EXAMINING DECISION-MAKING SURROUNDING THE USE OF MANAGED LANES BY KATY FREEWAY TRAVELERS: A PROSPECT THEORY APPROACH

A Dissertation

by

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ABSTRACT

Most previous research that models travelers' behavior in using managed lanes (MLs) versus a toll-free route has derived the individual's route-choice decision using a utility maximization approach. More recent models incorporating risk are based on expected utility theory (EUT). However, violations of some key assumptions of the EUT have led to the development of nonexpected utility theories, among which prospect theory (PT) has been one the most widely examined.

This study examined if PT is superior to EUT when predicting route/mode choice and understanding travelers' behavior in the case of MLs by embedding PT proposed value function and probability weighting functions in the utility estimation. From both EUT and PT approaches, this study used survey data from 2012 to predict the mode choices that include MLs and toll-free alternatives, and provided estimates of the value that travelers are willing to pay (WTP) for travel time savings on MLs. The responses from the survey were examined using advanced discrete choice modeling techniques. Significant and interesting general findings resemble those in previous studies that use PT, including the fact that individuals weight probabilities. Two survey design methodologies, D_b-efficient and adaptive random, were tested in this survey. Estimates from the EUT and PT approaches, as well as from previous studies on Katy Freeway travelers, are compared. The results of this study indicate that Katy Freeway travelers are more risk averse when in a situation of being late for work than they are with potential savings in travel time, and they, on average, demonstrate a sense of optimism when the chances of facing a longer travel time are high.

PT based models, particularly the model embedding with probability weighting, outperforms EUT based models in terms of the predicative power. On average, models with probability weighting resulted in more than 65 percent of all mode choices correctly predicted, while conventional EUT models predict about 35 percent of choices correctly among four alternatives. Compared to previously available route choice studies, the

relatively low willingness to pay (WTP) measures (\$8 to \$14/hour) calculated in this study from the PT models may deserve further investigation. Empirical findings from this study would help the policy makers set up appropriate project goals and toll rates to meet the increasing traffic demand of Katy Freeway travelers.

The patronage of toll facility and MLs largely depends on the potential benefits (more reliable travel time and/or travel time savings) offered by such a facility. How the travelers actually perceive the potential benefits may have a significant influence on the use of MLs. This is about the belief that the travelers have on the facility. In lieu of the significant improvement in predicative power of the models embedding probability weighting functions and because of the stochastic nature of travel times, in future survey efforts it might be helpful to collect information regarding Katy Freeway travelers' actual belief on the benefits from using the MLs, and compare their 'belief' with the actual probability of reliable travel time and savings. Such comparison might help verify the accuracy of the probability weighting functions obtained in this study.

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TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

Page

1. INTRODUCTION

Many cities in the United States are examining the potential for managed lanes (MLs) to alleviate escalating traffic congestion and provide revenue for transportation. Most of the previous research on travelers' decision-making among using the MLs versus general purpose lane (GPL) has focused on route-choice decision making from a conventional utility maximization approach known as the random utility model (RUM). The random utility model typically assumes the individual faces no risk, and the most well-known RUM is the simple multinomial logit (MNL) model. Such models essentially assume the individual knows the travel time s/he faces on each route taken.

Another recently used theoretical framework underlying choices or decisions is expected utility theory (EUT) (de Palma and Picard 2005). Both EUT and RUM propose that people generally would act rationally to maximize their utility from the decisions that they have made or will make. The EUT is attractive because it incorporates risk that the individual faces when making his or her choice, and it is the expected utility that is maximized. Despite the wide use of the RUM, and recent innovations relying on EUT, peoples' decision-making can deviate in many aspects from some key assumptions inherent in each theoretical approach. In particular, several key assumptions of EUT have been criticized by behavioral scientists because empirical modeling indicates that individuals make choices that are inconsistent with them. This criticism has led to the development of nonexpected utility theories, such as prospect theory (PT) (Kahneman and Tversky 1979; Ramos, Daamen et al. 2011), or cumulative prospect theory (CPT – see Tversky and Kahneman (1992)). CPT has been extensively applied to several subfields within economics, psychology and decision theory, and more recently to route choice behavior in the field of transportation (Avineri and Prashker 2003; Avineri 2004; Avineri and Prashker 2004; Avineri and Prashker 2005; Avineri 2006; Chin 2008; Connors and Sumalee 2009; Avineri and Chorus 2010; Gao, Frejinger et al. 2010; Hu, Sivakumar et al. 2012). Based on their work, Avineri and Prashker (2003, 2004, 2005) indicated that CPT may be a more appropriate approach in the prediction of route choice decision than conventional utility theory frameworks. To our knowledge, none of the CPT-based studies focus on route choice when managed lanes (MLs) are an option.

PT essentially proposes that choice decisions are made based on the gains and losses measured with respect to a reference point (RP), where any relevant values (positive) above the RP are perceived as gains, while those below the RP (negative) are viewed as losses. As oppose to assumptions of EUT and RUM where the final state of the expected wealth or individual welfare status finally determines the choice-making, PT posits that the relative gains or losses against the reference point are the key factors in choices the decision-maker faces. CPT also allows for the possibility that decision making when gains are at stake may be treated differently than when losses are at stake (Tversky and Kahneman 1992). For example, in our context, travelers might weight the losses associated with being late more than they do the gains with arriving early. That is how travelers would evaluate gains and losses in travel time with respect to a reference point that is pertinent in transportation route choice. For example, Avineri and Prashker (2004) assume the usual or average travel time for a specific route is the reference point for every survey respondent, but it may also be natural to use the actual travel time experienced as the reference point. A recent study by Masiero and Hensher (2011) suggests that it is in fact inappropriate to assume a fixed and deterministic reference point that is the same for all travelers. Their findings instead indicated significant adjustment in the assessment of gains and losses pivoted around a moved reference alternative. Our study used the travel time of the most recent trip that each individual actually took as the reference point (which is potentially different for every single respondent) for each traveler's route choice decision.

Another important aspect of CPT in situations involving transportation risk is that the underlying uncertainty or stochastic nature of a trip's travel time might impact the preferences for the choice of a route. In an EUT model, well-defined probabilities characterize the distribution and choice makers are assumed to understand this.

However, several researchers (Kahneman and Tversky 1979; Quiggin 1982; Tversky and Kahneman 1992) have argued that people may translate ‘objective’ (science or observation-based) probabilities using weights that correspond to a non-linear weighting function, resulting in over- or under-weighting of such probabilities. This weighting can be identified by introducing a probability weighting function (pwf). If the utility functions underlying choices make the assumption that an individual does not weight probabilities, but in fact he/she does, then we might expect that use of the incorrect underlying model will lead to poor predictive power. At best, use of the wrong model may lead to biased coefficient estimates, and at the extreme, prediction of incorrect route choices.

This study is the first attempt to examine the potential application of PT/CPT using stated preference data to predict choice decision-making between MLs and toll-free alternatives. Using a PT proposed value function and pwfs, the results of the analysis provide useful information in relation to travelers’ attitudes towards both ambiguous and risky mode choices, as well as how Katy Freeway travelers value the occurrence/chances of experiencing delay on their choices between the general purpose lanes versus the managed lanes. The frequency of unexpected shorter or longer trip time relative to their most recent trip also measures the travel time reliability and as such behaviorally more realistic values may be obtained from capturing travelers’ attitude towards reliability. From this analysis, this study will estimate the travelers' WTPs for travel time savings and/or travel time reliability on MLs from both EUT and PT approaches. Estimates of maximum WTP were obtained by fitting the SP survey data using discrete choice models, and this study will also compare the estimates with results of previous studies using EUT on Katy Freeway in 2008 (Patil, Burris et al. 2011) and 2010 (Patil, Burris et al. 2011; Devarasetty, Burris et al. 2012). Travelers with similar characteristics are grouped by variables, such as gender, age, household income, etc, because travelers in different group may behave differently in their use of MLs. Parameters of the value functions as well as pwfs will be obtained for each group of travelers. Unlike previous studies that investigate either risk attitudes, data collected from the 2012 Katy Freeway Survey allows us to evaluate travelers' attitude towards ambiguity in this study. Non-linear models formulated in this study are capable of embedding risk/ambiguity attitudes as well as probability weighting, and to this end we are able to conduct an apple to apple comparison of the effect/change of the incorporation of prospect theory proposed value and/or probability weighting function in mode choice prediction over a conventional utility theory model would otherwise predict. To the best knowledge of the authors, none of previous research on applying prospect theory on mode choice prediction could do such a comparison.

This study will also examine the performance of the two different survey design strategies for their ability in parameter estimation as well as the predictive power of the discrete choice models. By including the probability of occurrence of the hypothetical travel time of each alternative (MLs vs. GPLs) in the survey, this study is the first attempt to test the efficiency of two design strategies (D_b-Efficient and Adaptive Random) used to generate the SP questions. The prediction success for the models will be compared to investigate how survey design strategies may have influence on the predictive capabilities of the models, which are critical for traffic and revenue forecasting for managed lanes. The implied VTTS estimated by using data generated from the two design strategies will be compared with previous study (Patil, Burris et al. 2011; Devarasetty, Burris et al. 2012) using conventional utility theory models but similar D_b-Efficient and Adaptive Random design strategies.

2. OBJECTIVES

The primary purpose of this research is to examine if PT performs better than EUT when predicting and understanding travelers' behavior in the use of MLs. The specific objectives of this research are as follows:

1) To design an on-line survey collecting needed data to develop EUT and PT based mixed logit models. The survey was designed using two strategies (D_b-Efficient and Adaptive Random). In this survey, under each design strategy, each respondent will be given three stated preference questions.
2) To estimate the parameters of the PT proposed value function and pwfs in utility estimation, and compare the efficiency of the two design strategies (D_b-efficient and Adaptive Random) in mode choice decisions from a prospect theory approach. This study uses the most widely used probability weighting functions from previous research in behavior science (Tversky and Kahneman 1992; Wu and Gonzalez 1996; Prelec 1998; Gonzalez and Wu 1999).
3) To investigate the psychological phenomena identified by PT in other research areas in travelers' choice decision-making between MLs and a toll-free alternative. These phenomena include: loss aversion, risk aversion and seeking in the domain of gain and loss, probability weighting for loss and for gain.
4) To estimate the WTPs (value of travel time savings (VTTS) and travel time reliability (VOR)) for ML travelers from both EUT and PT proposed approaches. To compare WTP estimates of the respondents for the 2012 survey with WTP estimates from previous stated preference surveys in 2008 and 2010.
5) To test the impact of question framing in the stated preference survey on the estimates of WTPs (VTTS and VOR). The two question framing strategies

include: (1) the traveler's most recent travel time was implicitly assumed as the reference point, (2) the travel time are explicitly indicated as gains or losses in the question.

6) To compare the prediction power for models using the conventional expected utility and proposed PT approaches, and examine the changes due to incorporating probability weighting functions in the calculation of utility by comparing the prediction power and the efficiency of parameter estimation.
7) To conduct a segmentation analysis and investigate any difference of attitude towards risk and the use of probability weighting by different groups based on respondents' trip characteristics and demographics.

Some recent research on travelers' route choice decisions-making have provided evidence of several violations of the assumptions underlying EUT (Avineri 2004; Avineri and Prashker 2004; Avineri 2006; Avineri and Bovy 2008; Chin 2008; Gao, Frejinger et al. 2010; Hu, Sivakumar et al. 2012). These studies suggest potentials for the application of PT to improve on predictive power for travelers' route choices-making. However, there is no previous studies used stated preference data to examine route choice between MLs and general purpose lanes like the case of Katy Freeway Managed Lanes in Houston. Prediction of the MLs patronage needs to consider several factors that may influence the decision making: (1) the relatively more reliable trip in terms of travel time but additional toll cost for using the MLs as a paying SOV or (2) the extra time spent for passengers pick-up to travel for free in the MLs or (3) the slower but toll-free travel in the GPLs. However, an EUT model might be incapable to capture such a decision-making process involving individual characteristics (social and economic) and psychological considerations.

Using the data from an online stated preference survey conducted in September 2012, this research will help examine the impact of psychological factors (risk seeking and aversion, as well as probability weighting) on Katy Freeway travelers' decision-making between the MLs versus GPLs. This study will also empirically estimate parameters of the PT proposed value function and probability weighting function to predict travelers' choices between the MLs and GPLs for groups with different socio-economic characteristics. The empirical results of the PT models could help improve our understanding of travelers' behavior in the use of MLs, and particularly calculating the travelers' WTP. A more accurate traffic prediction and WTP estimate will help improve on transportation planning, cost/benefit analysis, and revenue projections.

3. LITERATURE REVIEW

This section first introduces the development of prospect theory, the rationale behind PT, its successor the cumulative prospect theory (CPT), as well as the difference between PT/CPT and classical expected utility frameworks. Current research in the application of PT in route choice decision in the field of transportation is also presented followed by a brief introduction of the value of travel time savings and reliability. An introduction of the stated preference survey designs ends this section.

3.1 Status of Current Research in Prospect Theory

In the research area of decision theories, a risky prospect differs from an uncertain event in that the probability of a possible outcome is assumed to be known in risky prospect, instead it is not assumed to be known in uncertain prospect (Tversky and Fox 1995). A normative approach was taken in the conventional way of predicting travelers' responses to risk and uncertainty takes with assumption of travelers' rationality in route/mode choices decision-making. Utility has been used as a measure of the total satisfaction perceived/received by a decision maker from the consequence of a made decision. The assumption of rationality incorporated in transportation models can be traced back to statistics and economics, with an assumption that rational people behave as "Homo economicus" who are trying to maximize their utilities and minimize the risk and uncertainties associated with their choices or decision (Avineri and Bovy 2008). In the transport field, the expected utility theory (EUT) and random utility maximization (RUM) are the dominant behavioral decision theories. An utility function in an EUT model, particularly the probability weighting, is usually represented by a linear function.

EUT assumes that the individual's choice is made under with known risk and RUMs assume that the choice is made under certainty. However, the assumptions are often violated given the variability in key attributes, for example the travel time, arrival time of a trip. What is more, the linear utility specification under RUM assumes individual decision-maker (travelers in this study) faces certainty. From a psychological perspective, the attitude towards risk/uncertainty is very critical in decision-making, particularly in situations like travel route/mode choices in which travelers may have experienced varying travel times in their repeated trips along the same corridor.

Decision making under a risky situation can be considered as a choice between prospects. A prospect (x_1, p_1; ...; x_n, p_n) is a contract that might yields outcome x_i with probability p_i of occurrence, where $p_1+p_2+...+p_n = 1$. Three tenets were incorporated in the application of expected utility theory to choices between prospects (Kahneman and Tversky 1979):

(i) Expectation: $U(x_1, p_1; ...; x_n, p_n) = p_1u(x_1) +...+ p_nu(x_n)$. This equation suggests that the total utility of a prospect is the expected utility of all its outcomes.

(ii) Asset Integration: (x_1, p_1; ...; x_n, p_n) is acceptable at asset position w iff $U(w+x_1, p_1; ...; w+x_n, p_n) > u(w)$.This equation suggests that the domain of the utility function is the final state instead of the gains or losses incurred from a made decision.

(iii) Risk Aversion: u is concave ($u'' < 0$). A negative second order derivative suggests that risk aversion can be represented by concavity of the utility function.

In EUT, the utilities of outcomes are weighted by their associated probabilities. Several choice problems in behavioral economics and psychology show that there are certain amount of cases that peoples' preferences systematically violate the axioms of expected utility framework. For example, the violation of the transitivity of the Independence Axiom (X>Y, Y>Z $\rightarrow$ X>Z) can be illustrated in the following choice problems. One of the best known counter-example of certainty effect exploited in EUT is introduced by Allais (1953). Another example illustrated by Kahneman and Tversky (1979) indicating such violations in following problem 1 and 2 is a variation of Allais' example. In the example, N is the number of respondents who answered each problem, and the percentage who choose each option is given in brackets.

Problem 1: You are given the following two options. Which would you prefer?

Option A: Winning	Option B: Winning
\$2,500 with probability 0.33 \$2,400 with probability 0.66 \$0 with probability 0.01 N = 72 [18]	\$2,400 with certainty [82]

Problem 2: You are given the following two options. Which would you prefer?

Option C: Winning	Option D: Winning
\$2,500 with probability 0.33 \$0 with probability 0.67 N = 72 [83]	\$2,400 with probability 0.34 \$0 with probability 0.66 [17]

The results of the above choice experiments show that 82 percent of the subjects chose B in Problem 1, and 83 percent of the subjects chose C in Problem 2 with significance level of each preference is 0.01. Individual patterns of choice analysis suggests that a majority of respondents (about 61 percent) shows a pattern of preference violating expected utility theory as illustrated in the inequality below:

$$100\%\times u(2{,}400) > 33\%\times u(2{,}500) + 66\%\times u(2{,}400)$$

According to Allais (1953), with $u(0) = 0$, the first preference implies $34\%\times u(2{,}400) > 33\%\times u(2{,}500)$ while the second indicates the reverse which is $34\%\times u(2{,}400) < 33\%\times u(2{,}500)$. It should be noted that Problem 2 is converted from Problem 1 by a simple reduction of a 66% chance of winning 2,400 from both prospects. The change of a sure gain into a probable one resulted in a greater reduction in desirability of Option D in the context of Problem 2 than an impact that would occur when in situations that both the original and the reduced prospects are uncertain.

The same phenomenon has been observed in a similar but simpler demonstration according to Allais (1953). The experiment involves only two-outcome gambles as shown below:

Problem 3: You are given the following two options. Which would you prefer?

Option A: Winning	Option B: Winning
$4,000 with probability 80% N = 95 [20]	$3,000 with certainty [80]

Problem 4: You are given the following two options. Which would you prefer?

Option C: Winning	Option D: Winning
$4,000 with probability 20% N = 95 [65]	$3,000 with probability 25% [35]

In the above pair of problems, more than 50 percent of the respondents violated assumptions of expected utility theory. The most observed pattern of preferences in Problems 3 and 4, respectively, is not compatible with the utility theory which assumes that $u(0) = 0$. The choice of *B* implies $u(3{,}000)/u(4{,}000) > 4/5$, and instead the preference of Problem 4 suggests the reverse inequality $u(3{,}000)/u(4{,}000) < 4/5$. The prospect *C* (4,000, 20%), for example, can be expressed as (*A*, 20%), while the prospect *D* (3,000, 25%) can be written as (*B*, 25%). According to the substitution axiom of an expected utility framework, if prospect (B, p_1) is preferred to (A, p_2), then it can be inferred that any form of probability mixture of $(B, p_1/n)$ must be preferred to the mixture of $(A, p_2/n)$. Kahneman and Tversky's (1979) demonstrated that subjects in their experiments did not obey this axiom because a reduction of the probability of winning from 100% to 25% (100/4) has a bigger influence than that of the reduction from 80% to 20% (80/4). These choice problems shown above illustrate several common attitudes toward risk and/or chance that cannot be captured by the expected utility frameworks.

Decision making under risk generally can be viewed as a choice among several prospects/alternatives. Expected utility theories indicate that the utilities of outcomes are weighted by the associated probabilities. Normative models, as shown in some recent studies, provide some but limited explanations of travelers' systematical violation of the assumptions of rational behavior (Avineri and Prashker 2004; Avineri and Bovy 2008). This is consistent with researchers' consensus that a linear value function does not truly represent the actual value that travelers might place in the evaluation of the risk and uncertainty in the domain of gains and losses, respectively, against their reference points. A reference point usually is the status quo (the expected travel time in this study). Because systematic deviations from the predictions of classical EUT have often been observed in behavioral studies (Avineri and Bovy 2008), economists, including McFadden (2000) and Ben Akiva et al. (2002), indicated that "it is important to include the psychological perspective of the decision-making process into an understanding of traveler behavior" (Li and Hensher 2011).

Among the several descriptive theoretical frameworks trying to capture the systematic violations, Kahneman and Tversky's (1979) prospect theory (PT) offers a potential alternative to RUM and EUT. The prospect theory was first formulated in the field of psychology and behavioral economics, PT and its successor, cumulative prospect theory (CPT) (Tversky and Kahneman 1992), have been widely examined in other research areas such as behavioral economics and psychological studies (Tversky and Kahneman 1981; Thaler and Johnson 1990; Tversky and Kahneman 1992; Camerer and Ho 1994; Wu and Gonzalez 1996; Roberts, Boyer et al. 2008; Harrison, Humphrey et al. 2010). In the CPT framework, weighting is applied to the cumulative probability distribution instead of the probabilities associated with individual outcomes. More recently, several travel behavior studies have examined PT in analyzing travelers' behavior with respect to the risk and uncertainty in their route/mode choices (Avineri and Prashker 2003; Avineri and Prashker 2004; Avineri and Prashker 2005; Chin 2008; Schwanen and Ettema 2009; Ben-Elia and Shiftan 2010; Gao, Frejinger et al. 2010; Masiero and Hensher 2010; Nicolau 2011).

