cost Coefficient= -2.65 + 0.49(High income) + 0.14(Med income) +0.23 (Urgent trip) +0.23 (Employed) +0.30 (Age<34) + 0.29(Age>54) + 0.22(Drive alone) – 0.21(Drive another) + 0.24(Freq<4/month) + 0.18 (Freq 4~12) + 0.22 (Weekday) + 0.23 (Delay experienced)

Due to the linear formulation for each of the variables, the interaction effects actually imply the sensitivity (elasticity) values for the estimated random parameters. Given the negative signs for the base values, 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, or young people were the most sensitive toward travel time.

Table 25 Mixed Logit Model with Interaction Effects (1000 draws)

Independent Variables	SP – ML Peak	SP – ML Before Peak	SP – ML After Peak	SP-ML Ad. Pass.	RP-ML
ASC	-3.59 (-17.7)	-3.11 (-11.4)	-3.60 (-16.0)	-2.70 (-22.1)	-2.96 (-4.24)
Male	-0.15 (-2.21)	-	-	-	-
Young People (16-34)	0.94 (6.80)	-0.41 (-2.9)	0.26 (2.22)	0.21 (3.00)	-
Med Income (50~150K)	0.30 (3.13)	-	-	-0.17 (-2.65)	-
High Income (>150k)	1.11 (8.99)	-	0.45 (3.21)	-	-
Employed	0.59 (5.40)	-	-	-	-
Sunpass User	0.97 (7.19)	-0.36 (-2.21)	-	-	1.65 (2.48)
Mandatory Trip	0.62 (7.33)	-	-	-	-
Less Freq. (<4/month)	0.40 (2.68)	1.02 (5.06)	0.75 (4.00)	0.62 (5.57)	-
Med. Freq. (<12/month)	0.80 (3.64)	1.99 (7.19)	1.24 (4.60)	0.73 (4.51)	-
Weekday Trip	0.27 (2.62)	-0.42 (-2.63)	0.39 (2.55)	-	1.20 (3.62)
Flexible Trip	-	-	-	-	
Urgent Trip	0.34 (3.72)	0.78 (6.24)	-	0.49 (6.60)	-
Delay Experienced	-	-	-	-	-
Short Trip (<20 miles)	-0.40 (-5.15)	-	-0.36 (-3.46)	-	-
Drive Alone	-	-	0.26 (2.39)	-	-
Drive Another	1.68 (20.09)	-	-	-	-

Random parameters in utility functions	**Mean**	**STD**
Time	-0.38 (-76.61)	0.12 (76.61)
Reliability	-2.05 (-38.98)	0.68 (38.98)
Cost	-2.65 (-69.09)	0.87 (69.09)

Heterogeneity	Time	Reliability	Cost
High Income (>150K)	-	-0.21 (-1.86)	0.49 (5.88)
Med Income (50~150K)	-	-	0.14 (2.12)
Urgent Trip	0.02 (2.13)	0.27 (3.24)	0.23 (4.15)
Employed	0.03 (2.93)	0.19 (1.65)	0.23 (2.91)
Short Trip (<20 miles)	-	0.85 (7.55)	-
Med. Trip (20~40 miles)	-	0.74 (6.82)	-
Young People (<34)	-0.04 (-4.21)	0.26 (2.79)	0.30 (4.78)
Old People (>54)	0.02 (2.31)	0.19 (2.35)	0.29 (5.01)
Male	-	0.20 (2.53)	-
Drive Alone	0.07 (5.81)	-	0.22 (2.97)
Drive Another	0.14 (9.75)	-0.29 (-2.36)	-0.21 (-2.56)
Mandatory Trip	-	-	-
Less Freq. (<4/month)	0.03 (2.42)	0.64 (6.83)	0.24 (3.91)
Med. Freq. (<12/month)	0.04 (2.18)	0.36 (2.39)	0.18 (2.00)
Sunpass User	0.06 (4.32)	-	-
Weekday Trip	-	-	0.22 (3.21)
Delay Experienced	0.03 (3.87)	0.26 (3.18)	0.23 (4.35)
Flexible Trip	-	-0.18 (-2.12)	-

Model Performance: Log Likelihood Function = -14009.99, McFadden Pseudo R-squared = 0.572
All variables shown are significant at 5% significance level

As the purpose of this study is to examine the impacts of heterogeneity on values of travel time, and travel time reliability, the derived formulas 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 incorporating variables of time, reliability, and cost, one could provide a full analysis on values of travel time and travel time reliability. In this regard, the total values (including both main and interaction effects) were computed for each of the potential sources of heterogeneity and were subtracted from the base value. Accordingly, VOT and VOR elasticity values for each of the segments could be calculated as:

$$\Delta VOT_i = VOT_{segment\ i} - VOT_{Base} = (\frac{Time_{\ segment\ i}}{Cost_{\ Segment\ i}}) - (\frac{Time_{\ Base}}{Cost_{\ Base}})$$

$$\Delta VOR_i = VOR_{segment\ i} - VOR_{Base} = (\frac{Reliability_{\cdot segment\ i}}{Cost_{\ Segment\ i}}) - (\frac{Reliability_{\ Base}}{Cost_{\ Base}})$$

