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Investigating preference heterogeneity in Value of Time (VOT) and Value of Reliability (VOR) estimation for managed lanes

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A B S T R A C T

This paper presents an empirical study in investigating user heterogeneity of Value of Time (VOT) and Value of Reliability (VOR). Combined Revealed Preference (RP) and Stated Preference (SP) data were used to understand traveler choice behavior regarding the usage of managed lanes (MLs). The data were obtained from the South Florida Expressway Stated Preference Survey, which focused on automobile drivers who had traveled on the I-75, I-95, or SR 826 corridors in South Florida. Mixed logit modeling was applied and indicated an average value of $13.55 per hour for VOT and $16.13 per hour for VOR. Potential sources of heterogeneity in user sensitivities to time, reliability, and cost were identified and quantified by adding interaction effects of the variables in the mixed logit model. The findings indicated that various socioeconomic demographic characteristics and trip attributes contributed to the variations in VOT and VOR at different magnitudes. 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.

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. The strategies may include access control, vehicle eligibility, variable pricing, or a combination thereof. MLs can include express lanes, high occupancy vehicle (HOV) lanes, reversible lanes, truck-only toll lanes, and vehicle-restricted lanes. ML strategies can help better manage congestion and provide choices to travelers. Users can pay tolls for reduced travel time and improved travel time reliability, and their willingness to pay is often reflected as Value of Time (VOT) and Value of Reliability (VOR).

With increasing emphasis on ML strategies in the US, it is critical to understand the behavioral aspects and underlying causalities of the users' willingness to pay in the ML context, in order to evaluate the program impacts and effectiveness. Transportation agencies are facing multifaceted challenges to accommodate ML strategies into existing infrastructure, such as pricing structures, transit operations, and social equity concerns. Understanding the demand and choice behavior of ML

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users is essential for prescribing solutions to the aforementioned challenges. One of the key elements is to examine the VOT and VOR distributions or variations across different users and under different circumstances.

Many studies have been conducted in estimating VOT and VOR, and investigating the influencing factors (Calfee and Winston, 1998; Patil et al., 2011; Tilahun and Levinson, 2010, 2009; Asensio and Matas, 2008; Sheikh et al., 2003; Liu et al., 2004, 2005; Small et al., 2005; Zheng et al., 2010; Carrion and Levinson, 2013; Ghosh, 2001; Lam and Small, 2001; Hensher, 2001; Batley and Ibanez, 2012; Bhat and Sardesai, 2006; Cherchi and Ortúzar, 2011; Devarasetty et al., 2012). Taste preference was mainly addressed by adopting advanced logit models, such as mixed logit, through the realization of random parameters (Patil et al., 2011; Tilahun and Levinson, 2010, 2009; Asensio and Matas, 2008; Liu et al., 2004, 2005; Small et al., 2005; Zheng et al., 2010; Carrion and Levinson, 2013; Ghosh, 2001; Hensher, 2001; Batley and Ibanez, 2012; Bhat and Sardesai, 2006; Cherchi and Ortúzar, 2011; Devarasetty et al., 2012). Market segmentation techniques were also employed in some cases to account for the taste variations among different groups of users (Patil et al., 2011; Liu et al., 2005; Zheng et al., 2010; Ghosh, 2001; Lam and Small, 2001; Tilahun and Levinson, 2009). However in both cases, the focus was mainly on the contributing factors toward the choice of ML alternatives, without accounting for user heterogeneity to the full extent. In the first case, mixed logit modeling recognizes the preference heterogeneity by allowing some coefficients to be random parameters, but it does not identify the source of heterogeneity in the taste variations. In the second case, segmentation is somewhat ad hoc in addressing user heterogeneity, and the results can vary largely depending on how the segments are defined for the variables of interest.

Empirical studies also revealed substantial variations in VOT and VOR estimation. For instance, VOT estimates vary from \$3.88/h (Calfee and Winston, 1998) to as high as \$47.50/h (Patil et al., 2011), while VOR ranges between \$2.31/h (Tilahun and Levinson, 2009) and \$56.54/h (Asensio and Matas, 2008). In general, researchers attributed these variations to several aspects, including demographic characteristics, transportation alternative attributes, and regional economy. However, the large variations in VOT and VOR estimates may warrant further investigation, especially in the aspect of user heterogeneity.

Given the above motivation, this study intends to extend the mixed logit modeling approach to reveal and quantify potential sources of user heterogeneity. The objective is to investigate whether and to what extent the taste variations can be explained by the observed individual and trip-related attributes. This paper contributes to the literature by providing an empirical study in assessing user heterogeneity, and advancing the understanding of travelers' willingness to pay in the context of MLs. The findings can be incorporated into the demand modeling process and lead to better planning practices to facilitate policy and investment decisions.

2. Literature review

In the United States, the focus on VOT and VOR estimation started around mid-1990s following the first successful high-occupancy toll project at Orange County, California. Table 1 provides a chronological list of past VOT and VOR studies, with a brief summary on the data used, the model structures employed, and the estimated values.