To summarize, the primary differences between PT and EUT are in four key aspects:

- Reference dependence: the PT proposed value functions are different for the domains of gains and losses against the reference point that is often the current wealth position/status, and the EUT models instead specify a utility function over the final wealth/state. Put in another words, PT posits that people tend to pay more attention to the change of wealth position, such as if it is a gain or loss. Instead, EUT assumes that people will generally try to maximize their utility regardless of the change in their wealth position.
- Diminishing sensitivity: PT assumes decreasing marginal values of both gains and losses. Decreasing marginal utility suggests a concave utility function over monetary gains and a convex utility function over monetary losses. In another words, people are generally more sensitive to changes near their status quo than to changes remote from their status quo. The implication of diminishing marginal utility is consistent with natural intuition: the first spendable dollar is used on the most useful thing, the second on the second-most, etc. In terms of utility, each additional dollar brings less value added into the utility than the one before would.
- Loss aversion: in PT, people place higher value on the disutility of a loss than the added utility introduced from an equivalent gain, indicating that the losses loom larger than gains (Kahneman and Tversky 1979). Put it another way, people tend to have a preference towards avoiding losses over acquiring an equivalent amount of gains.
- Paradox weighting function: a nonlinear probability weighting function is used to accommodate Allais' paradox (Allais 1953) in PT models, while it is the probability of occurrence being directly used as weights in EUT models. The Allais paradox is a typical choice problem illustrating an discrepancy of actually observed choices with the predictions of expected utility theory based models.

In PT, the choice behavior can be viewed as in two steps: an initial editing phase and a subsequent evaluation phase. It is in the editing phase that the route choice alternatives are organized and reformulated by the application of heuristics, and the prospect is then subjectively evaluated in the evaluation phase. The evaluation phase consists of two elements: a value function, $v(x)$, and a probability weighting function, $\omega(p)$, where x is the change of status (gain or loss) relative to the status quo while p is the stated probability. It is the value function, $v(x)$ that reflects the subjective value of the outcome and measures the deviations from the reference point into gains and losses. A decision weight (ω) is obtained from each probability of occurrence (p) using a given probability weighting function. The value of ω is a measurement of how travelers actually perceive the impact of the probability (p) on the overall value of prospect V. Different weighting functions are associated with positive (gain) and negative (loss) outcomes, V^+ and V^-, respectively. The overall utility of a prospect can be obtained by $V = V^+ + V^-$ (Equation 1):

$$V^+ = \sum_{i=0}^{n} \omega^+(p_i) \times v^+(x_i)$$
$$V^- = \sum_{i=-m}^{0} \omega^-(p_i) \times v^-(x_i)$$

Equation 1

where $\omega^+(p_i)$ and $\omega^-(p_i)$ is the weighting of the occurrence probability of the i^{th} outcome for gain and loss, respectively. In PT, outcomes are the gains and losses against a reference point, which is often considered as the status quo. The value functions of gain and loss, respectively, are given by Equation 2:

$$\begin{cases} v^+(x) = x^\alpha, & if\ x \geq 0 \\ v^-(x) = -\lambda(-x)^\beta, & if\ x \leq 0 \end{cases}$$

Equation 2

where $v^+(x)$ and $v^-(x)$ are the outcome utilities of gain and loss, respectively; x is the change of status (such as travel time saving) measured against the RP; α and β measure the degrees of diminishing sensitivity which specifies the marginal value of gains and losses; λ specifies the degree of loss aversion, which sybolizes the aggregation of negative experiences with incurred losses.

The travel time of travelers' most recent trip is used as the reference point in this study. Data needed for discrete choice modeling can be obtained from setting up hypothetical scenarios with probabilistic occurrence of losses and/or gains. Parameter estimates of the value function will be obtained for travelers with similar characteristics in groups, such as gender, age, household income, and trip purpose. Because these factors/variables may significantly affect travelers' decision in the use of ML so it would be interesting to see, for example, if high-income travelers may tend to use the ML more frequent than low incomers would. A plot of one possible value function looks like the one as shown in Figure 1. For travelers with different trip purposes, the value functions may also be different. This study will also investigate how trip purpose might affect the estimation of value functions for travelers with similar trip purposes in a discrete choice model.

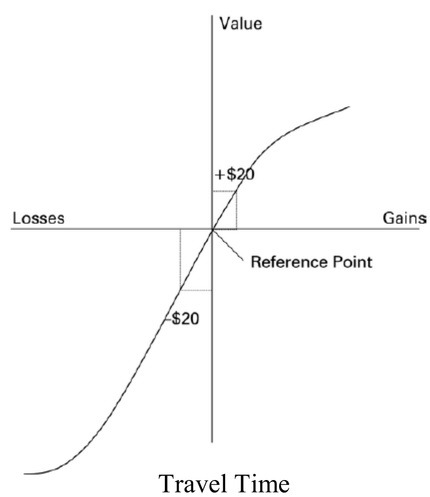


Figure 1 Hypothetical Value Function

The widely used probability weighting functions of gain and loss are given by Equation 3:

$$\omega^{+}(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{\frac{1}{\gamma}}}$$
$$\omega^{-}(p) = \frac{p^{\delta}}{(p^{\delta} + (1-p)^{\delta})^{\frac{1}{\delta}}} \qquad \textbf{Equation 3}$$

where $\omega^{+}(p)$ and $\omega^{-}(p)$ is the weighting functions of gain and loss, respectively; γ and δ define the curvature of the weighting function. In prospect theory, the changes in probabilities near 0 or 1 are assumed to have a bigger impact on peoples' preferences than the impact of comparable changes in a range with middle probabilities. This disproportional impact resulted from changes in probability results in probability weighting functions different from those functions proposed by conventional utility theories. The probability weighting functions could be in a variety of forms as shown in Figure 2. A typical probability weighting function can take a shape of either S-shaped or inverted S-shaped near the end points.

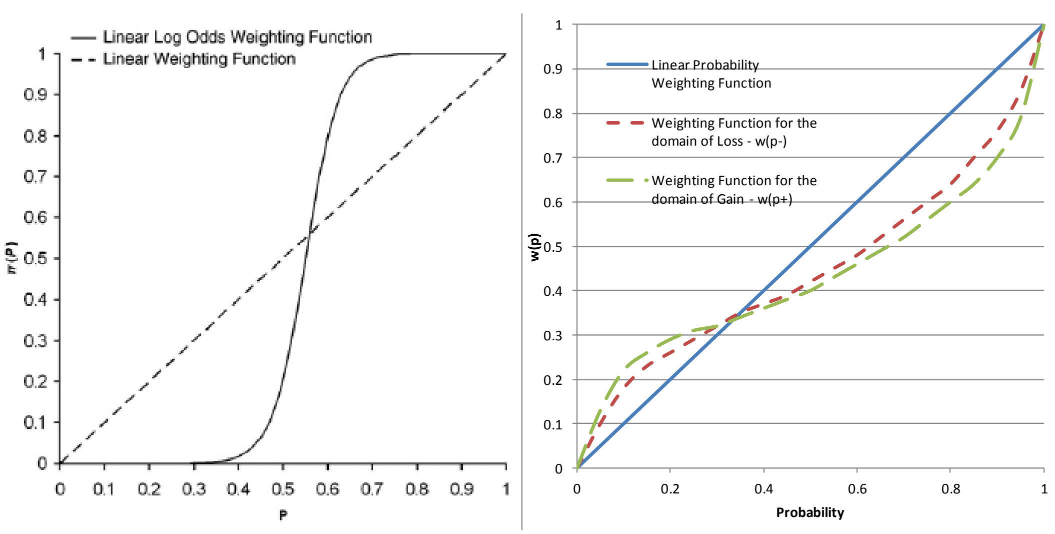


Figure 2 Probable Probability Weighting Functions

Data needed for estimating the parameters of a probability weighting function incorporated in a utility function includes travelers' attitude towards extreme events. Highly unlikely events are either ignored or overweighed in that people are limited in their ability to comprehend and evaluate extreme probabilities. That is the difference between high probability and certainty is either neglected or exaggerated. This may also be applicable for the travelling commuters between Katy and Downtown Houston. An example below may help illustrate the importance of inclusion of probability weighting in utility estimation. When choosing between the GPLs and MLs for a given trip, commuters in the first place may need to consider how reliable a route is and what is the chance that she/he could arrive at work on time or being late. In this case, the MLs might offer a more reliable travel time and generally faster travel (this is because the MLs were designed and operated in way to offer more reliable and faster trip) than the GPLs would. Devarasetty et al. (2012) indicated that the weighted average travel time savings perceived by the Katy Freeway travelers from using the MLs is about 12.6 minutes. This is much higher than the average travel time savings actually observed by the AVI and Wavetronix sensors. Therefore, for travelers choosing GPLs it is high likely that they may underestimate high probability and overweight low probability of gain, while in the contrary in the domain of loss (overestimate high probability and underestimate low probability of loss); (2) for travelers chosen MLs it is more likely that they may overestimate probability in the domain of gains and underestimate probability in the domain of losses.

3.2 Previous Studies Applying Prospect Theory in Route Choice Models

The violations of EUT in stated route-choice preferences have been studied by Avineri and Prashker (2004) with a focus on the certainty effect and inflation of small probabilities. Their study results, based on travelers' single-choice stated preferences, indicated that PT may help explain the two violations: (1) certainty effect (known as the Allais paradox), which describes the extreme underweighting of high probabilities, makes a certain travel-time prospect very attractive and (2) inflation of small probabilities. Their study results illustrate common attitudes toward risk that cannot be captured by the expected utility model.

Avineri and Prashker (2003; 2005) adopted PT in analyzing travelers' route choices between two alternative routes with different travel-time distributions. Their results from route-choice laboratory experiments and computer simulations indicated that increasing travel-time variability for a less attractive route could affect the choice of a specific route, and the generated results are different from those predicted by both EUT and CPT models. The authors suggested that the deviation of prediction by the CPT models might be because PT was not designed to address repeated decision tasks, such as route choices, and another limitation is that their predictions were based on the PT parameters estimated by Tversky and Kahneman (1992).

Chin (2008) attempted to explain the inelastic behavior of automobile drivers in response to road pricing from a PT approach. Experimental results from the study suggested that people are risk averse with regard to losses of time in the event of uncertainty. Moreover, PT can also explain the phenomenon that drivers were reluctant to switch route (from toll road to toll-free road) or change departure time because people are inclined to remain in the status quo when confronted with uncertain losses.

Using empirically estimated coefficients of CPT's value and weighting functions, Schwanen and Ettema (2009) investigated the usefulness of CPT in the context of employed parents' coping with unreliable transport networks when collecting their child(ren) from the nursery at the end of the workday. Using stated preference data, they estimated the coefficients characterizing CPT's value and weighting function, suggesting that the EUT-based axioms are violated systematically when coping with travel time variability. These violations include reference dependence, loss aversion, framing effects, risk seeking, distorted perception of probabilities (particularly in the area of two ending points), and nonlinear preferences.

Using estimates from the model based on the CPT framework of Tversky and Kahneman (1992), Gao et al. (2010) predicted path choice in a risky network based on RUT and PT. The two behavioral paradigms generated significantly different path-sharing predictions and the authors suggested that CPT is a better framework relative to EUT.

Ben-Elia and Shiftan (2010) studied travelers' route-choice behavior using a learning-based model when information was provided in real time. Their results indicated that information and experience have a combined effect on travelers' route choices. Their results implied that incorporating insights from PT helped improve the travel behavior modeling, and provided some support to the generalization of PT regarding risk-seeking in the domain of losses.

In light of consumers' asymmetric preferences over gain and loss, Masiero and Hensher (2010) investigated PT assumptions (loss aversion and diminishing sensitivity) with a reference pivoted choice experiment in a freight transport framework. Their results suggest a significant improvement in the goodness of fit of the model when preferences were modeled asymmetric using PT-based principles.

Using revealed preference data collected in 1998 on the SR91 corridor in Orange County, California, Hu et al. (2012) investigated the feasibility and validity of non-EUT approaches (including PT) in a revealed preference context. They found that each non-EUT model used in their study has important behavioral insights to offer, and both EUT and non-EUT models can be applied to the revealed preference context. Their results indicate that PT model provide a marginally improved model fit over EUT models. The PT model they used was to predict the route choice between a toll road and a toll-free alternative. The utility function for each alternative they used are similar to the one used in our study, however, they only applied the model on revealed preference data and they used a reference point (travel time) which is the same for each individual. Our study will test the PT model on both stated preference and revealed preference data that has never been conducted before, and the reference travel time in our study may be different for each individual survey respondent. Assuming an one-for-all reference travel time for every traveler apparently does not fit the real situation that each traveler is facing every day.

Another significant contribution of our study will be an establishment of specific value function and weighting function for each group of Katy Freeway travelers with similar characteristics. None of previous studies on PT empirically estimated the coefficients of value function and probability weighting function for travelers with similar characteristics. By having PT-based value and weighting function, this study may help improve the overall prediction accuracy of the use of MLs for the facility operating agency.

3.3 Value of Travel Time Savings

The value of travel time savings (VTTS) is one of the primary components of transportation infrastructure investment evaluation. Early studies on VTTS date back to 1960s (Becker 1965; Beesley 1965). Mackie et al. (2001) indicated that any reduced travel time could be used in a more enjoyable and useful activity, resulting in changes in the travel utility. VTTS is also often referred to as the value of time (VOT) and represents the travelers' willingness to pay as the trade-off to reduce their travel time (Mackie et al. 2001). The VTTS is the marginal rate of substitution (MRS) between time and monetary cost yielding the ration of coefficients used in linear models. Revealed preference and stated preference are the two primary approaches being used in determining the value of travel time. Revealed preference data is obtained from travelers' actual commuting choices, while respondents in SP surveys are usually asked to choose a travel option from a set of travel scenarios for a typical trip.

The value each traveler placed on travel time savings is affected by many factors including the time of day of the trip, trip purpose, trip characteristics (free-flow or congested), trip length, travel mode, and size of the travel time savings (Mackie, Jara-Diaz et al. 2001). For example, Wardman (1998) found that the VTTS was generally greater for commuting than leisure travel. Patil et al. (2011) estimated the VTTS for different situations including one normal situation and six urgent situations. Their findings indicated that travelers' VTTS in an urgent or important travel situation is higher than in a normal situation. They also found that, among different urgent situations tested, travelers placed highest value for travel time savings when running late for an appointment. Travelers' personal characteristics, including age, gender, employment status and income also affect their value of travel time savings. For instance, Patterson et al. (2005) suggested that commuting women were often less time sensitive than men were. Small et al. (1999) estimated that the value of travel time is about 20 to 50 percent of the wage rate for work trips.

Hensher (2001) suggested that revealed preference data is usually inappropriate for estimating VTTS if as the only source of attribute-trading because some attribute levels may be absent in the revealed preference data so that the predictor variables may exhibit high levels of multicollinearity. Travelers' VTTS is typically estimated from the discrete choice models using SP survey data. VTTS is derived as the marginal rate of substitution (MRS) between travel time and cost in the choice models (Button, Vega et al. 2010). Cherlow (1981) reviewed studies on the evaluation of VTTS and indicated that the estimated VTTS could be as low as 9 percent to as high as 140 percent of the wage rate. Lam and Small (2001) estimated the average VTTS to be $22.87 per hour, or equivalently 72 percent of the average wage rate. More recently, attention has been given in recent literature to estimate the VTTS on the MLs. Using SP survey data, GDOT (2010) estimated the VTTS of passenger car users ranges from $7 to $15 per hour, and VTTS varied with the type of vehicles. Their VTTS estimate for 6-axle truckers is higher than that of passenger cars. FDOT estimated the VTTS for I-25 travelers in Miami, and their estimates range from $2.27 to $79.32 per hour with a mean value of $32 per hour (Perk, DeSalvo et al. 2011).

3.4 Value of Travel Time Reliability

Value of reliability (VOR) is the travelers' willingness to pay for a reduction in the day-to-day variability of travel time by one unit, and VOR is a measurement of the value that travelers placed on the reliability of estimated travel time (Brownstone and Small 2005). VOR can be obtained from the MRS between travel time variability and cost in the discrete travel choice models. Travel time variability was defined differently in different studies. For example, it could be the difference between the 90th percentile and 50th percentile travel time (Lam and Small 2001). It could also be the difference between the 75th and the 25th percentile of travel time (Small, Winston et al. 2005) as well as the standard deviation of the travel time. This study defines variability as a percentage of the average travel time.

VOR has been empirically estimated by several studies. Either revealed preference or stated preference survey data or a combination of the two could be used to estimate the VOR. Previous studies indicated that the estimated the VOR could be 3.22 times the VOT (Small, Noland et al. 1999), while Tilahun and Levinson (2010) found that travelers value VOR very close to their VOT based on data from a stated preference survey. Using revealed preference data of travelers in Los Angeles, another study by Small et al. (2005) indicated that the estimated the median VOR to be 85 percent of the average wage rate ($19.56/hr). Recent study suggest that travelers' VOR varies under different travel situations. For example, Concas and Kolpakow (2009) indicated that the VOR, under ordinary travel circumstances with no major travel constraints, was estimated to be 80 to 100 percent of the VOT, and up to three times that of VOT under the constraint of non-flexible arrival/departure.

Individual's socio-economic characteristics, such as gender, age, income, etc may also influence the travelers' VOR. Small et al. (2005) indicated that women, middle-aged motorists, as well as motorists in smaller households have higher VOR value than other travelers because travelers in the three categories are inclined to use toll lanes more often. A study by Lam and Small (2001) indicated that the Women's VOR was almost twice that for men. Using stated preference data, Devarasetty et al. (2012) indicated the combined estimate of VTTS and VOR was $50/hour and their estimate is very close to the estimate from the actual Katy Freeway usage (as measured using actual tolls paid and travel time saved on the managed lanes).

3.5 Managed Lanes

Huge loss of travel time and environmental problems has been caused by traffic congestion in metropolitan cities such as Houston, Texas. A recent Texas Transportation Institute (TTI) study found that traffic congestion caused Americans to spend an extra 4.8 billion hours traveling in 2010 as well as consumption of an extra 1.9 billion gallons of fuel (Schrank, Lomax et al. 2011). Not including the additional cost in pollution from emissions, such extra time spent and fuel consumed is estimated to be worth approximately $101 billion.

To reduce problems caused by congestion, the concept of MLs was introduced aiming to use the limited highway capacity in a more efficient way by effectively and efficiently allocating traffic to different lanes other than the GPLs. According to definition by the Federal Highway Administration (FHWA), managed lanes are "a limited number of lanes set aside within an expressway cross section where multiple operational strategies are utilized, and actively adjusted as needed, for the purpose of achieving pre-defined performance objectives" (FHWA 2004). Based on such definition, HOV lanes, HOT lanes, and exclusive special use lanes (e.g., express lanes, bus only lanes) all belong to the category of ML facility.

The operational strategies across various types of MLs are shown in Figure 3.

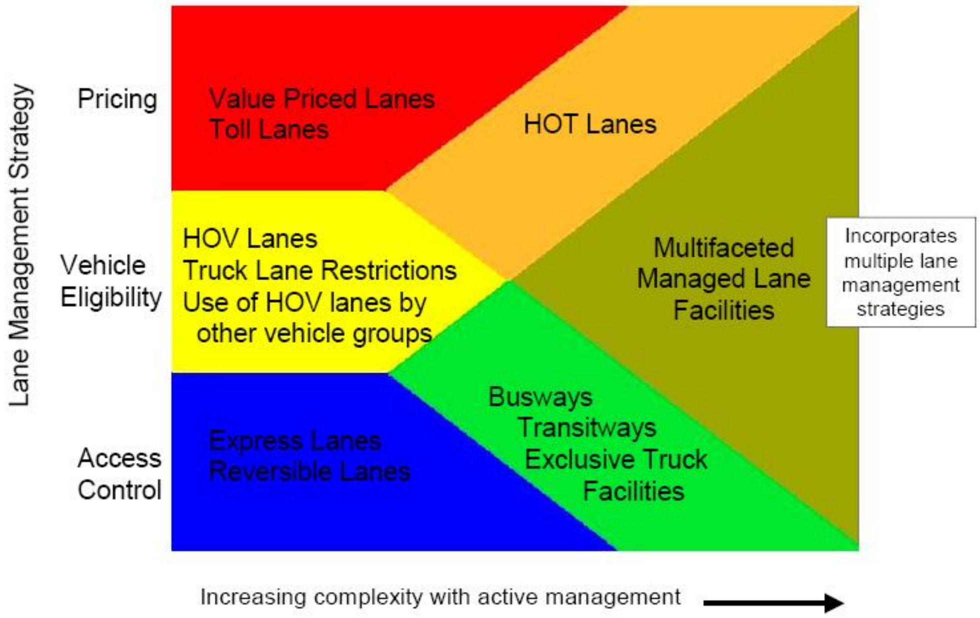


Figure 3 Operational Strategies and Types of Facilities in a Managed Lane
Source: FHWA (2004)

MLs are designed and operated by regulations to provide a more reliable and/or a faster travel alternative for travelers. As opposed to the frequently congested general purpose lanes during the peak hours, by law the ML facilities generally are operated to maintain free-flowing (or close to) speeds. As shown in Figure 4, the average speeds in the GPL of Katy Freeway are widely spread from around 20 to 75 mph, while average speeds in the MLs generally stayed between 60 and 70 mph. The eastbound Katy Freeway MLs' speed variations were smaller than GPLs during peak hours (7:00 AM to 9:00 AM) for 2009 (weekdays excluding holidays). Part of the reason that MLs are more reliable than the GPLs is because nearly 70 percent of the ML travelers are able to drive between 60 and 70 mph, while only 40 percent of GPL travelers are able to travel at those speeds. In addition to promoting ride-sharing or carpooling through varying the tolls by vehicle occupancy (lower tolls for HOVs), MLs also encourage transit use. This is because most facilities would allow transit vehicles to use the lane for free such that a transit may offer a quicker ride than driving in GPLs. Furthermore, an efficiently operated ML may even carry more traffic than a general purpose lane (Burris, Patil et al. 2009). In summary, properly operated MLs may provide travel time savings to travelers and may reduce fuel consumption and pollution.