As an example, sample elasticity values for high income segment will be calculated as:

$$\Delta VOT_{High\ income} = \left[\left(\frac{-0.38}{-2.65+0.49}\right) - \left(\frac{-0.38}{-2.65}\right)\right] \times 60 = 1.95\ \$/hour$$

$$\Delta VOR_{High\ income} = \left[\left(\frac{-2.05-0.21}{-2.65+0.49}\right) - \left(\frac{-2.05}{-2.65}\right)\right] \times 60 = 16.36\ \$/hour$$

This can be interpreted as, when all other conditions equal, being in the high income category is expected to increase the values of VOT and VOR by $1.95 and $16.36 per hour, respectively.

Similar calculations could be done for all other segments. Results are presented in Table 26 and also illustrated in Figures 18 and 19. Zero values imply insignificant values for both the numerator (either time or reliability) and the denominator (cost).

The values from Table 26 need to be applied with extra care. First, it should be noticed that these are single-effect elasticity values, which means their direct application is restricted to the situation where no other segment effects are present. Second, due to the non-linear formula for VOT and VOR, linear summations of the single-effects are not feasible. In other words, if one desires to calculate the impacts of two or more different segments simultaneously (which is something popular in the dataset), he cannot simply add up the results from table 26. This should be done directly based on the formulas for time, reliability, and cost. For instance, the impacts on VOR for a young male individual on a short trip are calculated as:

$$\Delta VOR_{Male,young,short\ trips} = \left[\left(\frac{-2.05+0.26+0.2+0.85}{-2.65+0.30}\right) - \left(\frac{-2.05}{-2.65}\right)\right] \times 60 = -\$27.5/hour$$

Table 26 Single Effect Heterogeneity in VOT and VOR

Heterogeneity Sources	ΔVOT	ΔVOR
High Income (>150K)	1.95	16.36
Med Income (50-150K)	0.48	2.59
Urgent Trip	0.32	-2.28
Employed	0.07	-0.30
Short Trip (<20 miles)	0	-19.25
Med. Trip (20-40 miles)	0	-16.75
Young People (<34)	2.12	-0.71
Old People (>54)	0.55	0.87
Male	0	-4.53
Drive Alone	-0.95	4.20
Drive Another	-3.57	2.68
Mandatory Trip	0	0
Less Freq. (<4/month)	0.11	-11.31
Med. Freq. (<12/month)	-0.34	-5.36
Sunpass User	-1.36	0
Weekday Trip	0.78	4.20
Delay Experienced	0.07	-2.03
Flexible Trip	0	4.08

The elasticity values are further illustrated in Figures 18 and 19 in order to provide a more informative schematic view of user heterogeneity in view of VOT and VOR.

As shown in Figure 18, high income people along with individuals younger than 35 years old had the highest VOT sensitivity. It is reasonable to assume that high income people perceive higher values of time due to their profitable work/business hours, and therefor 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. 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 temporal constraints, and are expected to show higher VOTs.

Medium income travelers (household income between 50K-150K) and old people (54 years old or older) also revealed considerable contributions to higher VOT, followed by employed travelers, less frequent trips and delay experienced travelers, which led to slightly higher VOT values than their counterparts.

It is 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 revealed that drive alone and drive with another passenger modes were accompanied with lower VOT than driving with two or more passengers. This may be due to the reason that driving with additional passengers would receive toll discount or cost sharing, that lead to higher usage of MLs and higher willingness to pay.