As exhibited in Table 1, generally two major sources of data were used for VOT and VOR studies – revealed preference (RP) and stated preference (SP) data. RP data reflect the actual choices made by travelers, which are either directly observed or self-reported through a survey. Although the RP method removes the uncertainty of the travelers' decisions, it has been criticized for the lack of sufficient information on the unchosen alternatives, possible correlation between different effects,

Table 1
Summary of previous studies on VOT and VOR analysis.

Study	Data	Model structures	VOT (\$/h)	VOR (\$/h)
Calfee and Winston (1998)	SP	Ranked-ordered Logit	3.88	Not measured
Hensher (2001)	SP	Multinomial Logit	8.69	Not measured
		Mixed Logit	9.38–9.42	
Ghosh (2001)	RPSP	Mixed Logit	20.27	30
Lam and Small (2001)	RP	Bivariate Logit	22.87	31.69
Liu et al. (2004)	RP	Mixed Logit	12.81	20.63
Small et al. (2005)	RPSP	Mixed Logit	11.92–21.46	5.40–19.56
Bhat and Sardesai (2006)	RPSP	Mixed Logit	12.19	3.27–6.05
Liu et al. (2007)	RP	Mixed Logit	6.82–27.66	17.49–39.24
Asensio and Matas (2008)	SP	Mixed Logit	15.51	23.1–56.54
Tilahun and Levinson (2009)	SP	Mixed Logit	9.54–25.43	Not measured
Li et al. (2010)	SP	Multinomial Logit	28.28	40.39
		Mixed Logit		
Tilahun and Levinson (2010)	SP	Binomial Logit	7.44–8.07	2.31–7.44
Cherchi and Ortúzar (2011)	RPSP	Mixed Logit	10.89–25.41	Not measured
Patil et al. (2011)	SP	Logit	7.4–8.6	Not measured
		Mixed Logit	8–47.5	
Devarasetty et al. (2012)	SP	Mixed Logit	28	33
Batley and Ibanez (2012)	SP	Mixed Logit	24	49.68
Carrion and Levinson (2013)	RP	Mixed Logit	9.15	5.99
Sheikh et al. (2014)	RP	Direct Estimation	36–26	Not measured

and the lack of ability to evaluate future (non-existent) alternatives (Dumont and Falzarano, 2015). SP data, on the other hand, evaluate users' behavior under different hypothetical scenarios. The SP approach is known to provide reliable estimates since it can minimize the correlation between the effects, ensure full knowledge of the alternatives when making decisions, and obtain a robust understanding of personal behavior by observing multiple choices from one individual.

However, the study results are also highly dependent on the SP survey design, including question phrasing and the level of information provided to the respondents. In addition, SP data are not based on actual market behavior and, therefore, their validity is usually of concern. A model estimated exclusively from SP data may not be able to accurately predict the actual market behavior. Previous literature found that typical SP survey tended to underestimate VOT compared with RP studies (Ghosh, 2001; Hensher, 2001). As a result, many studies used combined RP and SP data, in order to gain benefits of both sides (Hensher and Bradley, 1993; Brownstone et al., 2000; Bhat and Casterlar, 2002; Earnhart, 2002). This approach is expected to increase the model efficiency, correct the potential bias from separate RP/SP data, and allow the evaluation of alternatives or attributes that are not identifiable from RP only data (Ben Akiva et al., 1994). For this study, both RP and SP data were employed for the estimation of VOT and VOR, which is further discussed in the Data section.

Discrete choice modeling was widely applied in estimating VOT and VOR, in which the choice trade-off between toll cost and time savings/reliability provides an indication of how much the users value their travel time and the reliability of travel time. While standard logit models (binary/multinomial) may provide a simple solution in VOT and VOR estimation, using a single set of VOT and VOR estimation to represent the entire population could not account for user heterogeneity and may lead to erroneous policy implications. In this regard, random-parameter (also known as mixed) logit structure has gained popularity and considered a powerful tool in VOT and VOR estimation (Patil et al., 2011; Tilahun and Levinson, 2010, 2009; Asensio and Matas, 2008; Liu et al., 2004, 2005; Small et al., 2005; Zheng et al., 2010; Carrion and Levinson, 2013; Ghosh, 2001; Hensher, 2001; Batley and Ibanez, 2012; Bhat and Sardesai, 2006; Cherchi and Ortúzar, 2011; Devarasetty et al., 2012). It allows each observation to have unique parameter estimates by allocating a random distribution (Train, 2009; Hensher and Greene, 2003) across individuals and scenarios, which can account for the preference heterogeneity among the users.