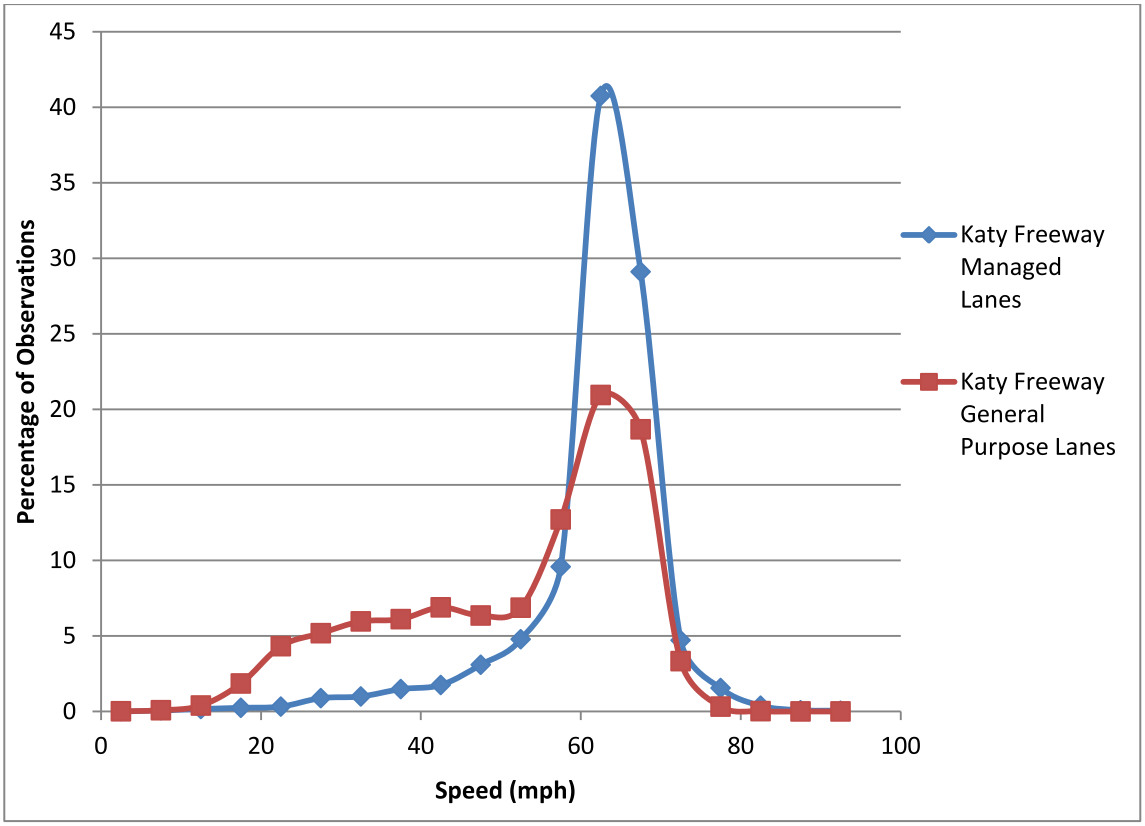


Figure 4 Speed Variation on Katy Freeway (Eastbound) during Peak Hours
Source: Devarasetty et al. (2012)

3.6 Stated Preference Survey Designs

Stated preference (SP) surveys have been widely used in the areas of marketing and travel demand modeling to estimate value of time and/or reliability or forecast travelers' behavior. SP survey is considered as an efficient method to study consumers' evaluation of multi-attributed products and services (in this study the different potential travel alternatives, for instance MLs versus GPLs). This is particularly true when the alternatives are hypothetical and/or some attributes may not currently exist. In a typical SP choice experiment, the survey respondents are asked to choose between two or more alternatives (hypothetical or not), with each alternative in the choice set defined by a set of attributes. Such difference in attribute levels will be used by the respondent uses to weigh or tradeoff between the alternatives. For example, in the case of the route choice experiment in this study, the traveler has two routes to choose from, the GPLs and the Tollway lanes in the Katy Freeway. Suppose the alternative of GPLs has a travel time of 20 minutes and is toll-free, and the alternative of Tollway lanes has a travel time of 15 minutes but with a toll of $2.00. Values of these attributes (potential travel times and toll) allow the respondent to tradeoff between the alternatives, and the information could then be obtained by researchers through varying these attributes within and between the alternatives. Additionally, how attribute levels are determined across different alternatives in a SP experiment in the design process might directly influence on the statistical significance of the choice model estimation (Hensher 2004; Rose, Bliemer et al. 2008). The experimental design may also impact the estimation of each attribute's contribution to the observed choices, and the researcher can control certain factors within the study through assignment of attribute levels. An essential part in SP survey design is the choice of appropriate attribute levels to create tradeoffs. Data collected from the stated preference experiments may be used to model individual preferences and the parameters estimation corresponding to each of the attributes can be used to model the choice.

In this research we propose two survey design strategies: (1) D_b-Efficient, and (2) Adaptive Random. The following sections discuss the survey design basics, a brief introduction to orthogonal design, followed by efficient design and the adaptive random design.

3.6.1 Full factorial designs

A choice design can be viewed as a matrix with columns and rows representing the choice situations and attributes. For each alternatives in the choice experiments, values in the matrix represent the attribute levels of each alternative (Rose, Bliemer et al. 2008). A design is considered full factorial when all possible combinations of attribute levels are listed . For example, a simple study with four attributes with two attributes taking five levels and two at three levels, the possible number of choice situations for this design will be $4\times5\times5\times3\times3 = 900$ combinations in the full factorial design. This type of design is resource extensive and most of the times impractical to present to the respondents, therefore it is neither practical nor economical if the number of alternatives, attributes, and levels of the attributes are more than 2 or 3. Such as the relatively simple study mentioned above the combination would be overwhelming to any single respondent. Therefore, fractional factorial designs were developed as possible ways around this problem.

3.6.2 Fractional factorial designs

A fractional factorial design, as the name implies, is any design that has fewer rows than the full-factorial design. The fractional design can be achieved by either randomly selecting fixed number (say x) of choice situations from the full factorial, or assigning the first x choice situations to the first respondent, the second x choice situations to the second respondent. In this way assignment each respondent is only shown a subset of choice situations from the total number of choice situations included in the full factorial design. Having fewer rows (choice situations) in a fractional design may result in confounding effects among some attributes and indistinguishable from each other. Biased outcomes can be generated in some situations that, for example, a respondent may be given only low or high values of a certain attribute. Such biased results could be avoided in an attributed level-balanced design where the subsets are chosen in a more structured way. A design with all the levels occur equally within each factor is considered as level balanced, and two design strategies can be used to achieve level balance: orthogonal designs and efficient designs. This study will focus on the later as it was used in the survey design in this study.

3.6.3 Orthogonal designs

Orthogonality involves the idea of non-overlapping and uncorrelated structure between the attributes of the design. A design is viewed as orthogonal if it satisfies attribute level balance and all parameters are estimable independently (ChoiceMetrics 2012). Orthogonality can be achieved by choosing the levels of the attributes statistically independent of each other. The possibility of inducing correlations in attributes due to design error can be reduced if Orthogonality is achieved. If a design is orthogonal then it is possible to estimate the independent influence of each attribute on the choice outcomes (Rose, Bliemer et al. 2008). The sum of inner product of any two columns is zero in an orthogonal design, and such a design is mainly used for linear models. In another words, orthogonal designs can help remove the multicollinearity and minimize the variance of parameter estimates in linear models (Rose, Bliemer et al. 2008). In the presence of multicollinearity the variances of the parameter estimates are not minimized. For example, the variance-covariance (VC) matrix for a linear regression model is given as $VC = \sigma^2[XX]^{-1}$, in which the VC matrix is directly proportional to $[XX]^{-1}$ with a given σ^2. If a design is orthogonal, the elements of the VC matrix is minimized, which is desirable because the resulting variances are smallest and consequently the t-ratios generated are maximized from the model.

These designs are widely used in many previous studies partly because such designs are easy to construct and independent estimation of influence of attributes on choice is possible. However, in some situations orthogonal designs are not applicable when all the factor level combinations are not feasible or they do not make sense in real world situation. Moreover, in discrete choice modeling, the orthogonality of the design may not be preserved when blocking (a subset of choice situations) is used. As indicated by Rose and Bliemer (2008), it is difficult to maintain the orthogonality of the design if some blocks in the data are over or under-represented, which may be caused by low response. Additionally, model parameters estimated using the data from SP surveys may deviate from what was originally intended from the survey design. Rose et al. (2008) indicated that in the data actually used to estimate the discrete choice models the orthogonality may not be preserved in most cases, even when the survey design was essentially orthogonal. The loss of orthogonality can be attributed to several factors: (1) in a situation that each respondent will be given just a fraction of a full factorial orthogonal design, orthogonality can then be lost in the fractional dataset, and this is particularly true in a survey with unevenly distributed subsets of design matrix; (2) inclusion of non-design attributes (such as socio-economic characteristics: age, gender, income, etc.) that are invariant over the alternatives and choice situations for a respondent will introduce correlations among these socio-economic variables and other design attributes; (3) the trade-offs between the alternatives are eliminated by the existence of dominant alternative in some choice situations because dominant alternative does not help gain much information; (4) some choice situations are not economically sounded in real world situation so that no information will be obtained from responses on those choice situations (Bates 1988).

Although orthogonal design is still a preferred strategyin some linear modeling, however, discrete choice models are not linear, particularly the PT-based utility functions and probability weighting functions that will be used in this study. Thus, designs that are more appropriate for logit and other discrete choice models are discussed in the next section.

3.6.4 Efficient designs

A design is considered as efficient if the parameters have been estimated with the smallest standard errors resulting in the largest possible *t* statistics that indicate a significant influence (other than a zero) on the choices. To generate an efficient design, the attribute levels across various choice sets are chosen according to an appropriate efficiency criterion, and such design results in a minimized asymptotic standard errors of the parameter estimates of the discrete choice models (Bliemer, Rose et al. 2006). An efficient design can "either improves the reliability of the parameters estimated from the stated choice experiment data at a fixed sample size or reduces the sample size requirements for a chosen level of reliability of parameter estimates for a given experimental design" (Huber and Zwerina 1996). In this section, the two most commonly used efficiency criteria (A-efficiency and D-efficiency statistics) are introduced. Both efficiency criterion are specified to minimize the error statistic calculated from the asymptotic variance covariance (AVC) matrix. A-efficiency criterion tries to minimize the A-error of the asymptotic variance covariance (AVC) matrix (the trace of the AVC matrix, see Equation 4), and D-efficiency criterion tries to minimize the D-error of the AVC matrix (the determinant of the AVC matrix, see Equation 5). The D-error statistic equals the determinant of the AVC matrix. It is found that the D-efficiency criterion is more commonly used in the literature because relative D-error is invariant to different types of coding of the design matrix and is computationally efficient to update. The relative A-efficiency of any two design matrices, instead, depends on the type of coding scheme used for the attribute levels in the design (Huber and Zwerina 1996; Kuhfeld 2005; Rose and Bliemer 2008). It should be noted that these statistics are calculated using the AVC matrix from one complete design assuming a single respondent (Rose, Bliemer et al. 2008).

$$A - error = \frac{Trace(AVC)}{K} \qquad \textbf{Equation 4}$$

$$D - error = \det{(AVC)^{1/K}} \qquad \textbf{Equation 5}$$

where, K = number of parameters.

For the reason it is relatively easy and convenient, efficient linear design was widely used, and such design can then be converted to choice designs which might be appropriate for estimating discrete choice models (Louviere and Woodworth 1983;

Batsell and Louviere 1991; Lazari and Anderson 1994; Huber and Zwerina 1996; Johnson, Kanninen et al. 2007). An efficient design for a discrete choice model involves estimating the variance-covariance matrix for a particular choice model. Unlike the continuous linear model, the asymptotic variance-covariance matrix of a discrete choice model is equal to the inverse of the Fisher information matrix (Equation 6). Therefore, a linear design may not be an appropriately efficient approach to generate a discrete choice design.

$$AVC = -\frac{1}{N}\left[\frac{\partial^2 LL(\boldsymbol{\beta})}{\partial\boldsymbol{\beta}\partial\boldsymbol{\beta}'}\right]^{-1}$$ **Equation 6**

where, *N* is the number of respondents; *LL* is the log-likelihood function for the discrete choice model; and β is a vector of parameters used in the model.

To estimate the AVC matrix for the choice model, understanding of the design and the estimated parameter values ***(β)*** is needed. The Fisher information for the logit model can be calculated using Equation 7.

$$E[I(\beta|X)] = \frac{\partial^2 L(\beta|X)}{\partial\beta\partial\beta'} = \sum_{s=1}^{S} X_s'(P_s - p_s p_s')X_s$$ **Equation 7**

where, $X_s = [x_{1s,}....x_{Js}]', \; p_s = [p_{1s,}..., p_{Js}]', and \; P_s = diag(p_{1s,}..., p_{Js}).$ x_{js} is a k-vector of the attributes of alternative *j* in choice set *s,* and p_{js} is the probability of choosing alternative *j*, in choice set *s*.

Because it is not possible to know the parameter values before implementation of the survey and estimation of the choice model, assumptions have to be made for these values, for example, an educated guess. These guesses are consistent with Bayesian statistical analysis. Based on the way these priors of the parameters are assumed, the D-error statistic also need minor modifications. For example, travel time might be a negative influence on choice, ceteris paribus, and thus a negative value, as a prior, to the travel time coefficient might be appropriate. If the priors are assumed to be all zeros thenresulting designs are called D_z-efficient designs (Equation 8), while the D_p-efficient designs are designs with non-zero priors assumed (Equation 9). Because the assumption of the priors has a direct influence on the efficiency of the design so it is very important to choose the right priors to generate an efficient design. But it is difficult particularly for a study that has no previous similar research to refer to.

$$D_z - error = \det\left(AVC(0|X)\right)^{1/K} \quad \textbf{Equation 8}$$

$$D_p - error = \det\left(AVC(\beta|X)\right)^{1/K} \quad \textbf{Equation 9}$$

To overcome such difficulties, for situations when the priors were not known with certainty the Bayesian techniques were developed and are gaining popularity among some stated choice modelers (Sandor and Wedel 2002; Ferrini and Scarpa 2007; Scarpa and Rose 2008). Those designs using Bayesian techniques are called D_b-efficient designs, and they are discussed in the next section.

3.6.5 Bayesian efficient designs

The D-error (Equation 5) can be calculated giving information on the design as well as the parameter estimates are available. But most of the time the parameter estimates are unknowns and need to be estimated from the stated preference experiment data. In some cases but very rare, it is possible to obtain priors from the literature or previous similar studies. However, the experimental design using those priors is only efficient for the specified priors assumed in that some uncertainty still exists in the values. Bliemer, Rose et al. (2006) indicated that an design with lowered efficiency may be obtained with incorrectly specified priors. To avoid obtaining a lowered efficiency of the design from using incorrectly specified priors, Sándor and Wedel (McFadden 1973) proposed the Bayesian techniques. Instead of assuming a deterministic value for the priors, the priors are taken from a random distribution. The levels of attributes assigned across different alternatives in the SP questions are determined by the D_b-Efficiency criterion that will minimize the Bayesian D_b-error. The designs obtained are thus known as Bayesian efficient designs.

The Bayesian D_b-error can be calculated as Equation 10.

$$D_b - error = \int_{\tilde{\beta}} \det AVC(\tilde{\beta}|X)^{1/K} \, \phi(\tilde{\beta}|\theta) d\tilde{\beta}$$ **Equation 10**

where, $\phi(\tilde{\beta}|\theta)$ is the joint distribution of the assumed parameter priors, θ are the corresponding parameters of the distribution, and K is the number of parameters in the model.

The integral of the D_b-error (Equation 10) cannot be analytically calculated, but an approximation can be obtained in several methods. Pseudo-Random Monte Carlo simulation is one of the most common approximation methods. In this method, R independent draws are taken from each of the prior distributions of the K-parameters. D_b-error can then be computed for each of the designs for each of the R draws. The average of all the computed D_b-errors is then used as the final D_b-error of the design (Equation 11).

$$\widehat{D}_b - error = \sum_{r=1}^{R} \det AVC(\tilde{\beta}^r|X)^{1/K} \, /R$$ **Equation 11**

where, $\tilde{\beta}^r = [\tilde{\beta}_1^{\,1}, ..., \tilde{\beta}_k^{\,r}]$, and r denotes the draw (1,2,…,R).

The R pseudo random numbers are obtained by first generating R random numbers (u_k^r) from an uniform distribution in the interval [0, 1], and the draws are computed using Equation 12.

$$\tilde{\beta}_k^r = \Phi_k^{-1}(u_k^r)$$ **Equation 12**

where, $\Phi_k(\tilde{\beta}_k \mid \theta_k)$ denotes the cumulate distribution function of $\tilde{\beta}_k$.

3.6.6 Adaptive random design

The adaptive random design is a design where the current attribute values in a stated preference question were generated conditional on the respondents' response to a previous SP question. As an example in this study, if a respondent chooses to pay for driving alone in the managed lanes in previous question then the toll is increased in the current question to see if he/she still chooses the toll option. In this way, it is possible to better attempt to derive the traveler's willingness to pay for using the lane.

3.7 Discrete Choice Modeling

Because responses from the stated preference survey conducted in 2012 will be modeled using several discrete choice models, in this section various modeling techniques for discrete choice in this study are described.

3.7.1 Multinomial logit model

The multinomial logit (MNL) model was initially developed to model choice behavior (Sandor and Wedel 2002), and these models can be used to model travelers' choice behavior. According to standard random utility theory, the utility generated from choosing an alternative *j* (*j* = 1,2,…J) in a given choice set s (*s* = 1,2,…S) by an individual *i* (*i* = 1,2,…n) can be written as Equation 13. In a choice, each individual chooses an alternative maximizing his/her utility (*U*), which is in linear form (Equation 13).

$$U_{i,j,s} = \boldsymbol{\beta}'\mathbf{X}_{ijs} + \boldsymbol{\gamma}_{\boldsymbol{j}}'\boldsymbol{Z}_{\boldsymbol{is}} + \epsilon_{i,j,s} \qquad \textbf{Equation 13}$$

where, $\mathbf{X}_{ijs}$ denotes the vector of attributes of alternative *j* as perceived by individual *i*; $\mathbf{Z}_{is}$ is the vector of characteristics of individual *i*; $\boldsymbol{\beta}$ is the vector of coefficients weighing the alternative specific attributes; $\boldsymbol{\gamma}_{\mathbf{j}}$ is the vector of alternative specific coefficients weighing individual characteristics; and $_{\text{i,j,s}}$ denotes the error components which may be due to unaccounted measurement error, correlation in the parameters, unobserved individual preferences, and other similar unobserved characteristics of the choice-making.

$\beta' \quad _{ijs}$ and $\gamma_j^{'} Z_{is}$ in Equation 13 are the systematic part of the utility function. The error components ($\epsilon_{i,j,s}$) is the stochastic part or random part. Random utility model assumes that the value of the error term is known to the individual while the researcher does not. This suggests that the choice maker is not facing risk or uncertainty when making a decision in such situation. An example below illustrates the systematic part of a utility function (Equation 14):

$$\begin{aligned} V_{ij} = \beta_0 + \beta_1 * TravelTime_{ij} + \beta_2 * Reliability_{ij} \\ +\beta \quad * TravelCost_{ij} + \gamma_{\mathrm{j}} * Income_i \end{aligned} \qquad \textbf{Equation 14}$$

where β_k denotes the estimated coefficient of each independent variable X; γ_{j} denotes the estimated coefficient of income for mode j; $TravelTime_{ij}$ denotes the travel time for mode j for individual i; $Reliability_{ij}$ is the travel time reliability for mode j for individual i; $TravelCost_{ij}$ denotes the cost of travel on mode j for individual i, and $Income_i$ is the income of individual i.