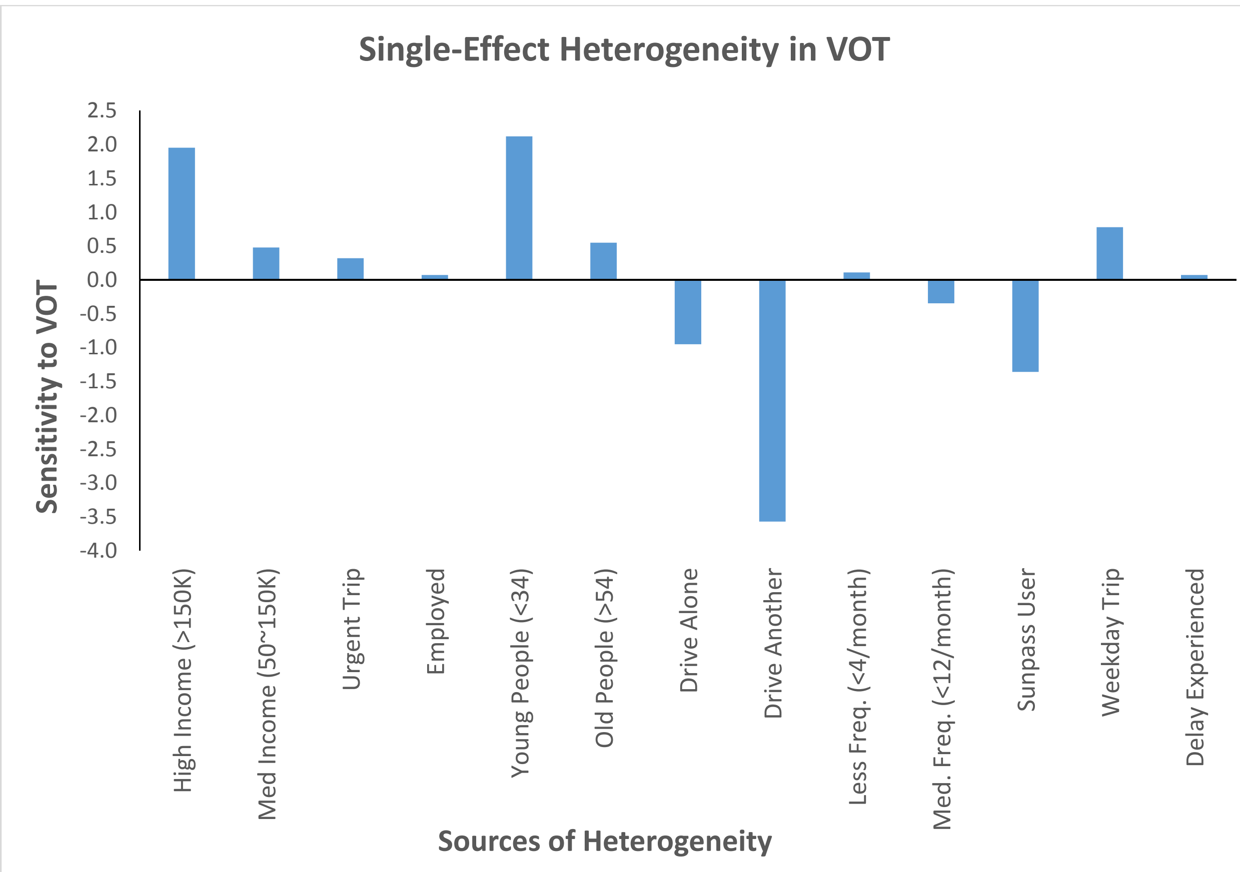


Figure 18 Single Effect Heterogeneity in VOT.

In view of VOR, Figure 19 shows that medium and high income individuals showed higher sensitivity. As expected, weekdays also contributed to higher VOR values. Lower reliability values for urgent trips and delay experienced individuals might signify that in public belief, urgency and delay are usually interpreted based on the need for shorter travel time and not reliability.

Travelers older than 54 showed higher VOR while younger travelers (younger than 35) showed slightly lower VOR compared with middle aged travelers. Female travelers exhibited considerable higher VOR than males. 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.

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 statistical findings presented in Chapter 4, where travelers with arrival flexibility from both RP and SP subsamples showed higher usage of MLs than those without arrival flexibility.