Another commonly applied approach to address user heterogeneity is market segmentation, which identifies and divides travelers into subsets of users that may exhibit similar taste and preference when facing ML alternatives. In this approach, various socio-economic-demographic (SED) or trip characteristics were used to capture the taste variation among the users such as male vs female (Ghosh, 2001; Lam and Small, 2001), commuter vs non-commuter (Zheng et al., 2010), time periods of day (Liu et al., 2005; Tilahun and Levinson, 2009), urgent trip vs unurgent trip (Patil et al., 2011), transponder subscriber vs non transponder subscriber (Tilahun and Levinson, 2009), etc. Some studies considered single segmentation, while others applied multiple segmentations. The drawbacks of the segmentation approach mainly include the lack of explicit criteria to identify the appropriate number of segmentations, and the thresholds for the segments. Due to the limitations, segmented VOT and VOR often fail to address heterogeneity appropriately.

Although past studies usually included various types of explanatory variables (e.g. gender, age, income, etc.), the role of these attributes in explaining the heterogeneity around the mean of random parameters were rarely explored or quantified. Only few studies focused on addressing heterogeneity while estimating VOT and VOR (Small et al., 2005; Bhat and Sardesai, 2006; Cherchi and Ortúzar, 2011). Small et al. (2005) estimated the distribution of VOT and VOR by allowing both observed and unobserved heterogeneity. They recognized substantial unobserved heterogeneity based on the significance of standard deviations of the random parameters, but didn't identify the sources of associated heterogeneity (Small et al., 2005). Bhat and Sardesai (2006) examined the impact of unobserved heterogeneity on VOT and VOR estimation, and found that VOT was relatively unaffected if unobserved heterogeneity was ignored, but VOR was inflated considerably. Similar to Small et al. (2005), they also didn't identify the potential heterogeneity sources (Bhat and Sardesai, 2006). Cherchi and Ortúzar (2011) tested systematic and random heterogeneity on VOT estimates and found significant lower VOT estimates from RP data compared with SP data, but they didn't identify any contributing sources (Cherchi and Ortúzar, 2011).

Given the above findings from the literature, this study aims to conduct an in-depth investigation to reveal and quantify the sources of user heterogeneity in VOT and VOR. This paper adds to the literature by providing an empirical study in examining whether and to what extent the taste variations can be explained by the observed individual and trip-related attributes.

3. Methodology

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

It is considered 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 SP survey). Accordingly, the utility of alternative i evaluated by person n under situation (scenario) t could be expressed as (Hensher and Greene, 2003):

$$U_{itn} = \beta_n' X_{itn} + [\eta_{itn} + \varepsilon_{itn}] \quad (1)$$

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 the 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 mixed model is observed in the error term. 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 the 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,

$$L_i(\beta_n|\eta_{in}) = \frac{\exp(\beta'_n X_{in} + \eta_{in})}{\sum_j \exp(\beta'_n X_{jn} + \eta_{jn})} \tag{2}$$

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

$$P_{in}(\beta_n|\phi) = \int_{\eta_{in}} L_{in}(\beta_n|\eta_{in}) f(\eta_{in}|\phi) d\eta \tag{3}$$

One popular perspective of 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 for everyone 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.

To further examine whether the taste variation across users can be explained by the observed individual and trip-related attributes, the interaction terms between the random parameters with each of the exogenous variables can be added to the utility function as follows:

$$\boldsymbol{U}_{in} = \beta X_{in} + \beta_{TT} TT_{in} + \beta_{TTR} TTR_{in} + \beta_{TC} TC_{in} + \gamma_{TT}(S_{in} * TT_{in}) + \gamma_{TTR}(S_{in} * TTR_{in}) + \gamma_{TC}(S_{in} * TC_{in}) + \varepsilon_{in} + \eta_{in} \tag{4}$$

where β = coefficient vector of non-random parameters
X_{in} = columnar vector of non-random explanatory variables
β_{tt} = coefficient of "travel time" as a random parameter
TT_{in} = "travel time" for individual n in alternative i
β_{ttr} = coefficient of "travel time reliability" as a random parameter
TTR_{in} = "travel time reliability" for individual n in alternative i
β_{tc} = coefficient of "travel cost" as a random parameter
TC_{in} = "travel cost" for individual n in alternative i
S_{in} = a subset of X_{in}, which represent potential sources of heterogeneity
γ_{tt} = interaction coefficient vector for travel time
γ_{ttr} = interaction coefficient vector for travel time reliability
γ_{tc} = interaction coefficient vector for travel cost

In this study, three variables of interest including travel time (TT), travel time reliability (TTR), and travel cost (TC) were considered as random parameters. Interaction terms between the three random parameters and the individual and trip attributes were tested to investigate user heterogeneity. In Eq. (4), if the γ_{TT}(or γ_{TTR} or γ_{TC}) is significant, then the interacted variable S_{in} is considered as a source of heterogeneity. As the random parameters reflect disutility (β_{TT}, β_{TTR}, β_{TC} are expected to be negative), positive γ_{TT}(or γ_{TTR} or γ_{TC}) indicates lower sensitivity of the utility function towards that specific random variable (i.e. lower total impact of the variable on the utility function), while negative interaction coefficients indicate higher sensitivity towards the random parameter (Hensher et al., 2005). The sensitivities toward travel time, travel time reliability, and travel cost can then be further interpreted to represent taste variations in VOT and VOR.