In a linear utility specification the VOT can be calculated for this example (Equation 14). The VOT is the ratio of the partial derivative of utility function with respect to travel time to the partial derivative of utility function with respect to travel cost. In a similar way, VOR can be computed as the ratio of the partial derivative of utility function with respect to travel time reliability to the partial derivative of utility function with respect to travel cost. Put it in another way, the VOT can be derived as $_1/$, and VOR as $_2/$ in Equation 14.

One assumption of MNL is that the error terms are identically and independently distributed (IID) as type I extreme value distribution with a mean of zero. Under the IID assumption, the probability that individual *i* chooses alternative *j* in a given choice set can be calculated as (Equation 15):

$$\text{Prob (choice } j \text{ individual } i\text{, s, } \boldsymbol{\beta}, \mathbf{X}_{ij}, \boldsymbol{\gamma}_{\mathbf{j}}, \mathbf{Z}_{\mathbf{i}}) = \frac{\exp\left(\boldsymbol{\beta}'\mathbf{X}_{ijs} + \boldsymbol{\gamma}_{j}'\boldsymbol{Z}_{is}\right)}{\sum_{j=1}^{J} \exp\left(\boldsymbol{\beta}'\mathbf{X}_{ijs} + \boldsymbol{\gamma}_{j}'\boldsymbol{Z}_{i}\right.} \quad \textbf{Equation 15}$$

Another assumption in MNL is the independence of irrelevant alternatives (IIA) property which implies that the ratio of choice probabilities of a pair of alternatives is independent of other alternatives. The the estimation process is simplified by assuming the IIA property, but such property may not be desirable as has been shown in a classic transportation example known as the blue bus, red bus problem. Such problem illustrates that MNL models are only appropriate for modeling truly independent alternatives. Because the stated preference survey in this research includes alternatives such as travelling on the general purpose lanes, carpooling or driving alone on the MLs with tolls that vary with the time of day, Hensher and Greene (2003) indicated that it is possible that the correlations of unobserved information across alternatives (probably across choice situations as well) is high. High correlations will results in a violation of the IIA assumption of the MNL model. However, such IIA problem of the conventional MNL model might be eliminated by nested logit (NL) models as well as several other approaches that were developed to break or relax the IIA assumptions.

3.7.2 Nested logit model

The NL model overcome the IIA property of the MNL model by allowing for correlations between alternatives within one level of the nest. By creating a hierarchical structure of the alternatives, a NL model groups similar alternatives within a nest level (Ben-Akiva and Lerman 1989; Train 2003). The error terms within a nest for each alternative can be correlated with each other, but the error terms of alternatives in different nests are not (Hensher, Rose et al. 2005; Silberhorn, Boztug et al. 2008). The NL model is a combination of different standard logit models with one primary difference: the error component of the alternatives does not necessarily need to have the same distribution for a NL model. For example, a two-level nested structure for a typical trip on Katy Freeway in Houston is shown in Figure 5. At the “top”/first level of the nest, the individual faces options like whether to drive alone or carpool. At the second level, or “bottom” level, the drivers make a decision whether to travel on MLs or GPLs. Such a nested structure may illusively suggest that one decision has to be made “before” the other. However, these choices could actually be made simultaneously without jeopardizing the NL model.

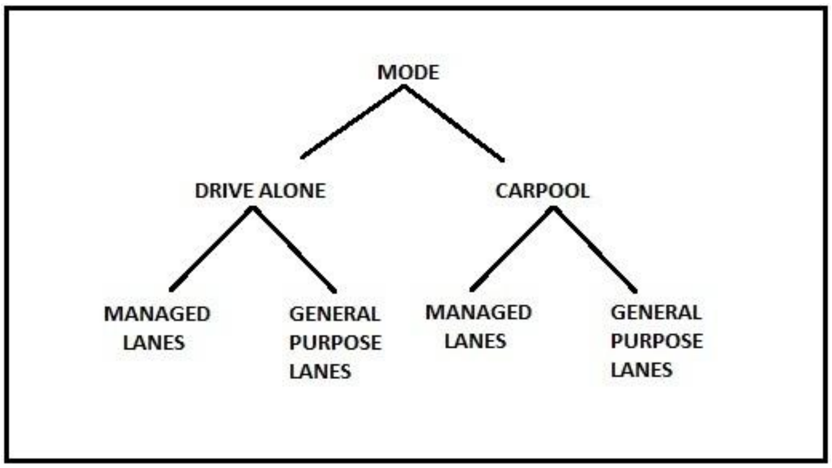


Figure 5 Tree Structure of Nested Logit Model

The probability that an individual *i* (*i* = 1,2,3,…n) chooses an alternative *j* (*j* = 1,2,3,…J) of nest *m* (m = 1,2,3,…M) in a choice set *s* (*s* = 1,2,3,…S) can be calculated using Equation 16. The probability is the product of the conditional probability of choosing alternative *j* in nest *m* with the probability of choosing nest *m* (Knapp, White et al. 2001; Greene 2003). The VOT and VOR can be derived from the same methods described previously for the MNL model.

$$\text{Prob}\left(\text{alternative } j, \text{nest } m | \text{individual } i, s, \boldsymbol{\beta}, \mathbf{X}_{ij}, \boldsymbol{\gamma}_{\mathbf{j}}, \mathbf{Z}_{\mathbf{i}}\right) = \mathrm{P}_{\mathrm{jm}} = \mathrm{P}_{\mathrm{j|m}}\mathrm{P}_{\mathrm{m}} \qquad \textbf{Equation 16}$$

where, $P_{j|m} = \frac{\exp(\boldsymbol{\beta}'\mathbf{X}_{ijs|m})}{\sum_{j=1}^{J_m}\exp(\boldsymbol{\beta}'\mathbf{X}_{ijs|m})}$ = conditional probability of choosing alternative j in nest m,

$P_m = \frac{\exp(\boldsymbol{\gamma}_j'\boldsymbol{Z}_{ism}+\boldsymbol{\tau}_m\boldsymbol{I}_m)}{\sum_{m=1}^{M}\exp(\boldsymbol{\gamma}_j'\boldsymbol{Z}_{ism}+\boldsymbol{\tau}_m\boldsymbol{I}_m)}$ = probability of choosing nest m,

$I_m = \ln\sum_{j}^{J_m}\exp(\boldsymbol{\beta}'\mathbf{X}_{ijs|m})$ = inclusive value (IV), and

$\boldsymbol{\tau}_m$ = a measure of correlation between alternatives in nest m.

3.7.3 Mixed logit model

The mixed logit model as a tool for modeling discrete choice data is very promising (Hensher and Greene 2003). In addition to accounting for individual's observed and unobserved heterogeneity in the models, a mixed logit model can be used to model repeated responses from individuals (panel data), modify error structures, and accommodate heteroscedasticity (non-constant variance) from a variety of sources (Brownstone and Train 1999; Bhat and Castelar 2002; Greene, Hensher et al. 2006; Greene and Hensher 2007; Hensher, Rose et al. 2008).

The parameters in the random utility function (Equation 13) in a mixed logit model are assumed to be random (as the name implies) and may vary across individuals to accommodate heterogeneity. The parameters are specified as in Equation 17:

$$\boldsymbol{\beta}_{ik} = \overline{\boldsymbol{\beta}}_k + \boldsymbol{\sigma}_k\boldsymbol{\upsilon}_{ik} \qquad \textbf{Equation 17}$$

where $\bar{\beta}_k$ denotes the population mean for the k^{th} attribute; υ_{ik} denotes the individual specific heterogeneity with zero mean and standard deviation (scaled to) 1, and σ_k denotes the standard deviation of the (assumed) distribution of the β_{ik}'s around $\bar{\beta}_k$.

These parameters or coefficients are usually assumed to be taken from some widely used distributions (for example, the normal, log normal, and triangular). In theory, parameters for the toll cost, travel time, and travel time variability can be random parameters assuming different distributions. However, remember that objectives of this study are to estimate the value of travel time savings and value of travel time reliability, which both are ratios of two parameters. Patil, et al. (2011) indicated it may add complexity in estimating the VTTS and the VOR when assuming random distributions for travel time, travel time variability, and toll cost. Furthermore, it is also critical to choose the right distribution for drawing meaningful inferences from the estimates. For example, it is counterintuitive if a normal distribution is assumed for any of the parameters, because a positive parameter may imply that respondents prefer longer travel times or higher tolls. This problem can be avoided by assuming the lognormal distribution (with all values greater than zero) for some parameters. However, it is not without limitations because the longer tail of a lognormal distribution (relative to the normal distribution) may yield unrealistically large values (Patil, Burris et al. 2011).

One commonly used distribution in practice for the travel time parameter is the triangular distribution. The triangular distribution takes values from −1 to 1 with a mean of zero. The probability density of a triangular distribution is given as in Equation 18 (Hensher, Rose et al. 2005). For example, the travel time parameter can be constrained to take only negative values such that it matches our intuition.

$$t = \begin{cases} \sqrt{2U} - 1, & \text{for U} < 0.5 \\ 1 - \sqrt{2(1-U)}, & \text{otherwise} \end{cases}$$ **Equation 18**

Hensher et al. (2005) indicated that simulation can be used to derive the individual specific estimates using Equation 19 from a mixed logit model. Parameters can assume a triangular distribution with mean and standard deviation.

$$\hat{t} = \hat{\mu} - \hat{\sigma} \times t$$ **Equation 19**

where $\hat{t}$ denotes the individual specific parameter estimate; $\hat{\mu}$ denotes the estimated mean of the distribution, and $\hat{\sigma}$ denotes the estimated standard deviation of the distribution and t is as defined earlier.

The preference heterogeneity in the mean and heteroscedasticity in the variance can be accommodated in the mixed logit model through specifying the random parameters in Equation 20 (Greene and Hensher 2007; Patil, Burris et al. 2011).

$$\beta_{ik} = \bar{\beta}_k + \boldsymbol{\delta'}_k \mathbf{z}_i + \gamma_{i,k} \upsilon_{i,k} \qquad \textbf{Equation 20}$$

where, $\boldsymbol{\delta'}_k \mathbf{z}_i$ = the observed heterogeneity around the mean of the k^{th} random parameter (δ_k is to be estimated and $\mathbf{z}_i$ is a data vector which may contain individual specific characteristics such as the socio-demographic factors); $\upsilon_{i,k}$ = the vector that contains individual and choice-specific, unobserved random disturbances with $E[\upsilon_{i,k}]$ = 0 and Var$[\upsilon_{i,k}] = a_k^2$, a known constant; and $\gamma_{i,k} = \sigma_k \exp \eta'_k \mathrm{h}_i$ with $\exp \eta'_k \mathrm{h}_i$ as the observed heterogeneity in the distribution of $\beta_{i,k}$ (η_k is to be estimated and h_i is a data vector which may contain individual specific characteristics).

The parameter estimates from the model (Equation 20) can be used to estimate the values of VTTS and VOR for different groups with similar characteristics (Hensher, Rose et al. 2005). Patil et al. (2011) indicated that for travelers with different trip purpose and scenarios the VTTS could be very different.

In addition to the random parameter specifications, Hensher, Rose et al. (2008) indicated that mixed logit models have the capability to accommodate individual heterogeneity in the form of capturing alternative-related influences inthe error components. The utility function is thus specified with this addition as in Equation 21:

$$\mathrm{U}_{i,j,s} = \boldsymbol{\beta'}_i \mathbf{x}_{i,j,s} + \epsilon_{i,j,s} + \sum_{m=1}^{M} c_{jm} \mathrm{W}_{i,m} \qquad \textbf{Equation 21}$$

where, $c_{jm} = 1$ if error component *m* appears in the utility function of alternative j, and $W_{i,m}$ = effects associated with individual preferences within choices (alternatives).

The unobserved heterogeneity can be accounted for by assuming that $W_{i,m}$ is normally distributed with mean zero and the variance of $W_{i,m}$ is given by Equation 22 (Patil, Burris et al. 2011) .

$$\mathrm{Var}\left[W_{i,m}\right] = [\theta_{\mathrm{i}} \times \exp\,(\tau'_{\mathrm{i}}\mathrm{h}_{\mathrm{m}})]^2 \qquad \textbf{Equation 22}$$

where, $_{\mathrm{i}}$ are the scale factor for error component m, $_{\mathrm{i}}$ are the parameters in the heteroscedastic variances of the error components, and $\mathrm{h_m}$ denotes the data vector which contains individual choice invariant characteristics that produce heterogeneity in the variances of the error components.

The conditional probability with the above utility specification can be obtained using Equation 23 (Greene and Hensher 2007; Hensher, Rose et al. 2008; Patil, Burris et al. 2011).

$$\mathrm{Prob}_{i,s}(\mathrm{j_s}\ \mathbf{X}_{\mathrm{is}},\boldsymbol{\Omega},\mathbf{z}_{\mathrm{i}},\mathbf{h}_{\mathrm{i}},\mathbf{v}_{\mathrm{i}},\mathbf{W}_{\mathrm{i}}) = \frac{\exp\left(\boldsymbol{\beta}'\mathbf{x}_{ijs} + \sum_{m=1}^{M} c_{jm}\mathrm{W}_{im}\right)}{\sum_{j=1}^{J}\exp\left(\boldsymbol{\beta}'\mathbf{x}_{ijs} + \sum_{m=1}^{M} c_{jm}\mathrm{W}_{im}\right)} \qquad \textbf{Equation 23}$$

where, **Ω** = the parameter set that collects all the structural parameters (the underlying parameters in the model/equation).

Because the conditional probabilities are functions of the unobserved individual specific random terms, Hensher, Rose et al. (2008) indicated that Equation 23 cannot be used to form the likelihood function to estimate the parameters. However, the unconditional choice probability can be formed by integrating the heterogeneity out of the conditional probabilities using Equation 24.

$$\mathrm{Prob_{i,s}(j_s)} = \int_{\mathrm{v_i}}\int_{\mathrm{W_i}} \mathrm{Prob}_{i,s}(\mathrm{j_s}\ \mathbf{X}_{\mathrm{is}},\boldsymbol{\Omega},\mathbf{z}_{\mathrm{i}},\mathbf{h}_{\mathrm{i}},\mathbf{v}_{\mathrm{i}},\mathbf{W}_{\mathrm{i}})f(\mathbf{v}_{\mathrm{i}},\mathbf{W}_{\mathrm{i}})\mathrm{d}\mathbf{W}_{\mathrm{i}}\mathrm{d}\mathbf{v}_{\mathrm{i}} \qquad \textbf{Equation 24}$$

The unconditional choice probability is not integrable in elementary mathematical functions because it is not in a closed form (Equation 24). Therefore, simulation may be used to approximate the integral by taking random draws from each of the random parameters, then the utilities are computed for each of these draws (Bhat 2003; Train 2003). The calculated utilities from previous steps are used to calculate the probabilities for each draw and are averaged to calculate the unconditional probabilities in the final step (Equation 25).

$$\text{Simulated Prob}_{\mathrm{i,s}}(\mathrm{j_s}) = \frac{1}{\mathrm{R}}\sum_{\mathrm{r=1}}^{\mathrm{R}} \frac{\exp\left(\boldsymbol{\beta}'\mathbf{x}_{ijs} + \sum_{m=1}^{M} c_{jm}\mathrm{W}_{im,r}\right)}{\sum_{j=1}^{J}\exp\left(\boldsymbol{\beta}'\mathbf{x}_{ijs} + \sum_{m=1}^{M} c_{jm}\mathrm{W}_{im,r}\right)} \qquad \textbf{Equation 25}$$

where, the subscript *r* represents the r^{th} random draw, and R = number of random draws.

The simulated likelihood function can be obtained from the simulated probabilities, and it is known that the number of draws and sample size can affect the estimation procedure. It is natural that small number of draws may need less computation time but may result in less precise results, but large number of draws may yield sound results at the expense of a high amount of computational time. It is not uncommon that a complex model may even take days for estimation. Hensher (2001) indicated that Halton draws performs more efficient and generates more precise results than random draws, and 100 to 500 Halton draws may yield good result for model estimation (Greene, Hensher et al. 2006; Greene and Hensher 2007; Hensher, Rose et al. 2008). Therefore, 200 Halton draws is planned to estimate the mixed logit models in this study.

3.8 Summary

A literature review was conducted to track the development of prospect theory and its application in route choice models in previous studies. The existing literature on VTTS, VOR as well as the operation and policy of MLs was reviewed. This study also reviewed literature on efficient survey designs. Literature on different discrete choice models, including multinomial logit, nested logit, and mixed logit models, was reviewed. The data from the stated preference survey in 2012 will be modeled using discrete choice models to obtain estimates of interested parameters, including risk attitude parameters (α, β, and λ), probability weighting parameters (γ and δ), and preference parameters (such as toll cost). From these parameter estimates, the willingness to pay estimates can be obtained. Mixed logit models (EUT based as well as prospect theory proposed frameworks) will be used to model the survey responses because the mixed models can accommodate a variety of extensions to incorporate different effects and to better estimate the travelers' willingness to pay for travel time savings and travel time reliability.

4. DATA COLLECTION

To achieve objectives of this research, in previous chapter this study conducted extensive literature review, survey design methodologies, data collection, and survey data analysis using discrete choice modeling techniques. A discussion of the data collection follows.

4.1 2012 Katy Freeway Survey Design

The Survey (www.katysurvey.org) was created using Limesurvey, an open-source survey designing tool, and it was conducted from August 15, 2012 to September 19, 2012. The survey was advertised to the public through online and news media (see 4.4 for the administration of the survey). Residents of Houston who use the Katy Freeway on a regular basis or have used it recently were encouraged to participate in the survey.

The 2012 survey questionnaire consisted of four sections. The first section introduces the Katy Freeway (I-10) and Katy Tollway lanes and asks the respondents if they ever used them. If neither Katy Freeway nor Katy Tollway lanes have been used by the respondent, then the survey terminates. The respondent is then asked about their most recent trip on the Katy Freeway. About half of the respondents were randomly assigned a question asking about their actual recent trip towards downtown Houston and the other half about their recent trip away from downtown. Questions attempt to gather information about the purpose of the trip, if they used the GPLs or the Tollway lanes, day of the week, time of the day, time length of the trip, distance of trip on the Katy Freeway, the type of vehicle, the number of passengers, etc.

In the second section, respondents were then asked if they ever used the Tollway lanes, if they answered yes, and the reasons for using them. If they had not, their reasons for not using the lanes were sought. In the following, they were asked about the approximate number of their trips on the Katy Freeway in a week, how many were on MLs, the average toll paid, and the travel time they think that they have saved for using the MLs. In the third section the respondents were presented with three stated preference (SP) questions, with each SP question the respondent was asked to make a choice among 4 different modes of travel options on the Katy Freeway, and the last section consisted of questions regarding the socio-economic characteristics of the respondents.

4.2 Survey Details

4.2.1 Introduction to the new managed lanes

The Katy Freeway Managed Lane Survey begins with an introduction to the Katy Tollway and each respondent is asked if he/she has traveled on either the Katy Freeway (I-10) or Katy Tollway lanes in the past six months (Figure 6).