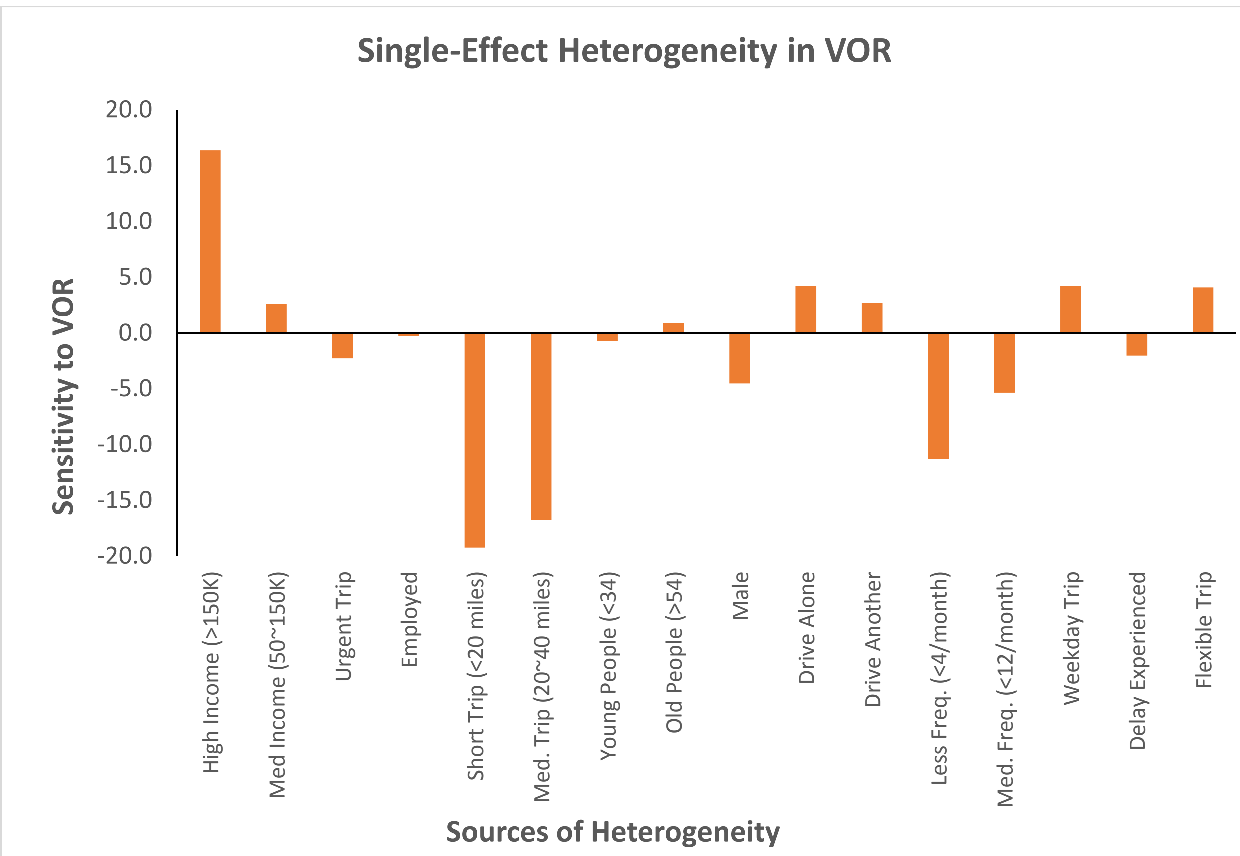


Figure 19 Single Effect Heterogeneity in VOR.

It should be noted that while the single-effect elasticity analysis provides valuable insights on individuals' economic perception of travel time and travel time reliability, these values need to be adopted with extra care, especially when it comes to combined segments. Single-effect elasticities only show the change in VOT/VOR when all other conditions being equal. Due to the non-linearity of VOT/VOR concepts, single-effect formulas cannot be linearly added up. In order to combine the effects of two or more segments, interaction formulas for time, reliability, and cost should be considered to obtain more accurate results.

Also, the interaction model still reflected significant standard deviations for all three random parameters. This indicated that probably there are unaddressed sources of heterogeneity in the model. This might happen due to several factors. First, the perceptions of travel time, cost, and reliability is 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 roles in travel behavior studies, were not accounted for. Adding attitudinal factors could possibly address the remaining heterogeneity in the model.

5.3 Summary of Findings in User Heterogeneity

Mixed logit model results indicated an average value of $9.41 per hour for VOT and $13.02 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., 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 desired for urgent trips mainly accompanied by an early shift.
- Less frequent trips (less than 12 trips per month) had positive contributions to ML alternatives, with 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), older individuals (54 years or older), and weekday trips would lead to higher values for both VOT and VOR.
- Urgent trips, less frequent trips (4 times or less per month), young individuals (34 years old or younger), and delay experienced travelers perceived higher values of time and lower values of reliability. This 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).
- Both driving alone and driving with one passenger reflected lower VOT, possibility because driving with additional passengers would receive toll discount or cost sharing, that lead to higher usage of MLs and higher willingness to pay.
- Short and medium trips (less than 40 miles) only affect VOR, both of which have significantly lower VOR values compared to long trips. Similarly, less frequent and medium frequent trips led to lower VOR values compared with very frequent trips (more than 12 times per month).

6. CONCLUSIONS

This report presents a comprehensive study in VOT and VOR analysis in the context of ML facility. Combined RP and SP data were used to understand travelers' choice behavior towards the usage of MLs. 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 $9.41 per hour for VOT and $13.02 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.

The model was further enhanced by adding interaction effects of variables, which help 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 indicate that various socioeconomic demographic characteristics and trip attributes do contribute 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 contribute to a better understanding on what attributes lead 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 strategy and policy evaluations, and impact analysis, etc.

The data used in this study may present certain limitations. 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 reflect their perceived values of reliability improvement.

Future study can extend this analysis in the context of modal shifts as ML 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 ML programs. 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.

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