4. Data

The study used data obtained from the South Florida Expressway Stated Preference Survey conducted between November 16 and December 15, 2011 (Resource System Group, 2012). The survey gathered information from automobile drivers who recently made a trip in the I-75, I-95, or SR 826 corridors. Among the three corridors, dynamically-priced express lanes currently exist on I-95 between the SR 112 interchange in the south and the Golden Glades interchange in the north. New express lanes are proposed on the other two corridors, including SR 826 (Palmetto Expressway) between Golden Glades and SR836 and I-75 between I-595 and SR 826.

The survey gathered information from 2041 respondents (1060 from I-95, 521 from I-75, and 460 from SR 826). Among the 1060 I-95 travelers, 513 were eligible for the ML (the reported on and off ramps were used to determine whether the trips were eligible to use the ML facilities). Each respondent faced eight SP scenarios. The final dataset contains 513 RP responses and 16,327 SP responses.

Five choice alternatives were offered in the survey, including general purpose (GP) lane, managed lane (ML) in peak hour, managed lane before the peak period (ML2), managed lane after the peak period (ML3), and managed lane with additional passengers (ML4). The first two alternatives (GP and ML) were presented to all survey participants, while the next two alternatives (ML2 and ML3) were provided only to those who reported a peak period trip, and the fifth alternative (ML4) was available only to those who reported a trip with two or fewer vehicle occupants.

A major limitation of the survey is that it did not included reliability in the SP survey design. In order to capture the impact of reliability, this study collected archived detector data from the Regional Integrated Transportation Information Systems (RITIS) CATT Lab, 2015 to derive travel time distributions. RITIS was chosen mainly because of its ability to distinguish GP lane and ML data. One year travel time data (2012) were collected for the entire segment of the ML facility within the study area. Four sets of data were retrieved, by direction (northbound and southbound) and by facility type (GP lanes and MLs). Travel time information were derived by hour of the day. The final travel time distribution data contain a matrix of 24 by 365 for each facility type by direction. Since this study focuses on freeway facilities, the semi-standard deviation measure was employed to represent reliability of travel time, where the free flow travel time (10 percentile travel time) instead of average travel time was used as the reference travel time. Travel time reliability data were applied only for I-95 respondents who were eligible to use the ML. Reliability data were matched to the respondents based on the time-of-day, travel direction and facility type of the trips.

Fig. 1 below shows the reliability measures by direction (northbound and southbound) by facility (GP and ML) by time of day.

Table 2 presents the personal and trip attributes considered in this study with their categories and the corresponding choice shares. According to the SP responses, the table suggests that the GP alternative was the dominant choice (over 50% share) for all except for high income people. The RP observations revealed that travelers who were male, employed, younger than 55, with annual household income above 50 K, subscribed with Sunpass, and with no delay experience showed higher usage of MLs than GP lanes. In terms of trip characteristics, mandatory trips (work/business/airport), more frequent trips (4 or more times per month), weekday trips, drive alone trips, longer trips (20 miles or longer) showed higher usage of MLs over GP lanes.

5. Model estimation and results

In order to address user heterogeneity, two mixed logit models were developed, which are – base model and heterogeneous model. Heterogeneous model was developed by adding interaction effects between random parameters and potential heterogeneity sources with the base model. Base model results can reveal whether there is significant preference heterogeneity in any of the random parameters (time, reliability, and cost), whereas heterogeneous model identify and measure different sources of heterogeneity.

5.1. Base model

Travel time, travel time reliability, and travel cost were treated as random parameters. Normal distributions were assumed for time and reliability parameters, while a triangular distribution was assumed for cost parameter. In order to

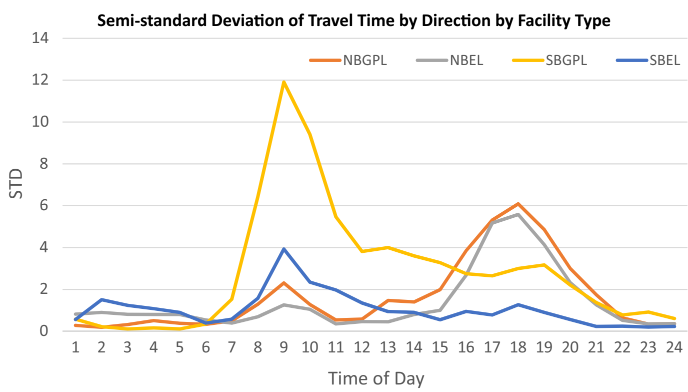

Fig. 1. Semi–standard deviation of travel time by time of day.

Table 2
Respondent choices by individual and trip characteristics.