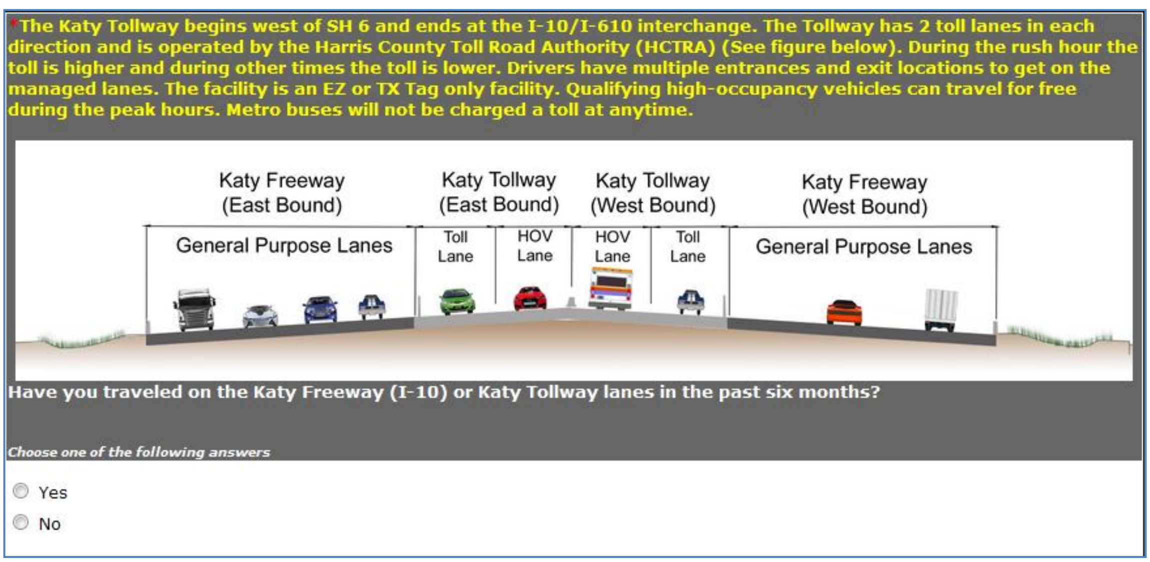


Figure 6 Introduction to the Katy Tollway

4.2.2 Details of respondent's most recent trip

If the respondent did not have a recent trip on the Katy Freeway (I-10) in the past six months, then the survey was terminated with a "Thank you" page. If the respondent used the Freeway or Tollway in the past six months, then about half of the respondents were randomly assigned a question asking about their actual recent trip towards Downtown Houston and the other half about their recent trip away from downtown. The respondent was then asked if that trip was on the GPLs or the Tollway lanes. If the respondent indicated that the travel was on the GPLs, then the locations where they got on and off the Freeway were determined. If the travel was on the Tollway lanes, then they were asked where they entered and exited the Tollway lanes. The survey also sought answers from respondents if they ever changed the entry or exit locations along the Katy Freeway in order to access the Tollway. The respondent was then asked several questions regarding their most recent Katy Freeway trip, such as day of the week and time of day of that trip, what type of vehicle used, etc. The complete survey questionnaire is attached in Appendix A of this report.

Respondents were then asked about their travel time on their last trip. The travel time is measured from the time they got in the vehicle to when arrived at their destination. The respondents were then asked if they ever used the Katy Tollway lanes. If they had used the Tollway lanes the main reasons for them to use the Tollway were sought. If they had not, the primary reasons for not using the Tollway were sought. Additionally, respondents' opinions on the levels of the law enforcement were collected.

Respondents were also asked the number of trips they made on the GPLs of the Katy Freeway in the last work week (Monday through Friday) with each direction of travel counting as one trip. If the respondent indicated that they had used the Tollway lanes, then the number of trips the respondent took during the last work week on the Katy Tollway lanes was requested.

4.2.3 Stated preference questions

A total of three SP questions were presented to each respondent in this section of the survey. In each of these three questions, the respondent was asked to make a choice among 4 different modes of travel options on the Katy Freeway. Although in the survey the scenarios were hypothetical, travel scenarios were largely created based on the information derived from the respondent's most recent trip on Katy Freeway towards/away from downtown Houston, so it is highly likely that many respondents had faced a similar situation before on their actual trips. The modes included SOV and HOV and varied based on time of day, travel time, travel time variability, and toll values. Modes in each SP question were:

1. Drive Alone on the General Purpose Lanes (DA-GPL)
2. Carpool on the General Purpose Lanes (CP-GPL)
3. Drive Alone on the Managed Lanes[1] (DA-ML)
4. Carpool on the Managed Lanes (CP-ML)

The stated preference (SP) questions were used to better understand how travelers choose between GPL and Tollway lanes on the Katy Freeway. The SP questions were designed based on prospect theory (PT) principles because PT may improve on traditional methods, such as expected utility theory (EUT) and random utility maximization (RUM), in predicting the use of Tollway lanes by Katy Freeway travelers. EUT and RUM propose that people act rationally to maximize their utility/benefit from the decision that they have made, and the most well-known RUM-based discrete choice model is the multinomial logit or MNL model.

SP questions in this survey were designed specifically to test and compare predictive results of mode choice using four discrete choice models. In the utility theory (UT) based conventional MNL model (see survey question Format A in Table 1 and an

[1] The Managed lanes in the Survey questions were presented as Tollway lanes to maintain consistency with the official name by the operating agency. This is because Katy Freeway travelers are familiar with the name Tollway lanes instead of managed lanes.

example in the first figure found on p. 52), the travel time for a hypothetical trip was generated in the design by using a random draw from an uniform distribution, while the Reference Point model (see survey question Format B in Table 1 and an example in the second figure found on p. 52) differs from the conventional MNL model in the specification of the utility function by including the PT proposed value functions, everything else being equal. The UT-based utility function assumes a linear relationship with attribute levels (travel time of a trip), while it is the difference of travel time relative to that of the most recent trip in the PT-based utility function. For example, in a conventional MNL model the average travel time of 20 minutes with a range of 17 to 23 minutes of a hypothetical trip was assumed and presented to the respondent, while in a Reference Point model the difference in travel time (± 3minutes) was presented to the respondent. The Reference Point model assumes that it is the differences in travel time (20 - 17 = 3 or 20 - 23 = -3 minutes) relative to the most recent trip determine the value of the utility function, and consequently the probability of the mode chosen. By comparing the predictive results of the conventional MNL models and Reference Point models (the two differ in the specification of the utility functions), it is possible to investigate if prospect theory could improve on traditional UT methods.

Table 1 Stated Preference Question Formats

Format	Sample Question Style	Brief Description
A: Conventional MNL Model	Average travel time of 20 minutes but can be anywhere from 17 to 23 minutes.	• The travel time was assumed to be taken from a uniform distribution. • Traditional utility function as used in UT methods • Travel on MLs was constrained to be faster than on GPLs.
B: Reference Point Model	For the GPL modes, the travel time can be up to 3 minutes shorter or longer than your most recent trip. For the ML modes, the travel time could be 9 to 11 minutes shorter than your most recent trip.	• The travel time was assumed to be taken from a uniform distribution. • PT proposed utility function using changes of status as attribute levels. • Travel on MLs was constrained to be faster than on GPLs. • The attribute levels of the utility function were presented as gain or loss relative to the reference point.
C: PT-pwf Model	7 times out of 10 the trip takes 25 minutes, and 3 times out of 10 the trip takes 18 minutes.	• The travel time was assumed to be taken from random probabilistic distribution. • Traditional utility function as used in UT methods • Utility function incorporating a probability weighting function. • Travel on MLs was constrained to be faster than on GPLs. • The attribute levels were assumed with a probabilistic occurrence.
D: PT-Full Model	For the GPL modes, 8 times out of 10 the trip takes 3 minutes longer than your most recent trip, and 2 times out of 10 the trip takes 13 minutes less than the most recent trip. For the ML modes, 9 times out of 10 the trip takes 19 minutes less than your most recent trip, and 1 times out of 10 the trip takes 15 minutes less than the most recent trip.	• The travel time was assumed to be taken from a random probabilistic distribution. • PT proposed utility function using changes of status as attribute levels. • Utility function incorporating probability weighting function. • Travel on MLs was constrained to be faster than on GPLs. • The attribute levels were presented as gain or loss relative to the reference point and assumed with probabilistic occurrence.

The PT-pwf model (see survey question Format C in Table 1 and an example in first figure found on p. 53) assumed that the travel time was generated from random distribution with a probabilistic occurrence. Likewise, the PT-Full model (see survey question Format D in Table 1 and an example in the second figure found on p. 53) differs in the specification of utility function. Based on these four discrete choice models, SP questions were presented in four formats and were designed to accommodate the linear and nonlinear utility functions proposed from utility theory based models and PT-based models, respectively. The travel time of a trip is by nature variant, and how likely a mode would be chosen partly depends on travelers' perceived reliability of that mode. For example, if the weather forecast indicated that there is 80 percent of chance of rain, then most of people would think it is going to rain and they will take an umbrella. In this case, the 80 percent was perceived as a certainty (100 percent). If it was forecasted that there was only a 10 percent chance of rain, most of people would not take an umbrella because they don't believe it is going to rain. Similarly, if a managed lane could offer a travel time with 80 percent reliability, travelers may consider it as 100 percent or close-to reliable. SP questions in this format were specifically designed to investigate how ML users value probability/reliability of travel time. By incorporating a probability weighting function in the PT-based utility functions, two formats of UT-based and PT-based SP questions were developed. This resulted in 4 formats for the SP questions. Note that each respondent will only be given questions in one of the four formats. Table 1 shows sample question style and brief description of the 4 formats.

The four survey designs of the SP questions were developed to predict the travel demand on the use of MLs using UT-based and PT-based mixed logit models. The conventional MNL model (Format A) will use conventional utility function while the PT-based models (Format B, C, and D) will incorporate PT-proposed value functions and/or probability weighting functions in the utility functions. In this approach it is possible to check the efficiency of the parameter estimation for the responses obtained from the four survey designs. The value of travel time savings and the value of travel time reliability will be estimated from these models. Estimates (utility theory-based and

PT-based) then can be compared with results from previous surveys conducted in 2008 and 2010. Route-choice decision prediction (success rates) will also be compared to check the prediction accuracy of the four models. How the attribute levels of each alternative were determined are discussed in the following sections. This study used two survey design strategies (D_b-Efficient and Adaptive Random) in generating the SP questions. Combining the four question formats, this generated eight SP question categories (see Figure 7).

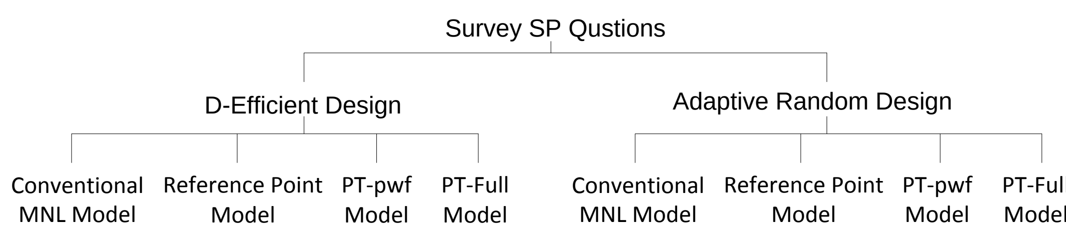


Figure 7 Survey Design Structure for SP Questions

Typical SP questions in the four formats can be found in Figure 8, Figure 9, Figure 10, and Figure 11. The four survey designs of the SP questions, two linear and two non-linear mixed logit models were developed for the survey responses to predict the travel demand on the use of MLs using respective UT-based and PT-based value function and probability weighting function.

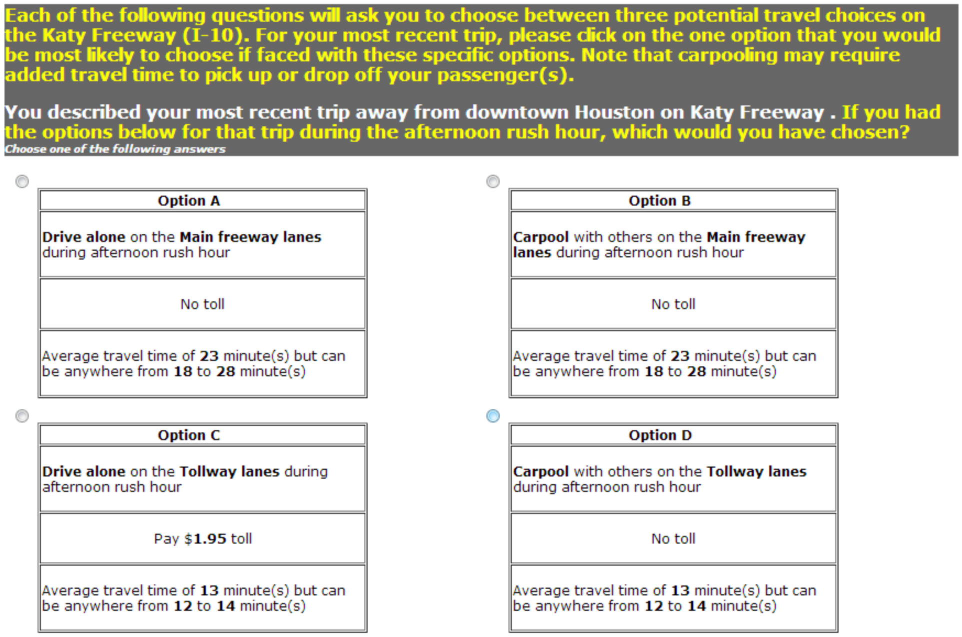


Figure 8 Stated Preference Questions in the 2012 Survey (Conventional MNL Model, A)

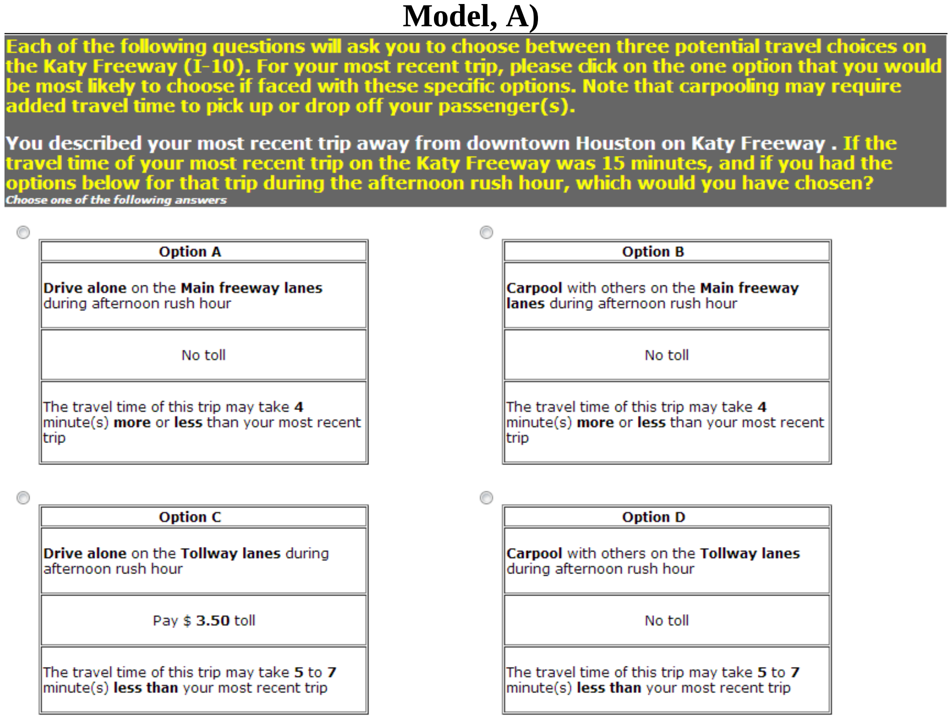
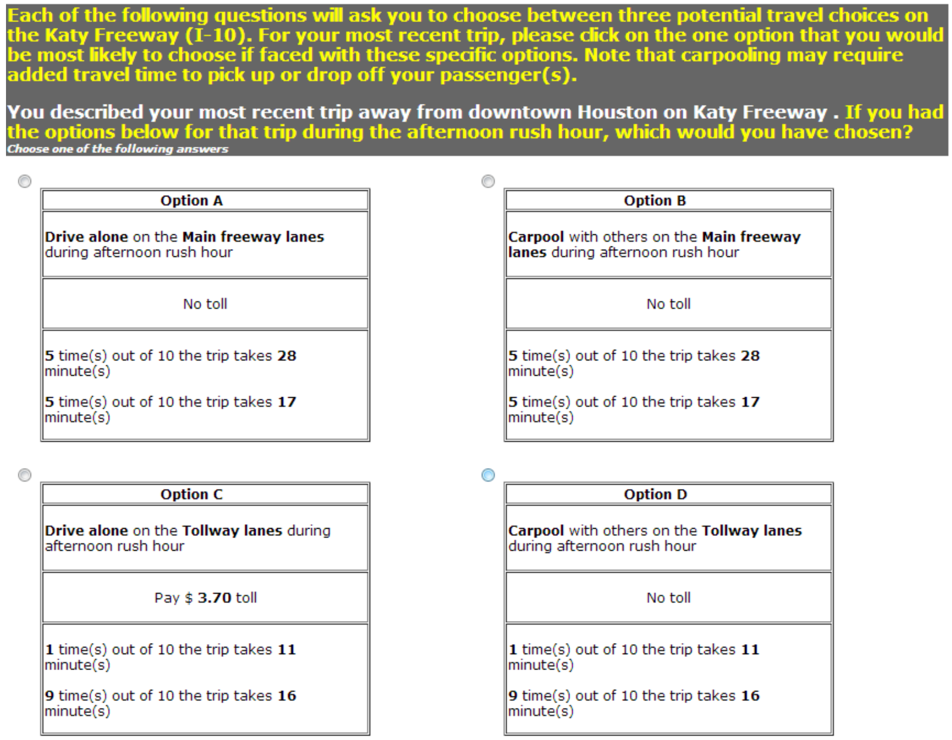


Figure 9 Stated Preference Questions in the 2012 Survey (Reference Point Model, B)



Each of the following questions will ask you to choose between three potential travel choices on the Katy Freeway (I-10). For your most recent trip, please click on the one option that you would be most likely to choose if faced with these specific options. Note that carpooling may require added travel time to pick up or drop off your passenger(s).

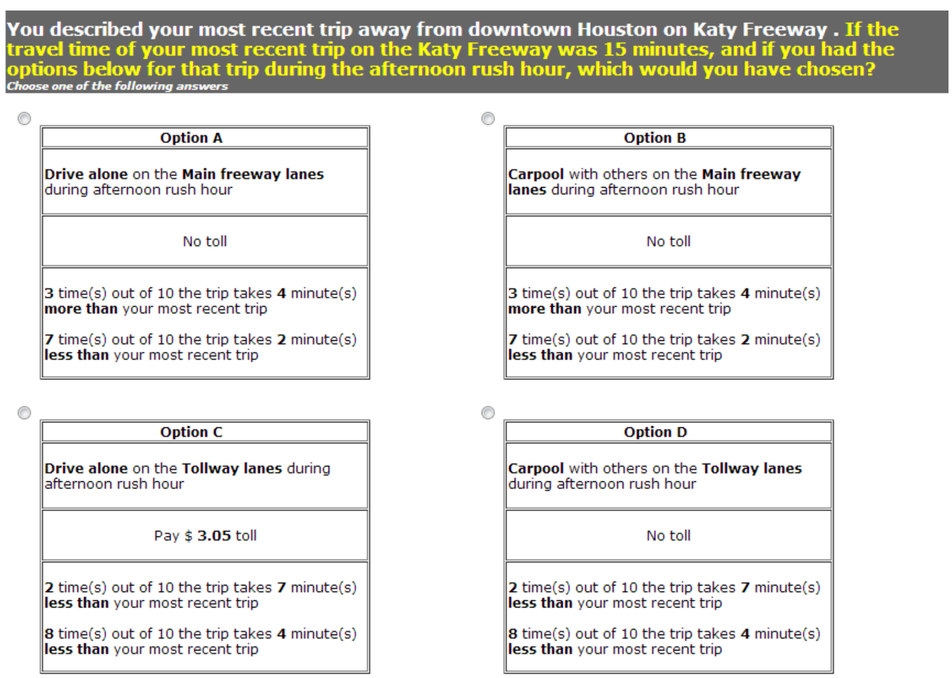
You described your most recent trip away from downtown Houston on Katy Freeway . If you had the options below for that trip during the afternoon rush hour, which would you have chosen?

Choose one of the following answers

Option A	Option B
Drive alone on the **Main freeway lanes** during afternoon rush hour	**Carpool** with others on the **Main freeway lanes** during afternoon rush hour
No toll	No toll
5 time(s) out of 10 the trip takes **28** minute(s) **5** time(s) out of 10 the trip takes **17** minute(s)	**5** time(s) out of 10 the trip takes **28** minute(s) **5** time(s) out of 10 the trip takes **17** minute(s)

Option C	Option D
Drive alone on the **Tollway lanes** during afternoon rush hour	**Carpool** with others on the **Tollway lanes** during afternoon rush hour
Pay $ **3.70** toll	No toll
1 time(s) out of 10 the trip takes **11** minute(s) **9** time(s) out of 10 the trip takes **16** minute(s)	**1** time(s) out of 10 the trip takes **11** minute(s) **9** time(s) out of 10 the trip takes **16** minute(s)

Figure 10 Stated Preference Questions in the 2012 Survey (PT-pwf Model, C)



You described your most recent trip away from downtown Houston on Katy Freeway . If the travel time of your most recent trip on the Katy Freeway was 15 minutes, and if you had the options below for that trip during the afternoon rush hour, which would you have chosen?