	Category	RP alternatives (%)		SP alternatives (%)				
		GP	ML	GP	ML	ML before peak	ML after peak	ML additional passenger
Personal attributes								
Age	16–34	40	60	51	24	3	6	16
	35–54	48	52	60	22	4	4	11
	55–75+	51	49	60	21	2	4	13
Gender	Male	45	55	57	23	3	4	13
	Female	51	49	59	21	3	4	13
Household income	Low (<50 k)	54	46	62	16	3	4	15
	Med (50 k–150 k)	48	52	59	23	3	4	11
	High (>150 k)	29	71	45	37	2	5	11
Employment	Employed	45	55	56	24	3	4	12
	Unemployed	63	37	64	14	2	4	16
Arrival flexibility	With Flexibility	44	56	59	21	4	4	12
	No Flexibility	56	44	57	22	3	4	13
Sun pass	User	45	55	57	23	3	4	12
	Not User	76	24	65	10	5	5	15
Trip attributes								
Trip urgency	Urgent	46	54	53	24	5	5	14
	Not Urgent	48	52	60	21	2	4	12
Trip purpose	Mandatory	39	61	55	26	4	5	10
	Non Mandatory	59	41	60	18	3	4	15
Trip frequency (per month)	Less Freq.(<4)	51	49	58	22	3	4	14
	Med Freq.(4–12)	39	61	53	25	5	5	12
	Very Freq. (>12)	37	63	60	22	3	5	9
Day of week	Week Day	42	58	57	24	3	5	12
	Weekend	64	36	61	18	3	3	14
Trip occupancy	Drive Alone	42	58	58	25	3	4	9
	Drive Another	56	44	50	14	2	3	31
	HOV3	55	45	66	23	4	7	0
Trip length (miles)	Short (<20)	57	43	62	18	3	4	13
	Med (20–40)	44	56	55	26	3	4	12
	Long (>40)	44	56	53	22	4	6	15
Delay experience	Have Experience	53	47	55	23	4	5	12
	No Experience	43	57	60	22	2	4	13
Total sample N		47	53	58	22	3	4	13
		513		16,327				

ensure that the coefficients remain negative for all observations, a linear constraint was imposed on the mean (μ) and standard deviation (σ) of the distribution, as $\frac{\sigma}{\mu} < 0.333$. This constraint is particularly important for cost parameter, as it ensures that the values are bounded between two negative values which ascertains the existence of finite moments (Daly et al., 2011).

Table 3 presents the model results for the base model. The mixed logit model revealed significant standard deviation values for all three random parameters, indicating the existence of taste heterogeneity among the users. Table 3 shows that for RP sample, individuals younger than 35, high income people, and sunpass users were more likely to use MLs. Mandatory trips and weekday trips also encouraged the usage of MLs.

In view of SP alternatives, a few additional observations could be made based on the model results. Female drivers were more probable to use 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; Podgorski and Kockelman, 2006; Mahirah et al., 2015; Dau, 2004).

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.

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.

Table 3
Mixed logit base model (1000 draws).

Independent variables	Parameter	Standard deviation
Random parameters in utility functions		
Time	−0.21 (−140.16)	0.07 (140.16)
Reliability	−0.25 (−25.72)	0.08 (25.72)
Cost	−0.93 (−57.71)	0.31 (57.71)

Independent variables	SP – ML peak	SP – ML before peak	SP – ML after peak	SP-ML additional passenger	RP-ML
Non-Random parameters in utility functions					
ASC	−3.99 (−40.5)	−3.84 (−29.4)	−4.21 (−43.7)	−2.95 (−50.5)	−2.98 (−4.82)
Male	−0.13 (−4.26)	–	–	–	–
Young people (16–34)	0.79 (19.80)	0.41 (5.38)	1.04 (16.76)	0.60 (15.59)	0.53 (1.84)
Med income (50–150 K)	0.33 (8.25)	–	–	−0.21 (−6.52)	–
High income (>150 k)	1.42 (29.54)	–	0.55 (8.42)	–	1.08 (3.60)
Employed	0.47 (8.84)	–	–	–	–
Sunpass user	0.75 (11.25)	−0.59 (−7.55)	–	–	1.19 (2.07)
Delay experienced	–	–	−0.55 (−10.2)	–	–
Mandatory trip	0.41 (11.19)	–	–	–	–
Arrival flexibility	–	−0.18 (−2.92)	–	0.07 (2.07)	–
Less freq. (<4/month)	0.61 (13.45)	0.83 (9.96)	0.73 (10.76)	0.83 (18.11)	–
Med. freq. (<12/month)	0.60 (10.36)	1.44 (14.00)	0.87 (9.13)	0.56 (8.40)	–
Weekday trip	0.24 (5.97)	−0.38 (−4.74)	0.22 (3.24)	–	1.11 (3.91)
Urgent trip	0.09 (2.65)	0.35 (5.43)	–	0.10 (2.68)	–
Short trip (<20 miles)	−0.25 (−7.77)	–	−0.16 (−3.10)	–	–
Drive another	−0.77 (−19.8)	–	–	–	–
VOT	$13.55				
VOR	$16.13				

Model Performance: Log Likelihood Function = −15268.94, McFadden Pseudo R-squared = 0.534
All variables shown are significant at 5% significance level; t-statistics are shown in parentheses.

Trip attributes were also important contributors to the model. Accordingly, mandatory trips were less prone toward temporal shift. Results also indicated that MLs were not an appealing option for short trips. However, they were more desirable 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 ML alternatives, with highest impacts on early shifts. It might suggest that very frequent trips were likely to reduce the probability of ML 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 attribute revealed that drivers with one passenger were less likely to use MLs in the peak period.

As can be seen in the model results, the standard deviation values were high and statistically significant for time, reliability, and cost. This provided solid evidence for the presence of heterogeneity among the 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. Heterogeneous model

In the heterogeneous model, 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.

Table 4 presents the results of the mixed logit model with interaction effects. All variables shown are significant at 5% significance level. The main effects were fairly comparable with the results from the mixed logit model without interaction effects, in terms of coefficient signs and values. The interaction model reflected a slightly better goodness-of-fit in terms of likelihood and rho squared values, which showed that taking heterogeneity into account improves the predictive power of the model.

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

$$\begin{aligned} \textit{Time Coefficient} = {} & -0.42 + 0.04(\textit{Employed}) - 0.04(\textit{Age} < 34) + 0.03(\textit{Age} \\ & > 54) + 0.08(\textit{Drive alone}) + 0.14(\textit{Drive another}) + 0.03(\textit{Freq} \\ & < 4/\textit{month}) + 0.08(\textit{Sunpass user}) + 0.04(\textit{Delay experienced}) \end{aligned} \tag{5}$$

Table 4
Mixed Logit Heterogeneous Model (1000 draws).

Independent variables	Parameter	Standard deviation
Random parameters in utility functions		
Time	−0.42 (−94.85)	0.14 (94.85)
Reliability	−1.94 (−38.89)	0.64 (38.89)
Cost	−3.50 (−47.94)	1.16 (47.94)

Independent variables	SP – ML peak	SP – ML before peak	SP – ML after peak	SP-ML additional passenger	RP-ML
Non-Random parameters in utility functions					
ASC	−2.78 (−13.94)	−2.81 (−10.22)	−3.38 (−15.02)	−2.63 (−21.9)	−2.48 (−3.64)
Male	−0.19 (−2.80)	–	–	–	–
Young people (16–34)	–	−0.35 (−2.55)	0.33 (2.76)	0.24 (3.57)	–
Med income (50–150 K)	0.23 (2.47)	–	–	−0.18 (−2.83)	–
High income (>150 k)	1.03 (8.60)	–	0.42 (2.96)	–	–
Employed	0.46 (4.30)	–	–	–	–
Sunpass user	0.76 (5.65)	−0.44 (−2.69)	–	–	–
Mandatory trip	0.56 (6.79)	–	–	–	–
Less freq. (<4/month)	–	0.73 (3.65)	0.51 (2.73)	0.53 (4.81)	–
Med. freq. (<12/month)	0.49 (2.31)	1.72 (6.27)	0.99 (3.75)	0.62 (3.94)	–
Weekday trip	–	−0.59 (−3.69)	–	–	1.11 (3.44)
Urgent trip	0.32 (3.56)	0.76 (6.06)	–	0.49 (6.69)	–
Short trip (<20 miles)	−0.45 (−5.95)	–	−0.36 (−3.46)	–	–
Drive alone	–	–	0.23 (2.19)	–	–
Drive another	1.63 (19.72)	–	–	–	–

Heterogeneity	Time	Reliability	Cost
High income (>150 K)	–	−0.19 (−1.67)	0.44 (6.09)
Med income (50–150 K)	–	–	0.19 (3.25)
Urgent trip	–	0.25 (3.17)	0.23 (4.83)
Employed	0.04 (3.64)	–	0.43 (5.98)
Short trip (<20 miles)	–	0.81 (7.56)	–
Med. trip (20–40 miles)	–	0.69 (6.71)	0.17 (2.77)
Young people (<34)	−0.04 (−3.87)	0.26 (3.03)	0.30 (5.43)
Old people (>54)	0.03 (2.84)	–	0.31 (6.25)
Male	–	0.17 (2.23)	–
Drive alone	0.08 (6.56)	–	0.29 (4.43)
Drive another	0.14 (10.29)	−0.29 (−2.49)	–
Mandatory trip	–	–	–
Less freq. (<4/month)	0.03 (2.31)	0.58 (6.48)	0.44 (8.01)
Med. freq. (<12/month)	–	0.32 (2.22)	0.27 (3.57)
Sunpass user	0.08 (5.82)	–	0.51 (5.99)
Weekday trip	–	–	0.29 (5.68)
Delay experienced	0.04 (3.99)	0.23 (2.95)	0.26 (5.68)
Arrival flexibility	–	–	–