Choose one of the following answers

Option A	Option B
Drive alone on the **Main freeway lanes** during afternoon rush hour	**Carpool** with others on the **Main freeway lanes** during afternoon rush hour
No toll	No toll
3 time(s) out of 10 the trip takes **4** minute(s) **more than** your most recent trip **7** time(s) out of 10 the trip takes **2** minute(s) **less than** your most recent trip	**3** time(s) out of 10 the trip takes **4** minute(s) **more than** your most recent trip **7** time(s) out of 10 the trip takes **2** minute(s) **less than** your most recent trip

Option C	Option D
Drive alone on the **Tollway lanes** during afternoon rush hour	**Carpool** with others on the **Tollway lanes** during afternoon rush hour
Pay $ **3.05** toll	No toll
2 time(s) out of 10 the trip takes **7** minute(s) **less than** your most recent trip **8** time(s) out of 10 the trip takes **4** minute(s) **less than** your most recent trip	**2** time(s) out of 10 the trip takes **7** minute(s) **less than** your most recent trip **8** time(s) out of 10 the trip takes **4** minute(s) **less than** your most recent trip

Figure 11 Stated Preference Questions in the 2012 Survey (PT-Full Model, D)

In a typical SP question, given a hypothetical set of trip characteristics, the respondent was asked to choose the option that best suited his/her travel preferences. Trip characteristics were determined primarily according to the respondent's answers to the questions pertaining to the respondent's most recent trip. The trip characteristics that are obtained in this manner include the trip time of day, day of the week, travel time and travel distance on the Katy Freeway/Tollway lanes of the most recent trip. These elements are used to build the text of the three stated preference questions. If a respondent did not answer any of the questions sufficient to build the SP question text, the survey randomly selects various attributes in a reasonable range. For example, in a case of missing the time of day for the respondent's most recent trip, the peak period (either morning or afternoon) was randomly selected. If the user did not provide their entry and exit location on the GPLs/Tollway lanes such that a travel distance could not be estimated, the survey assigned a travel distance of 12 miles for a trip on the Katy Freeway. The initial toll values were based on the current tolls along the Katy Freeway, but may vary considerably depending on the survey design. Variation in tolls in SP questions would help identify the influence of the toll on made choice. But to maintain reasonable scenarios it is necessary to observe some constraints. First, the toll was set at $0 for CP-ML during peak periods, and the toll was always $0 for CP-GPL and DA-GPL. Second, for the faster and more reliable travel on the MLs, the travel time and travel time variability (defined as the percentage variation of travel time from the average travel time) on the MLs was constrained lower than or equal to that of the GPLs.

The following sections discuss how the values of travel time, toll, and travel time variability were selected.

4.2.4 Time of day

The actual toll rates for using the Katy Tollway lanes vary according to the time of day, so it was reasonable to adjust the toll values for the travel scenarios depending on the respondent's recent trip start time toward/away from Downtown Houston. Time of day for the travel scenarios was determined according to Table 2. The time of day for the travel scenarios was determined according to the respondent's recent trip start time towards/away from downtown. In the cases where a respondent didn't answer the start time of his/her recent trip, the time of day of the trip was then assigned to either morning or evening peak period. If the respondent was previously asked about his/her trip towards downtown Houston, then the travel scenario was described as being during the morning peak period. The other scenarios were described as being during the evening peak hours if the trip was away from downtown. The toll costs during off-peak hours are constrained lower than during shoulder hours which are lower than during the peak hours. It should be noted that the actual toll rates are slightly different from those provided in the hypothetical scenarios, and the HOVs are free during peak periods and pay the regular toll rates during off-peak periods.

Table 2 Time of Day Based on Trip Start Time

Trip Start Time	Time of Day
12:00 AM to 6:00 AM	Off-Peak Hours
6:00 AM to 7:00 AM	Shoulder Period
7:00 AM to 9:00 AM	Morning Peak Period
9:00 AM to 5:00 PM	Shoulder Period
5:00 PM to 7:00 PM	Evening Peak Period
7:00 PM to 8:00 PM	Shoulder Period
8:00 PM to 12:00 AM	Off-Peak Hours

4.2.5 Trip distance

In the second part of the survey, the respondents were asked the points where they entered and exited the Katy Freeway. With this information, the traveler's trip distance on the Katy Freeway can be estimated. If there was no information obtained about the entrance and/or exit locations, then a trip distance of 12 miles on the MLs was assigned. To obtain a precise toll cost for the trip, it was also important to estimate the portion of the trip actually travelled on the MLs. In order to calculate the distance travelled on the MLs and GPLs, the Katy Freeway was then divided into two sections. Section one was defined as anywhere west of the MLs and section two was the section that contained the MLs. Only the distance traveled on the MLs (section two) was used to estimate the toll. In case of a ML distance less than 4 miles, it was forced to increase by 4 miles to create some difference in travel times between the MLs and GPLs. It should be noted that some respondents' whole trip could potentially be on section one, where there are no MLs. In this case, a distance of 12 miles on the MLs was assigned to calculate a hypothetical toll value. Based on this estimated trip distance on MLs, the toll costs are calculated using toll per mile generated using the two different design strategies.

4.2.6 Calculation of toll, average travel time, and maximum/minimum travel time

In addition to trip distance on Katy Freeway and time of day, it is necessary to incorporate average speeds, the toll per mile and the travel time variability on each of the sections to calculate the toll cost, average travel time, and maximum and minimum travel times for each individual's trip. The average speed on section one was assumed to be 60 mph regardless of the time of day, because this section is far from downtown and often has free-flow speeds.

The following example illustrates how the toll, average travel time, maximum and minimum travel time were estimated. Assume a respondent indicated that the travel distance on the Katy Freeway was 15 miles during peak hours, 5 miles on section one and 10 miles on section two. The following values for the speed, toll rate, and travel time variability on section two (Table 3) will be used to illustrate this.

Table 3 Example Values for Speed, Toll Rate, and Travel Time Variability

Modes	Average Speed (mph)	Travel Time Variability (%)	Toll (cents/mile)
DA-GPL	32.5	23	0
CP-GPL	32.5	23	0
DA-ML	52.5	14	33.33
CP-ML	52.5	14	0

The average travel time, toll and the maximum and minimum travel time for each mode can be calculated with the assumed values, and the example can be found in Table 4.

Table 4 Example Calculation of Travel Time, Toll, and Maximum/Minimum Travel Time for Each Mode

	DA-GPL and CP-GPL	DA-ML and CP-ML
Travel Time on Section 1 (rounded to the nearest minute)	(5/60)*60 = 5	(5/60)*60 = 5
Travel Time on Section 2 (rounded to the nearest minute)	(10/32.5)*60 = 18	(10/52.5)*60 = 11
Total Travel Time (minutes)	23	16
Toll	None	(0.33*10) = $3.30
Variability of Travel Time (calculated based on travel time on section 2) (minutes)	(18*0.23) = 4	(11*0.14) = 2
Maximum Travel Time (minutes)	23 + 4 = 27	16 + 2 = 18
Minimum Travel Time (minutes)	23 – 4 = 19	16 – 2 = 14

Additionally, two survey design strategies, the D_b-Efficient design and adaptive random design, were used to generate the toll cost per mile, average speed, and variability of travel time. Each respondent was randomly assigned and hence had an equal chance of receiving SP questions from one of the two designs. Discussions of the D_b-Efficient design, adaptive random design, and the resulting generated attribute levels are provided in the following sections.

4.2.7 Attribute levels generated by the D_b-Efficient design

A design is called D-efficient when the D-error of the asymptotic variance-covariance matrix of the parameter estimates of the discrete choice model is minimized. D_b-efficient (also called Bayesian efficient) designs are found by minimizing the D_b-error. Priors of parameters were assumed from normal distributions with non-zero means. The mean values of priors for the attributes toll and speed were obtained from the previous surveys conducted in 2008 and 2010, and from relevant literature for travel time variability. The mean and standard deviation of the priors used for obtaining the D_b-efficient design and the exact levels of attributes used for each mode at different times of day for the conventional MNL and Reference Point models are shown in Table 5. Three levels were assumed for each attribute in the deterministic models. For example, during the peak periods the speeds on MLs could be 50/52.5/55 mph, while on GPLs 30/32.5/35 mph. The speed differences between MLs and GPLs were constrained at around 20 mph in order to generate sufficient tradeoffs between choosing ML modes and GPLs modes. The 20 mph difference is a reasonable estimate based on speed analysis using TTI speed data (http://traffic.houstontranstar.org/hist/historydata.html).

Table 5 Mean, Standard Deviation of Attribute Priors, and Attribute Levels for Different Times of Day (MNL & RP Models)

Attribute	Attribute Levels				Mean Value of Priors[a]	Standard Deviation of Priors
	Mode	Time of Day				
		Peak Hours	Shoulder Hours	Off-Peak Hours		
Toll (cents/mile)	DA-GPL	0	0	0	-0.12	0.10[b]
	CP-GPL	0	0	0		
	DA-ML	16.67,33.33,50	8.34,16.67,25	4.17,8.34,12.5		
	CP-ML	0	0	0		
Speed (mph)	DA-GPL & CP-GPL	30,32.5,35	30,32.5,35	42.5,45,47.5	-0.50	0.30
	DA-ML & CP-ML	50,52.5,55	50,52.5,55	57.5,60,62.5		
Travel Time Variability (% of mean travel time)	DA-GPL & CP-GPL	14,23,33	14,23,33	5,11,18	-0.06	0.50
	DA-ML & CP-ML	10,14,18	10,14,18	4,8,12		

a) Prior is the coefficient of travel time estimated from the previous survey; b) Same as used in previous 2010 survey design.

The mean and standard deviation of the priors for the conventional MNL and Reference Point models are shown in Table 5. The assumed toll values were the same as for the PT-pwf and PT-Full models (Table 6). Because the travel time and its variability in PT-pwf and PT-Full models were presented as two probabilities in the utility function, one probability is defined as the best case while the other one the worst. For example, during the peak periods the speeds on the MLs could be 50/60/65 mph in the best case and remained 45 mph in the worst case. While on GPLs the best case speed is 40 mph and the worst case could be 20/25/30 mph. The speed values were selected for easy comparison to the speed values in the conventional MNL and Reference Point models, and to satisfy the constraint that the ML traffic flows faster than on the GPLs. The probability of each attribute level (say the best case) could be 0/10/20/50/80/90/100 percent, and the probability of the worst case will be 100 minus the probability of the best case. The seven levels of probability selected make it possible to estimate the parameters of the probability weighting functions proposed by prospect theory.

The D_b-efficient survey design was generated using the N-Gene package (ChoiceMetrics, 2012). Codes used to generate D_b-efficient design in N-Gene can be found in Appendix B. Pseudo-Random Monte Carlo simulation with 1,000 independent draws were used to simulate the priors of four models. The design for peak hours obtained from the software for the MNL and RP models are shown in Table 7, and PT-pwf and PT-Full models in Table 8. The Bayesian designs for off-peak and shoulder times were obtained by replacing the attribute levels, as shown in Table 5 and Table 6. The design for the MNL and RP models has 15 rows divided into 5 blocks of 3 rows with a D_b-error of 0.1376, while design for the PT-pwf and PT-Full models has 21 rows divided into 7 blocks of 3 rows with a D_b-error of 0.0363. Note that each respondent was randomly given a choice set from each block.

Table 6 Mean, Standard Deviation of Attribute Priors, and Attribute Levels for Different Times of Day (PT-pwf & PT-Full Models)

<table>
<tr><th rowspan="3">Attribute</th><th colspan="8">Attribute Levels</th><th rowspan="3">Mean Value of Priors</th><th rowspan="3">Standard Deviation of Priors</th></tr>
<tr><th colspan="2" rowspan="2">Mode</th><th colspan="2">Peak Hours</th><th colspan="2">Shoulder Hours</th><th colspan="2">Off-Peak Hours</th></tr>
<tr><th>Values</th><th>Probability</th><th>Values</th><th>Probability</th><th>Values</th><th>Probability</th></tr>
<tr><td rowspan="3">Toll (cents/mile)</td><td colspan="2">CP-ML</td><td>0</td><td>NA</td><td>0</td><td>NA</td><td>0</td><td>NA</td><td rowspan="3">-0.12</td><td rowspan="3">0.10</td></tr>
<tr><td colspan="2">DA-ML</td><td>16.67,33.33,50</td><td>NA</td><td>8.34,16.67,25</td><td>NA</td><td>4.17,8.34,12.5</td><td>NA</td></tr>
<tr><td colspan="2">DA-GPL & CP-GPL</td><td>0</td><td>NA</td><td>0</td><td>NA</td><td>0</td><td>NA</td></tr>
<tr><td rowspan="4">Speed (mph)</td><td rowspan="2">CP-ML & DA-ML</td><td>Best case</td><td>55,60,65</td><td>0%,10%,20%, 50%, 80%,90%,100%</td><td>55,60,65</td><td>0%,10%,20%, 50%, 80%,90%,100%</td><td>60,65,70</td><td>0%,10%,20%, 50%, 80%,90%,100%</td><td rowspan="4">-0.50</td><td rowspan="4">0.3</td></tr>
<tr><td>Worst case</td><td>45</td><td>1-probability$_{\text{Best Case}}$</td><td>45</td><td>1-probability$_{\text{Best Case}}$</td><td>55</td><td>1-probability$_{\text{Best Case}}$</td></tr>
<tr><td rowspan="2">DA-GPL & CP-GPL</td><td>Best case</td><td>40</td><td>1-probability$_{\text{Worst Case}}$</td><td>40</td><td>1-probability$_{\text{Worst Case}}$</td><td>50</td><td>1-probability$_{\text{Worst Case}}$</td></tr>
<tr><td>Worst case</td><td>20,25,30</td><td>0%,10%,20%, 50%, 80%,90%,100%</td><td>25,30,35</td><td>0%,10%,20%, 50%, 80%,90%,100%</td><td>35,40,45</td><td>0%,10%,20%, 50%, 80%,90%,100%</td></tr>
</table>

a) Prior is the coefficient of travel time estimated from the previous survey; b) Same as used in previous 2010 survey design.

Table 7 D_b-Efficient Design Generated for MNL & RP Models Using N-Gene Software (for Peak Hours)

Mode	DA-ML			CP-ML		DA-GPL		CP-GPL		
Choice Situation	Speed (mph)	Toll (cents/mile)	Travel Time Variability (%)	Speed (mph)	Travel Time Variability (%)	Speed (mph)	Travel Time Variability (%)	Speed (mph)	Travel Time Variability (%)	Block
1	55	50	14	55	14	30	33	30	33	1
2	52.5	33.33	14	52.5	14	30	33	30	33	4
3	55	16.67	10	55	10	30	14	30	14	5
4	50	16.67	18	50	18	32.5	23	32.5	23	1
5	52.5	33.33	10	52.5	10	35	33	35	33	3
6	52.5	50	18	52.5	18	30	14	30	14	3
7	52.5	33.33	18	52.5	18	35	23	35	23	5
8	50	16.67	18	50	18	32.5	14	32.5	14	4
9	52.5	50	10	52.5	10	32.5	23	32.5	23	2
10	50	33.33	10	50	10	30	14	30	14	2
11	55	50	10	55	10	32.5	33	32.5	33	3
12	55	50	14	55	14	35	33	35	33	4
13	50	33.33	14	50	14	32.5	23	32.5	23	5
14	50	16.67	18	50	18	35	23	35	23	2
15	55	16.67	14	55	14	35	14	35	14	1

Table 8 D_b-Efficient Design Generated for PT-pwf & PT-Full Models Using N-Gene Software (for Peak Hours)

Mode	DA-ML	DA-ML & CP-ML				DA-GPL & CP-GPL				
Choice Situation	**Toll (cents/mile)**	**Speed of Best Case (mph)**	**Probability of Best Case (%)**	**Speed of Worst Case (mph)**	**Probability of Worst Case (%)**	**Speed of Best Case (mph)**	**Probability of Best Case (%)**	**Speed of Worst Case (mph)**	**Probability of Worst Case (%)**	**Block**
1	16.67	60	20	45	80	30	20	40	80	1
2	50	65	0	45	100	25	50	40	50	4
3	50	60	90	45	10	20	80	40	20	7
4	50	65	100	45	0	20	50	40	50	2
5	50	65	0	45	100	20	90	40	10	3
6	16.67	55	10	45	90	25	90	40	10	5
7	16.67	60	90	45	10	25	10	40	90	6
8	16.67	55	10	45	90	30	100	40	0	7
9	33.33	60	80	45	20	20	100	40	0	5
10	16.67	55	80	45	20	25	10	40	90	2
11	50	65	100	45	0	20	80	40	20	1
12	16.67	55	20	45	80	25	0	40	100	4
13	50	55	20	45	80	30	100	40	0	2
14	16.67	55	50	45	50	30	80	40	20	1
15	50	60	50	45	50	30	90	40	10	7
16	33.33	60	80	45	20	20	0	40	100	6
17	33.33	65	10	45	90	30	10	40	90	5
18	33.33	65	0	45	100	30	20	40	80	3
19	33.33	65	50	45	50	25	0	40	100	6
20	33.33	55	90	45	10	25	20	40	80	4
21	33.33	60	1	45	99	20	50	40	50	3

4.2.8 *Attribute levels generated by the adaptive random design*

The second type of design strategy used in this study is the adaptive random attribute level generation method. In this method, the levels of each attribute (toll cost per mile, average speed, and travel time variability) for the first SP question were generated randomly from a given range of values for each attribute. The attribute levels used for each attribute at different times of day are shown in Table 9. The adaptive random design strategy is given the name for its smart adjusting attribute level generation method: the toll levels in subsequent (second and third) choice sets were generated partially based on the response to the respondent's prior choices. The toll rates will be increased by a random percentage anywhere from 30 to 90 if the respondent chose a toll option and decreased from 35 to 70 if a non-toll option was chosen for the previous SP question. In cases (very rare though) where the travel time for the GPL was given lower than that of ML (suggesting a faster travel in the GPL than in the MLs), then the travel time of ML was forced to be the same as that of the GPL.

Table 9 Attribute Levels Used for Generating Random Attribute Level Design

Attribute	Attribute Levels			
		Time of Day		
	Mode	Peak Hours	Shoulder Hours	Off-Peak Hours
Toll (cents/mile)	CP-ML	0+(0 to 10)	0+(0 to 7)	0+(0 to 5)
	DA-ML	5+(0 to 28)	5+(0 to 18)	5+(0 to 14.6)
	CP-GPL	0	0	0
	DA-GPL	0	0	0
Speed (mph)	CP-ML	55+(0 to 10)	55+(0 to 10)	60+(0 to 10)
	DA-ML	55+(0 to 10)	55+(0 to 10)	60+(0 to 10)
	CP-GPL	20+(0 to 15)	30+(0 to 15)	40+(0 to 15)
	DA-GPL	20+(0 to 15)	30+(0 to 15)	40+(0 to 15)
Travel Time Variability (% of mean travel time)	CP-ML	5+(0 to 15)	5+(0 to 15)	5+(0 to 15)
	DA-ML	5+(0 to 15)	5+(0 to 15)	5+(0 to 15)
	CP-GPL	25+(0 to 25)	20+(0 to 12.5)	15+(0 to 8.6)
	DA-GPL	25+(0 to 25)	20+(0 to 12.5)	15+(0 to 8.6)

4.3 Demographics of Respondents

Attributes of the respondents and their household may also affect the choice decision that drivers make. In order to investigate the influence, if any, of the travelers' characteristics on the route choice decision-making, the last section of the survey sought information about the respondents' socio demographic characteristics (see Appendix A).

4.4 Survey Administration

The survey was posted on a Texas Transportation Institute server and available for public access (www.katysurvey.org). The survey was active from August 15, 2012 to September 19, 2012. Residents of Houston who use Katy Freeway on a regular basis or have used it recently were encouraged to participate in the survey. Online and traditional media were used to advertise the survey to the public. The list of websites where the survey was advertised is shown below. Some of the advertising was free of charge, and some was paid service. To generate a constant flow of responses as well as to have a rough track of responses generated by each source, the ads were published on the website at different dates.

- HoustonTranStar Website (http://www.houstontranstar.org/) on August 15, 2012 - free
- Harris County Toll Road Authority (HCTRA) (www.hctra.org) on August 16, 2012 - free
- West Houston Association (http://www.westhouston.org/) on August 17, 2012 - free
- Social media
    - Targeted tweets to more than 50 targeted media and community groups and organizations through Twitter such as Fox News Traffic Anchor Michelle Merhar, who re-tweeted the survey to her many followers. Facebook posts to more than 25 targeted media, city organization pages such as KHOU, KTRK, Fox Traffic, H-GAC and TxDOT

    - Tweets on August 20 and retweeted on August 24, 2012 by TxDOT (https://twitter.com/) - HOU District – free
- Press Release to targeted Houston media
- Houston Chronicle (www.chron.com) on August 31, 2012 - paid
- KUHF interview with Dr. Mark Burris on September 4, 2012 (http://app1.kuhf.org/articles/1346777349-Commuters-Asked-For-Input-On-Katy-Freeway-Managed-Lanes.html) – free

4.5 Survey Results

A total of 1,067 surveys were completed. The online ad resulted in 55 clicked through to the survey link, but fewer than 9 completed the survey (see Table 10). Based on the data of survey respondents social media pushes through the month of August and September garnered approximately 115 survey completions. A press release distributed to targeted Houston media produced a spike in data responses between the dates of 8/21/2012 and 8/24/2012 resulting in a large number of survey responses (see Figure 12). A print ad as well as an online ad, shown in Figure 13 and Figure 14, was placed with the Houston Chronicle. A story produced by Houston Public Radio station, KUHF posted on 9/4/2012 coupled with the Chronicle ad produced another spike in data between 9/4 and 9/7. Some of this spike may be attributed to the ad placed in the Chronicle on 8/31/2012 as survey respondents may have read the ad between 9/4 and 9/7 upon returning home from the Labor Day holiday. A link to the 9/4/2012 KUHF story is posted here: http://app1.kuhf.org/articles/1346777349-Commuters-Asked-For-Input-On-Katy-Freeway-Managed-Lanes.html. In addition to the traditional and social media outlets publicizing the survey, Harris County Toll Road Authority (HCTRA) and Houston TranStar posted a link to the survey on their respective websites. The link to the TranStar website was very effective (see Table 10), but no referrals came directly from the HCTRA website.