Model Performance: Log Likelihood Function = −14125.29, McFadden Pseudo R-squared = 0.569.
All variables shown are significant at 5% significance level; t-statistics are shown in parentheses.

$$\begin{aligned} \textit{Reliability Coefficient} = {} & -1.94 - 0.19(\textit{High Income}) + 0.25(\textit{Urgent trip}) + 0.81(\textit{Distance} \\ & < 20\ \textit{miles}) + 0.69(\textit{Distance}\ 20 \sim 40\ \textit{miles}) + 0.26(\textit{Age} \\ & < 34) + 0.17(\textit{male}) - 0.29(\textit{Drive another}) + 0.58(\textit{Freq.} < 4/\textit{month}) + 0.32(\textit{Freq.}\ 4 \\ & \sim 12/\textit{month}) + 0.23(\textit{Delay experienced}) \end{aligned} \tag{6}$$

$$\begin{aligned} \textit{Cost Coefficient} = {} & -3.50 + 0.44(\textit{High income}) + 0.19(\textit{Med income}) + 0.23(\textit{Urgent trip}) + 0.43(\textit{Employed}) \\ & + 0.30(\textit{Age} < 34) + 0.17(\textit{Distance}\ 20 \sim 40\ \textit{miles}) + 0.31(\textit{Age} > 54) + 0.29(\textit{Drive alone}) \\ & + 0.44(\textit{Freq.} < 4/\textit{month}) + 0.27(\textit{Freq.}\ 4 \sim 12/\textit{month}) + 0.51(\textit{Sunpass user}) + 0.29(\textit{Weekday}) \\ & + 0.26(\textit{Delay experienced}) \end{aligned}$$

Due to the linear formulation for each of the variables, the interaction effects imply the sensitivity of the utility function towards each of the random parameters. Given the negative sign for the base values of the random parameters, a negative interaction effect adds to the coefficient value of the parameter therefore increases the absolute impact of the random parameter on the utility function, while a positive interaction effect leads to an estimate closer to zero. For instance, "high

Table 5
Heterogeneity in VOT and VOR based on partial derivatives.

Heterogeneity sources	ΔVOT	ΔVOR
High income (>150 K)	1.04	8.5
Med income (50–150 K)	0.41	1.91
Urgent trip	0.51	−2.25
Employed	0.23	4.66
Short trip (<20 miles)	0	−13.89
Med. trip (20–40 miles)	0.37	−10.74
Young people (<34)	1.43	−1.76
Old people (>54)	0.14	3.23
Male	0	−2.92
Drive alone	−0.84	3
Drive another	−2.4	4.97
Less freq. (<4/month)	0.45	−6.59
Med. freq. (<12/month)	0.6	−3.17
Sunpass user	−0.38	5.67
Weekday trip	0.65	3
Delay experienced	−0.16	−1.59

income" showed a negative interaction effect on reliability (−0.19) and a positive interaction effect on cost (0.44), which indicates that high income people were more sensitive to reliability and less sensitive to cost compared to low income people.

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

As an example, the impacts of high income on VOT and VOR are calculated as:

$$\Delta VOT_{High\ income} = \left(\frac{-0.42}{(-3.5+0.44)} - \frac{-0.42}{-3.5}\right) \times 60 = 8.24 - 7.20 = 1.04\$/h$$

$$\Delta VOR_{High\ income} = \left(\frac{-1.94-0.19}{(-3.5+0.44)} - \frac{-1.94}{-3.5}\right) \times 60 = 41.76 - 33.26 = 8.5\$/h$$

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 $1.04 and $8.5 per hour, respectively. Similar calculations could be done for all other interaction segments. Results are presented in Table 5 below.

The impacts on VOT and VOR of the heterogeneity sources are further illustrated in Figs. 2and 3 in order to provide a more informative schematic view.

As shown in Fig. 2, high income people (household income larger than 150 K) along with individuals younger than 35 years old had the highest positive impacts on VOT. It is reasonable to assume that high income people perceive higher VOT due to their profitable work/business hours, and therefore are likely to pay to get time savings. Younger individuals, on the other hand, are expected to have more complicated responsibilities including a variety of time-sensitive activities such as work, school, and social errands. Their higher VOT value stemmed from both higher sensitivity to time and lower sensitivity to cost.

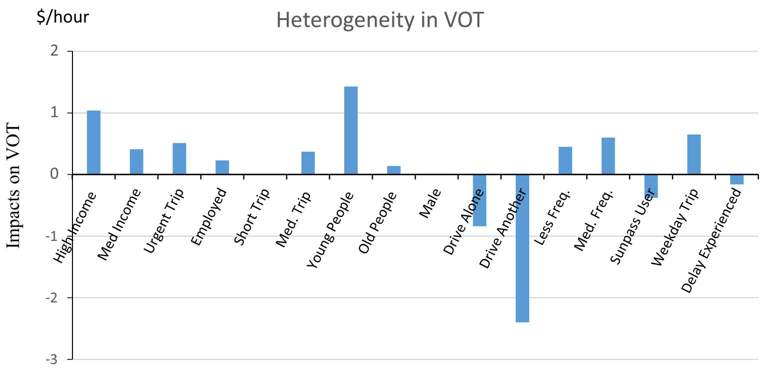

Fig. 2. Heterogeneity in VOT.