Table 10 Referral URLs for Completed Surveys

URL	Number of Referrals
http:\traffic.houstontranstar.org	420
None	388
Other	199
http://app1.kuhf.org/articles	33
http://instantnewskaty.com/	18
http://myemail.constantcontact.com	9

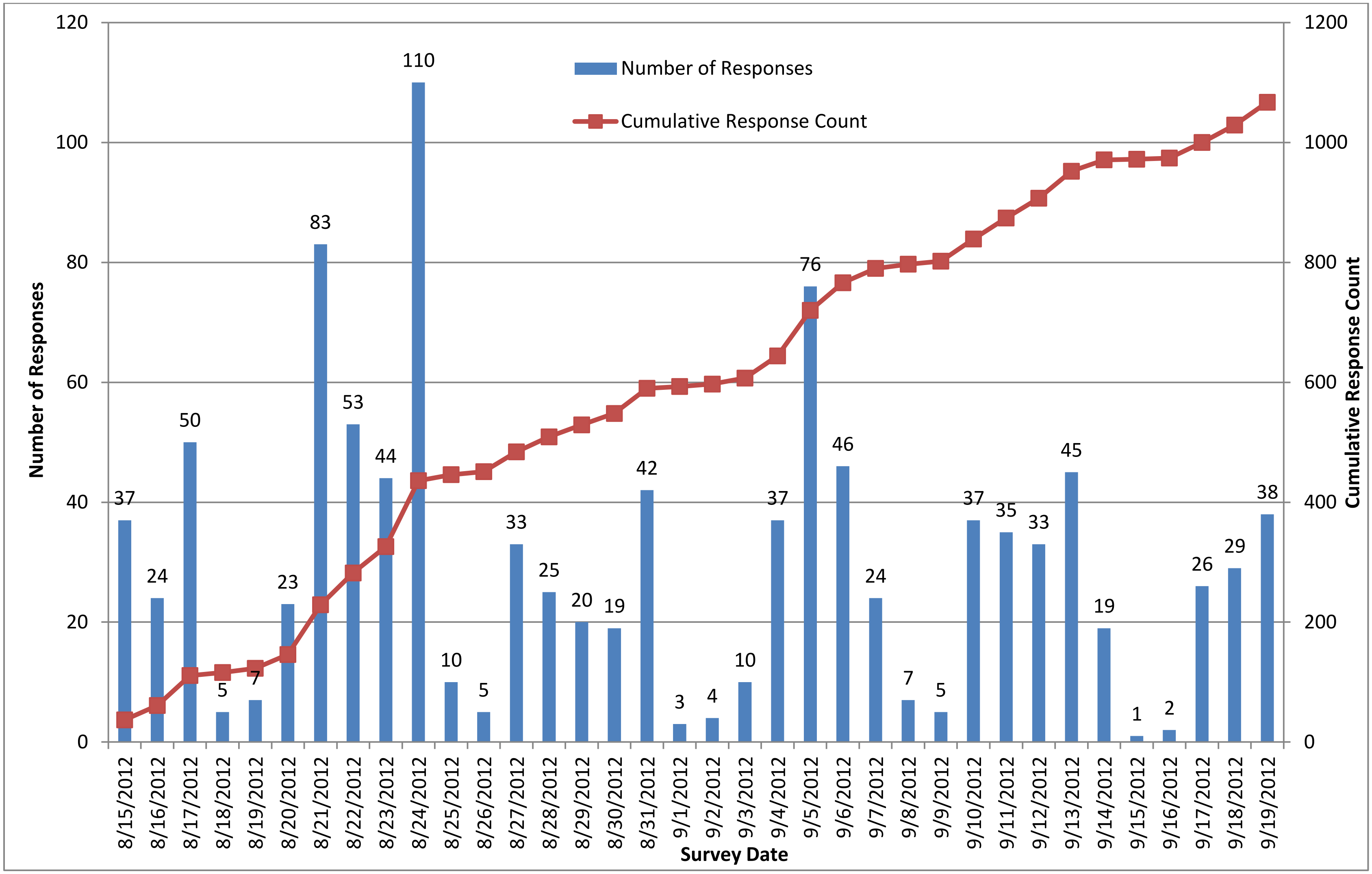


Figure 12 Response Rate by Date

Figure 13 Houston Chronicle Online and Print Ad

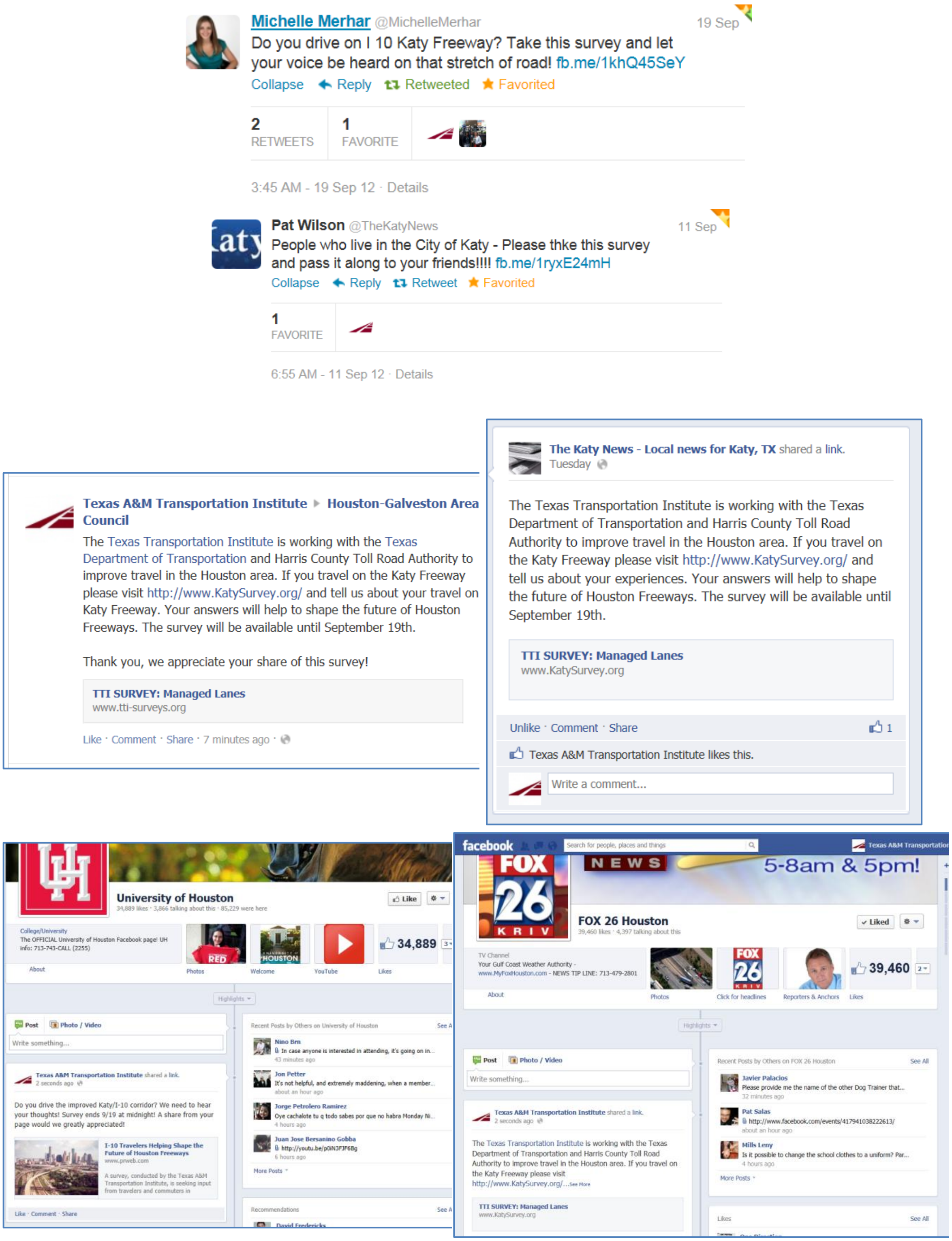


Figure 14 Social Media Posts Samples

4.6 Summary

An online travel survey of Katy Freeway travelers was conducted in 2012 to achieve objectives of this study. The 2012 survey received 1067 complete responses, of those 40 were a mode other than passenger car/SUV or Pickup and were thus removed from analysis. This resulted in 1027 useful responses. The data from the survey will be used to estimate the UT-based and PT-based models using mixed logit modeling methodology described in Section 3.7. Those route choice models will then be used to estimate travelers' values of travel time and/or travel time reliability. The values of travel time from the 2012 survey will then be compared with previous study (Devarasetty, Burris et al. 2012) across two design strategies (D_b-Efficient and Adaptive Random) in this study. This study will also compare the predictive success of models of conventional and PT-based models. Chapter 5 presents a preliminary analysis on the survey responses to help find sample demographic characteristics across design strategies and SP question formats, followed by an in-depth analysis of the survey data using discrete choice modeling techniques.

5. DATA ANALYSIS

The internet-based travel survey of Katy Freeway travelers conducted in 2012 garnered 1,067 completed responses. A very small number of these (40) were a mode other than passenger car/SUV or Pickup and were removed from analysis leaving 1027 responses. This chapter presents a summary of these 1027 responses. This study conducted a preliminary analysis on the survey responses as presented in Section 5.1. This preliminary analysis was useful and may help identify the significant sample demographic characteristics that greatly influence ML use as well as additional variables that require further analysis. The following sections present an in-depth analysis and discussion of the survey data, parameter estimation of various discrete choice models to predict the route choice and the VTTS estimates.

5.1 Preliminary Analysis

5.1.1 Descriptive analysis

To begin, the respondents' socio-economic and commute characteristics were compared based on the survey design they received. Respondents were very similar across all design types with only two significant ($p \leq 0.05$) differences. These were two of the reasons for using MLs (see Table 11). This indicates that travelers with similar characteristics and similar trips answered each group of questions. This makes it more likely than any differences in their choices of modes or VTTS are due to the survey design and not due to having different types of travelers receiving the different survey design types.

Table 11 Traveler Characteristics by Survey Design Method

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
Percent of each design type	12	14	13	13	13	12	10	13	100
Day of Travel of most recent trip on the freeway									
Weekday	89	87	90	90	93	93	94	95	91
Weekend	11	13	10	10	7	8	6	5	9
Direction of travel									
Towards downtown	48	49	45	49	49	53	39	58	49
Away from downtown	52	51	55	51	51	47	61	42	51
Use of GPLs/MLs (based on Travel Direction)									
GPLs (Towards downtown)	31	31	29	29	30	32	18	31	29
GPLs (Away from downtown)	32	34	26	28	25	29	36	21	29
MLs (Towards downtown)	18	17	14	21	18	22	21	27	20
MLs (Away from downtown)	19	18	32	22	26	17	25	22	22
Trip Purpose									
Commuting to or from my place of work	54	49	54	55	60	58	60	65	57
Recreational/Social/Shopping/ Entertainment/Personal Errands	21	22	20	21	21	23	19	15	20
Work related (other than to or from home to work)	18	24	20	23	17	17	17	13	19

Table 11 Continued

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
To attend class at school or educational institute	3	1	1	0	1	1	2	3	1
Other	4	2	3	1	1	0	1	2	2
Vehicle Type									
Passenger Car/SUV/Pick-up Truck	13	13	13	13	13	12	10	13	100
Driver or Passenger									
Driver	92	96	91	95	95	94	92	96	94
Passenger	8	4	7	4	5	6	8	3	6
Number of vehicle occupants									
1	69	72	76	72	70	70	73	80	73
2	22	18	18	16	22	20	18	14	19
3	5	6	5	5	4	4	6	1	4
4	2	3	1	6	1	2	1	3	2
5	2	1	0	1	3	4	2	1	2
Who did you travel with									
Co-worker/person in the same, or a nearby, office building	11	11	28	20	16	16	10	27	16
Neighbor	26	11	0	20	13	18	18	18	3
Adult family member	13	22	19	12	22	12	25	16	49

Table 11 Continued

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
Another commuter in a casual carpool (also known as slugging)	32	22	30	0	25	17	0	0	3
Child	13	18	12	15	24	11	22	27	23
Other	6	16	11	34	0	25	25	12	6
Ever Change of Entry or Exit to have easier access to/from the Managed Lanes									
Yes	53	47	43	53	39	56	45	53	49
No	47	53	57	47	61	44	55	47	51
Number of Change of Entry or Exit to have easier access to/from the Managed Lanes									
0	0	4	5	0	0	0	5	0	1
1	60	65	50	57	36	61	35	52	53
2	28	17	27	37	41	26	50	33	32
3	12	13	18	7	23	13	10	15	14
Respondents Indicated Travel Time of Their Most Recent Trip									
1 to 5 minutes	0	1	1	1	0	2	1	0	1
6 to 10 minutes	4	4	2	5	3	3	3	5	4
11 to 15 minutes	2	9	6	5	8	8	7	5	6

Table 11 Continued

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
16 to 20 minutes	13	10	8	12	7	8	16	10	10
21 to 25 minutes	12	10	11	12	6	3	10	8	9
26 to 30 minutes	15	14	9	13	11	17	6	8	12
31 to 35 minutes	4	7	10	10	9	8	5	10	8
36 to 40 minutes	9	10	5	10	8	3	8	11	8
41 to 45 minutes	14	12	14	8	18	15	17	9	14
46 to 50 minutes	3	5	10	3	7	4	3	6	5
51 to 55 minutes	3	2	4	2	3	2	3	3	3
56 to 60 minutes	5	7	10	9	5	8	6	15	8
60+ minutes	16	8	11	11	15	18	17	9	13
All Inclusive (Average Travel Time in minutes)	37	34	38	35	38	38	37	38	37
Ever Used the MLs									
Yes	77	75	63	79	74	73	66	74	73
No	23	25	38	21	26	27	34	26	27
Reasons for using the MLs (442 respondents)									
Access to/from to the Tollway lanes is convenient for my trips	10	23	10	13	8	13	10	13	12
Being able to use the lanes for free as a carpool*	19	17	12	14	10	14	5	9	26

Table 11 Continued

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
Travel times on the Tollway lanes are consistent and predictable	12	13	9	14	14	18	6	14	18
The Tollway saves time*	14	18	10	15	10	13	9	11	64
During the peak hours the Tollway will not be congested	13	16	9	13	14	13	9	12	34
The Tollway lanes are safer than the general purpose lanes	18	13	12	12	13	16	4	13	17
The Tollway lanes are less stressful than the general purpose lanes	15	15	11	13	11	13	8	13	36
Trucks and large vehicles are not allowed on the Tollway	18	13	7	10	16	20	5	11	14
Someone else pays my tolls	24	6	0	24	0	24	12	12	4
Other:	8	5	18	8	23	10	10	18	9
Reasons for NOT using the MLs (165 respondents)									
Access to/from to the Katy Tollway lanes is not convenient for my trips	7	8	5	3	8	10	6	11	18
I have the flexibility to travel at less congested times	5	8	13	11	8	12	6	2	20
I do not feel safe traveling on the Tollway lanes	0	2	2	0	2	0	2	0	3

Table 11 Continued

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
The toll is too expensive for me	7	11	10	30	16	17	14	15	36
The Tollway does not offer me enough time savings	16	17	13	14	10	12	14	17	34
I can easily use routes other than the Katy Freeway, so I'll just avoid Katy Freeway if I think there is a lot of traffic	12	4	11	3	6	10	4	2	16
It is too complicated / confusing to use the Tollway	2	2	10	8	10	4	8	4	15
I avoid toll roads whenever possible	16	9	10	11	10	10	14	13	28
I don’t want to have a toll transponder in my vehicle	9	8	5	5	4	4	2	7	13
I don’t have a credit card needed to setup a toll transponder account	0	2	0	0	2	0	2	2	3
I don't like that the toll changes based on the time of day	9	9	10	11	10	12	14	9	26
I don’t have anyone to carpool with	12	13	10	5	8	6	6	9	21
Other:	5	8	3	0	4	6	6	9	13

Table 11 Continued

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
Law Enforcement									
Providing too little enforcement on the Katy Tollway?	33	22	32	22	30	28	30	26	29
Providing too much enforcement on the Katy Tollway?	12	19	22	18	20	20	24	23	19
Providing the right level of enforcement on the Katy Tollway?	54	59	46	60	50	52	46	51	52
Number of Trips on the GPLs in Last Week									
0	10	9	13	9	19	12	10	13	12
1	8	7	6	10	8	8	9	3	7
2	10	15	14	8	10	14	12	10	12
2.5	1	0	0	0	0	0	0	0	0
3 to 5	22	23	25	33	22	23	28	27	25
6 to 10	43	39	39	31	35	37	36	40	37
11 to 15	4	5	3	6	5	3	2	5	4
16 to 20	2	1	0	2	2	2	3	1	1
21 to 25	0	1	0	1	0	0	0	0	0
26 to 30	0	0	0	0	1	1	0	1	0
30+	0	0	1	0	0	0	0	0	0

Table 11 Continued

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
Number of Trips on the MLs in Last Week									
0	30	38	28	28	36	30	27	32	31
1	12	16	14	10	13	13	12	9	12
2	15	9	16	13	6	12	10	17	12
2.5	1	0	0	0	0	0	0	0	0
3 to 5	26	23	15	31	18	30	24	26	24
6 to 10	15	13	27	18	25	13	28	16	19
11 +	0	1	0	0	1	1	0	0	0
Average Toll Paid Per Trip									
Less than $1.00	20	20	27	17	20	20	24	9	19
$1.00 to $1.99	21	26	19	23	7	20	15	20	19
$2.00 to $3.99	21	25	20	22	29	30	17	25	24
More than $4.00	16	9	19	16	22	13	27	19	17
Perceived Travel Time Savings									
Less than 2 minutes	1	0	3	1	1	3	3	1	1
3 to 5 minutes	6	6	5	8	3	6	4	6	5
6 to 10 minutes	12	17	12	13	11	13	8	13	13
11 to 15 minutes	15	9	14	12	15	13	10	14	13
16 to 20 minutes	11	4	9	14	7	6	18	9	9
21 to 25 minutes	4	6	0	5	2	8	7	7	5
26 to 30 minutes	2	1	3	5	4	4	2	5	3

Table 11 Continued

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
More than 30 minutes	3	1	2	1	4	3	1	1	2
Unsure	5	7	7	4	6	2	7	3	5
Pay for Parking in Houston									
Yes	15	20	19	17	16	15	21	18	17
No	85	80	81	82	83	85	79	82	82
Parking Cost Per Day ($)									
0	0	0	4	5	0	0	0	0	1
0.01 to 1.00	5	0	4	0	0	0	14	4	1
1.01 to 2.00	5	8	0	5	5	0	5	4	4
2.01 to 3.00	0	20	8	9	10	6	0	17	9
3.01 to 5.00	21	28	17	14	29	18	18	17	20
5.01 to 10.00	47	32	33	41	24	53	50	29	38
10.01 to 15.00	11	12	21	18	19	18	5	25	15
15.01 to 20.00	5	0	4	9	5	6	5	4	5
20.01 to 25.00	0	0	8	0	5	0	5	0	3
25.01 to 30.00	0	0	0	0	0	0	0	0	0
30+	5	0	0	0	5	0	0	0	1
Gender									
Male	61	64	58	53	54	58	60	60	58
Female	37	34	37	42	44	38	38	38	39
Age									
18 to 24	3	5	1	5	4	3	0	2	3

Table 11 Continued

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
25 to 34	29	24	29	22	25	23	28	25	26
35 to 44	25	17	27	29	27	23	26	27	25
45 to 54	19	28	19	25	19	24	18	26	22
55 to 64	17	20	14	10	16	16	17	15	15
64 or older	3	5	5	4	5	6	5	3	4
Refused	2	1	1	2	1	4	3	1	2
Race/Ethnicity									
White/Caucasian	72	78	75	71	79	73	69	78	74
Hispanic/Latino	8	9	5	5	8	8	6	8	7
African American	2	4	4	4	4	4	4	2	4
Asian American	4	2	7	5	0	3	9	4	4
Native American	2	0	1	0	0	0	1	1	0
Refused	11	5	4	11	7	11	11	5	8
Highest Level of Education									
Less than high school	0	1	0	1	1	1	0	0	0
High school graduate	4	3	2	7	1	2	5	3	3
Some college or vocational	20	20	16	15	17	24	27	18	19
College Graduate	44	41	50	50	50	46	35	41	45
Postgraduate degree	25	31	24	21	24	25	27	32	26
Income									
Less than $10,000	2	1	0	2	1	0	0	2	1
$10,000 to $14,999	2	0	1	2	1	0	0	1	1
$15,000 to $24,999	0	1	1	1	1	1	0	1	1

Table 11 Continued

Characteristic	Percent (%) of Travelers								
	D_b-Efficient				Adaptive Random				Overall
	Conventional MNL	Reference Point	PT-pwf	PT-Full	Conventional MNL	Reference Point	PT-pwf	PT-Full	
$25,000 to $34,999	4	4	2	1	2	0	4	1	2
$35,000 to $49,999	6	5	5	6	4	7	5	5	5
$50,000 to $74,999	11	14	14	12	11	13	14	15	13
$75,000 to $99,999	11	17	16	22	15	17	10	16	16
$100,000 to $199,999	37	35	31	32	41	39	44	32	36
$200,000 or more	10	14	14	9	11	13	10	9	11

* = significant (p <0.05) differences between respondents by survey design type.
A = these sum to more than 100% as respondents could select multiple answers to this question.
B = due to a mistake in the question skip pattern of the survey respondents who used MLs on their current trip were not asked their reasons for using the lanes.
C = due to a mistake in the question skip pattern of the survey respondents who used MLs on their current trip were the only group asked this question.