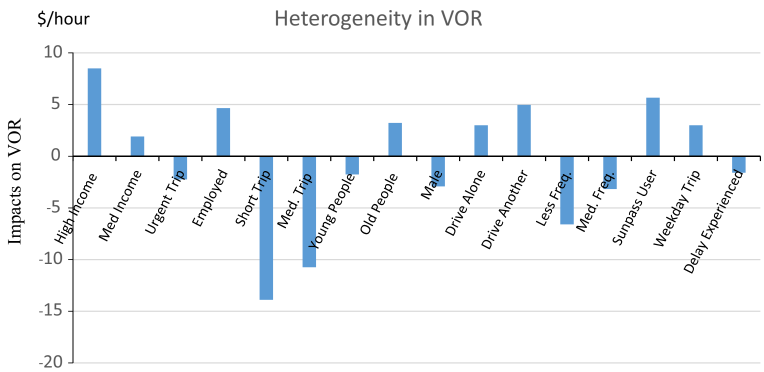

Fig. 3. Heterogeneity in VOR.

Weekdays were associated with higher VOT, perhaps because activity types and trip purposes on weekdays are different from weekends and mainly follow a fixed/rigid schedule. Medium income travelers (household income between 50 K and 150 K) and older people (54 years old or older) also revealed considerable contributions to higher VOT, followed by medium and less frequent trips.

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

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

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

In view of VOR, Fig. 3 illustrates that high income individuals showed the highest positive impacts. As expected, employed workers and weekdays contributed to higher VOR values. Female travelers, sunpass users and medium income travelers also exhibited considerable contributions to higher VOR values.

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

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

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

6. Analysis of user heterogeneity

Mixed logit model results indicated an average value of $13.55 per hour for VOT and $16.13 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 $150 K), and Sunpass users were more likely to utilize MLs.
- Low income people (annual household income less than $50 K) were less likely to use managed lanes unless they were being offered discount options such as additional passengers. This seems reasonable considering their monetary budget constraints. High income people were less prone toward early departures.

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

In view of the impacts on VOT and VOR, the interaction effects revealed significant user heterogeneity. Taking all the effects 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 $50 K), employed travelers, older individuals (54 years or older), and weekday trips would lead to higher values for both VOT and VOR.
- Urgent trips, less and medium frequent trips (12 times or less per month), medium distance trips (20–40 miles), and young individuals (34 years old or younger) perceived higher values of time and lower values of reliability, which may indicate that travel time savings might be more important for these trips/travelers.
- Female travelers showed considerably higher VOR than males, possibly because females are expected to have more complicated trip chain behavior or other activities that require on-time arrivals (e.g., escorting kids from/to schools).
- Sunpass users, drive-alone, and drive with one additional passenger travelers showed lower VOT and higher VOR, which mainly stemmed from the lower impacts of cost and time.
- Delay experienced travelers showed lower values for both VOT and VOR, which may indicate that people who were less willing to pay, would probably experience higher delays, or those with higher tolerance for delays exhibited less willingness to pay.
- Short (less than 20 miles) only affected VOR, which had significantly lower VOR values compared to long and medium distance trips.

7. Conclusions

This paper 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 toward the usage of MLs. Mixed logit modeling was applied to capture heterogeneity in users' choice behavior. The model revealed an average value of $13.55 per hour for VOT and $16.13 per hour for VOR (derived from the base model without interaction effects, Table 3), 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 helped recognize and quantify potential sources of heterogeneity in user sensitivities to time, reliability, and cost. The sensitivities were further employed to capture the user heterogeneity in VOT and VOR. The findings indicated that various socioeconomic demographic characteristics and trip attributes contributed to the variations in VOT and VOR at different magnitudes. This study provides a robust approach to quantify user heterogeneity in the values of VOT and VOR by incorporating the corresponding interaction effects for specific market segments. The results of this study contributed to a better understanding on what attributes led to higher or lower VOT and VOR and to what extent. These findings can be incorporated into the demand forecasting process and lead to better estimates and analytical capabilities in various applications, such as toll feasibility studies, pricing 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 have reflected their perceived values of reliability improvement.

Future study could incorporate unobserved characteristics such as attitudinal factors to further examine user heterogeneity and the variations in VOT and VOR estimation. Attitudinal factors, such as perspectives toward tolling in general, tolerance of congestion, and preferences in avoiding delay, may very well influence users' travel choices. Given the endogenous nature of attitudes, hybrid choice modeling techniques hold the potential to account for these latent preferences and explore the role of user attitudes in the propensity to use MLs.

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