5.1.2 Comparison of respondent by groups

Next, traveler characteristics were examined based on their choice of option in the SP questions. Each respondent could answer up to 3 SP questions and, therefore, each respondent may have up to 3 entries in this analysis, one for each SP question answered. In this analysis any differences in characteristics based on option selected may help identify characteristics that will be useful in modeling route choice. There were many significant ($p \leq 0.05$) differences in the characteristics of travelers based on option chosen (see Table 12). The values with significant differences by mode chosen as well as the variables that have the largest percentage difference by mode chosen, are the most likely to be significant variables in models of mode choice.

Travelers choosing to carpool on the GPLs were more likely to be on Recreational/Social/ Shopping/Entertainment/Personal Errands trips and less likely to be commuting to or from work. This was somewhat surprising since the MLs were cheaper, and often free, for carpools. In examining these respondents, they were over twice as likely (52% versus 20%) as commuting trips to be traveling in the off-peak period – and therefore not seeing nearly as much travel time savings from the MLs. Similarly, travelers who chose to carpool on the GPLs were much more likely to pay to park in Houston (30% versus 17% for other mode choices). This may again be due to Recreational/Social/Shopping/Entertainment/Personal Errands trips. These trips were more likely to have to pay for parking and, as noted earlier, were more likely to travel during off-peak. However, time of day had little impact on whether the traveler paid to park as the difference from peak (17.0% paid to park) to off-peak (17.2% paid to park) was very small. Therefore, time of day would appear to be an unimportant variable to include in the models. This is despite the fact toll rates and travel time savings vary in the SP questions by time of day. Therefore, this difference in the lanes should have already been accounted for.

Table 12 Traveler Data by Mode Choice (Online Survey)

Characteristic / Mode	Percent of Travelers Choosing Mode:				All
	DA-GPL	CP-GPL	DA-ML	CP-ML	
Day of Travel of most recent trip on the freeway*					
Weekday	91	84	94	89	91
Weekend	9	16	6	11	9
Direction of travel*					
Towards downtown	49	51	46	53	49
Away from downtown	51	49	54	47	51
Use of GPLs/MLs (based on Travel Direction) *					
GPLs (Towards downtown)	38	36	19	21	30
GPLs (Away from downtown)	39	30	19	18	30
MLs (Towards downtown)	11	15	27	32	19
MLs (Away from downtown)	12	19	35	29	21
Trip Purpose*					
Commuting to or from my place of work	59	40	55	60	58
Recreational/Social/Shopping/ Entertainment/Personal Errands	20	39	18	23	21
Work related (other than to or from home to work)	19	18	24	11	19
To attend class at school or educational institute	1	2	2	2	1
Other	1	2	1	3	2
Vehicle Type*					
Passenger Car/SUV/Pick-up Truck	53	3	26	18	100
Driver or Passenger*					
Driver	96	80	97	88	95
Passenger	4	20	3	12	5
Number of vehicle occupants*					
1	82	33	82	41	73
2	12	49	14	40	19
3	3	3	2	12	4
4	2	9	2	3	2
5	1	6	1	5	2

Table 12 Continued

Characteristic / Mode	Percent of Travelers Choosing Mode: DA-GPL	CP-GPL	DA-ML	CP-ML	All
Who did you travel with*					
Co-worker/person in the same, or a nearby, office building	12	25	22	25	16
Neighbor	4	4	8	3	3
Adult family member	67	61	51	51	48
Another commuter in a casual carpool (also known as slugging)	1	1	1	4	3
Child	31	28	21	27	23
Other	8	1	8	4	6
Ever Change of Entry or Exit to have easier access to/from the Managed Lanes*					
Yes	47	67	47	53	49
No	53	33	53	47	51
Number of Change of Entry or Exit to have easier access to/from the Managed Lanes*					
0	3	0	0	2	2
1	51	42	54	54	53
2	31	38	29	35	32
3	15	21	16	9	14
Respondents Indicated Travel Time of Their Most Recent Trip*					
1 to 5 minutes	1	2	0	0	1
6 to 10 minutes	5	4	3	2	4
11 to 15 minutes	7	10	5	4	6
16 to 20 minutes	11	6	11	8	10
21 to 25 minutes	9	16	10	7	9
26 to 30 minutes	12	15	10	12	12
31 to 35 minutes	8	6	8	9	8
36 to 40 minutes	8	8	8	8	8
41 to 45 minutes	13	16	13	16	14
46 to 50 minutes	4	7	7	4	5
51 to 55 minutes	2	0	3	3	3

Table 12 Continued

Characteristic / Mode	Percent of Travelers Choosing Mode:				All
	DA-GPL	CP-GPL	DA-ML	CP-ML	
56 to 60 minutes	8	8	8	9	8
60+ minutes	12	4	14	16	13
All Inclusive (Average Travel Time in minutes)	35	32	38	40	37
Ever Used the MLs*					
Yes	69	64	87	76	73
No	31	36	13	24	27
Reasons for using the MLs*					
Access to/from to the Tollway lanes is convenient for my trips	13	5	18	5	12
Being able to use the lanes for free as a carpool	25	33	18	52	26
Travel times on the Tollway lanes are consistent and predictable	17	18	28	14	18
The Tollway saves time	69	50	78	64	64
During the peak hours the Tollway will not be congested	34	45	41	37	34
The Tollway lanes are safer than the general purpose lanes	17	13	23	21	17
The Tollway lanes are less stressful than the general purpose lanes	37	8	48	41	36
Trucks and large vehicles are not allowed on the Tollway	12	10	23	18	14
Someone else pays my tolls	4	0	5	5	4
Other:	11	13	4	12	9
Reasons for not using the MLs *					
Access to/from to the Katy Tollway lanes is not convenient for my trips	19	16	24	4	17
I have the flexibility to travel at less congested times	20	36	16	19	19

Table 12 Continued

Characteristic / Mode	Percent of Travelers Choosing Mode:				All
	DA-GPL	CP-GPL	DA-ML	CP-ML	
I do not feel safe traveling on the Tollway lanes	3	4	0	0	2
The toll is too expensive for	39	16	26	33	35
The Tollway does not offer me enough time savings	38	28	29	21	33
I can easily use routes other than the Katy Freeway, so I'll just avoid Katy Freeway if I think there is a lot of traffic	18	4	16	10	16
It is too complicated / confusing to use the Tollway	12	16	13	40	15
I avoid toll roads whenever possible	33	32	18	6	27
I don’t want to have a toll transponder in my vehicle	13	16	16	10	13
I don’t have a credit card needed to setup a toll transponder account	3	0	3	0	2
I don't like that the toll changes based on the time of day	28	16	13	27	25
I don’t have anyone to carpool with	23	8	13	27	21
Other:	13	12	8	10	12
Law Enforcement*					
Providing too little enforcement on the Katy Tollway?	24	30	25	48	29
Providing too much enforcement on the Katy Tollway?	22	11	22	12	19
Providing the right level of enforcement on the Katy Tollway?	54	59	54	41	52
Number of Trips on the GPLs in Last Week*					
0	8	10	14	20	12
1	6	6	9	10	7

Table 12 Continued

Characteristic / Mode	Percent of Travelers Choosing Mode: DA-GPL	CP-GPL	DA-ML	CP-ML	All
2	11	12	14	11	11
2.5	0	0	0	0	0
3 to 5	25	30	29	22	25
6 to 10	44	37	29	31	37
11 to 15	5	1	3	5	4
16 to 20	1	3	2	2	1
21 to 25	0	0	1	0	0
26 to 30	0	0	0	1	0
30+	0	0	0	0	0
Number of Trips on the MLs in Last Week*					
0	40	33	22	24	31
1	12	14	13	12	12
2	12	12	14	10	12
2.5	0	0	0	0	0
3 to 5	24	14	29	22	24
6 to 10	11	27	22	32	20
11 to 15	0	0	0	1	0
16 to 20	0	0	0	0	0
21 to 25	0	0	0	0	0
26 to 30	0	0	0	0	0
30+	0	0	0	0	0
Average Toll Paid Per Trip*					
Less than $1.00	19	33	9	35	20
$1.00 to $1.99	25	25	16	13	20
$2.00 to $3.99	24	10	30	14	24
More than $4.00	16	8	20	17	17
Don't remember	16	25	25	20	20
Perceived Travel Time Savings (from using the MLs)*					
Less than 2 minutes	5	2	2	1	3
3 to 5 minutes	13	19	7	6	9
6 to 10 minutes	26	24	22	16	22
11 to 15 minutes	21	33	25	20	23
16 to 20 minutes	14	2	17	24	17
21 to 25 minutes	7	13	9	9	8
26 to 30 minutes	5	2	4	9	5

Table 12 Continued

Characteristic / Mode	Percent of Travelers Choosing Mode:				All
	DA-GPL	CP-GPL	DA-ML	CP-ML	
More than 30 minutes	2	6	5	4	4
Unsure	8	0	9	11	9
Pay for Parking in Houston*					
Yes	17	30	18	14	17
No	83	70	82	86	83
Parking Cost Per Day ($)*					
0	1	0	2	0	1
0.01 to 1.00	5	0	1	4	3
1.01 to 2.00	4	10	4	1	4
2.01 to 3.00	11	6	7	8	9
3.01 to 5.00	17	13	26	23	20
5.01 to 10.00	39	32	35	42	38
10.01 to 15.00	18	35	12	10	16
15.01 to 20.00	4	3	6	7	5
20.01 to 25.00	2	0	3	4	2
25.01 to 30.00	0	0	0	0	0
30+	0	0	4	0	1
Gender*					
Male	62	53	60	57	60
Female	38	47	40	43	40
Age*					
18 to 24	3	4	2	5	3
25 to 34	26	34	26	28	26
35 to 44	24	23	26	27	25
45 to 54	23	26	22	24	23
55 to 64	16	11	18	12	16
64 or older	6	3	5	1	5
Refused	2	0	1	2	2
Race/Ethnicity*					
White/Caucasian	77	65	82	69	76
Hispanic/Latino	6	8	7	12	7
African American	4	6	2	5	4
Asian American	4	8	3	6	4
Native American	0	0	1	0	0
Refused	10	13	5	8	8
Highest Level of Education*					
Less than high school	0	0	0	1	1

Table 12 Continued

Characteristic / Mode	Percent of Travelers Choosing Mode:				All
	DA-GPL	CP-GPL	DA-ML	CP-ML	
High school graduate	4	7	2	3	3
Some college or vocational	18	12	23	22	20
College Graduate	47	40	49	40	46
Postgraduate degree	27	37	24	30	27
Refused	4	4	2	4	3
Income*					
Less than $10,000	1	2	1	2	1
$10,000 to $14,999	1	0	1	1	1
$15,000 to $24,999	1	1	0	1	1
$25,000 to $34,999	3	0	2	2	2
$35,000 to $49,999	6	16	5	6	6
$50,000 to $74,999	16	17	13	13	15
$75,000 to $99,999	18	20	18	19	18
$100,000 to $199,999	40	36	43	47	42
$200,000 or more	12	8	16	9	13

* = significant ($p < 0.05$) differences between respondents by mode chosen.
A = these sum to more than 100% as respondents could select multiple answers to this question.
B = due to a mistake in the question skip pattern of the survey respondents who used MLs on their current trip were not asked their reasons for using the lanes.
C = due to a mistake in the question skip pattern of the survey respondents who used MLs on their current trip were the only group asked this question.

5.2 Parameter Estimation in Logit Model on Survey Data

In the previous section, a preliminary analysis of the data was conducted to check for sampling bias and identify the potential variables influencing the ML usage. To accomplish the proposed objectives of this research, in this section analysis of the survey data using advanced discrete models is presented. In this section, based on the four formats of the SP questions, mixed logit models were developed for the survey responses to predict the mode choices on the use of MLs from conventional utility theory and PT frameworks. From these models the VTTS and/or the VOR were estimated.

The first objective of this research is to estimate the PT proposed value functions and probability weighting functions and compare the prediction results (succeed rate) of travelers' route choice decision between the MLs and GPLs. In addition, the parameter estimates in the value function and probability weighting functions will be the indicators of the aforementioned psychological phenomena: loss aversion and risk seeking – this is our second objective. For example, α and β in the value function measure the degrees of diminishing sensitivity, and λ describes the degree of loss aversion. This will help us understand how Katy Freeway travelers value variance of travel time and the reliability, and the estimated probability weighting functions will improve our understanding if travelers would transform the probability of an event (uncertainty of the travel time of a trip in this study) using some decision weights. The shape of the hypothetical probability weighting functions has been discussed in Section 3.1 (see Figure 2). Here we discuss the shape of a probably value function (see Figure 15). As can be seen from the figure, in the domain of gain the value function is concave and suggests diminishing marginal utility in the arriving barely early area (we assume that the travelers may translate the travel time savings/losses into arriving early/late at their destination). This is understandable because travelers may expect to arrive at their destination (particularly the office/work site) just a few minutes (say one to five minutes) before the start time. Within this area, the earlier the arrival the higher the traveler would value that early arrival. In the arriving fairly early area the value function curve is flat because travelers may perceive the same benefit from arriving early - it does not matter if it is ten or twenty minutes early. The gain in travel time cannot exceed a certain value so the curve ends at a certain point. The value function curve in the domain of loss in the arriving barely late is much steeper than in the arriving barely early area. It is apparent that travelers would value arriving late a lot more than in the domain of gain. For example, to most people the damage caused by arriving five minutes late is much more than the benefit of arriving five minutes early, even the gain and loss in travel time are of the same magnitude. In the arriving too late area, the curve is almost flat because travelers may not place more value in the case of being too late for work – being one or two hours late or even longer may not make a significant difference when reaching some limit. This phenomenon, loss looms more to people than gain, has been repeatedly observed in previous studies (Knetsch and Sinden 1984; Knetsch 1989; Kahneman, Knetsch et al. 1991; Tversky and Kahneman 1991; Knetsch 1992).

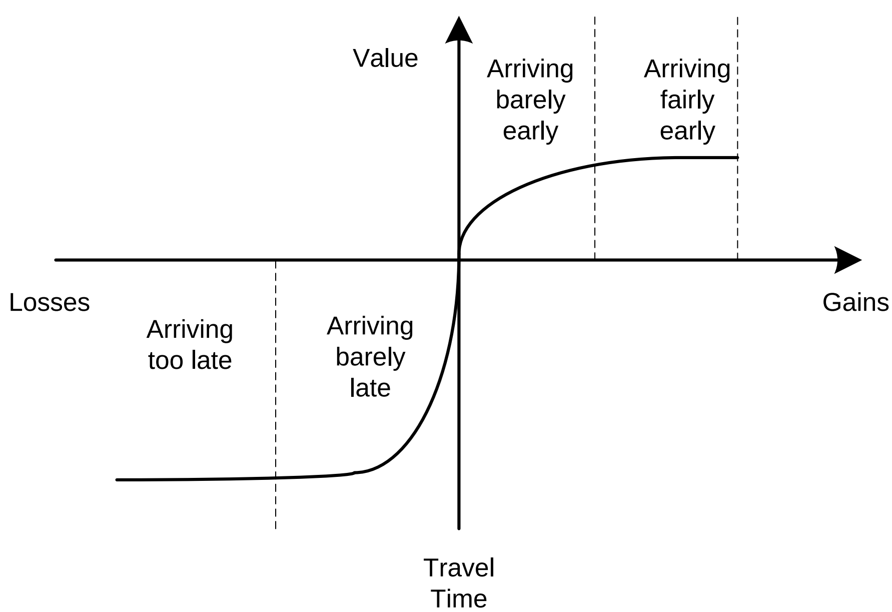


Figure 15 Probable Value Function for This Study

Based on the four design strategies of the SP questions, four types of logit models (UT based and PT based) were developed for the survey responses to predict the travel demand on the use of MLs using the conventional MNL models and mixed logit models with PT-based value functions and probability weighting functions. This would also allow us to compare the efficiency in the parameter estimates for the responses obtained from the four survey designs. The value of travel time savings (VTTS) and/or the value of travel time reliability (VOR) will be estimated from these four models, which is the third objective of this research. The WTP estimates from this study will be compared to those values from the previous surveys (2008 and 2010) to see if there is a difference in the WTP estimates. This will also help us empirically compare and conclude the more effective survey designs in estimating the WTP for a transportation facility which is non-existent or proposed, and this is the fourth objective of this research.

The fourth objective of this research is to test the impact of the framing of questions in the SP survey on the estimation of WTPs. This study proposes two question framing strategies. The first framing strategy presents the attribute levels (as in the conventional MNL model) as travel time, while the attribute levels were presented as travel time difference in a context that the most recent travel time used as the reference point. The fifth objective is to test the improvement of incorporating probability weighting functions in the calculation of utility by comparing the prediction power and the efficiency of parameter estimation, and our last objective is to conduct a segmentation analysis and investigate any difference of attitude towards risk and the use of probability weighting by different groups based on respondents' trip characteristics and demographics.

This section presents the results of various discrete choice models using the survey data collected from different question formats and design strategies (see Figure 7). To begin, this section starts with the conventional MNL model (see Figure 8 for an example question in this format). Because two survey design strategies (D_b-Efficient and

Adaptive Random) were used in generating the stated preference questions, we start the MNL model using D_b-Efficient produced survey response data, then the Adaptive Random data, then the All Inclusive data which is the combination of the two datasets. Similarly, the following sections present the modeling and results of Reference Point model (Figure 9), PT-pwf model (Figure 10), and PT-Full model (Figure 11).

5.2.1 Model estimation with the conventional MNL model (survey question format A)

In Section 5.1 the characteristics of the survey respondents were compared based on their chosen mode in the SP questions (Table 12). The modes included SOV or HOV on MLs or GPLs, and varied based on time of day, travel time, travel time variability, and toll values. This analysis provides some indication as to how different characteristics/variables may affect mode choice. However, such one dimensional analysis is constrained to incorporating only one variable at a time. In this section, using the stated preference data, the prediction and modeling of mode choice was developed using the multinomial Logit (MNL) modeling technique. The MNL model can incorporate multiple factors to provide a better understanding of the influence of included variables. Based on previous studies for mode choice models that include managed lanes, the models should include the travel time, travel time variability, and toll cost as explanatory variables at a minimum.

To predict the mode choice and estimate the value of time and time variability, the MNL model developed here included travel time, travel time variability, and toll rate (see Table 3). The data used for this model was from SP questions presented in Format A (see Table 1 and Figure 8) developed for two survey design strategies (D_b-Efficient and Adaptive Random) (see Figure 7). The utility functions (for the conventional ML model) for each of the four alternatives were given in Equation 26.

The basic, simple utility functions (for the conventional MNL model - Table 1, Format A) for each of the four alternatives (see Figure 8) are given as:

$$
\begin{aligned}
U_{\text{DA-GPL}} &= \beta_{TT} \times \text{TT} + \beta_{TTR} \times \text{TTV} \\
U_{\text{CP-GPL}} &= ASC_{cpgpl} + \beta_{TT} \times \text{TT} + \beta_{TTR} \times \text{TTV} \\
U_{\text{DA-ML}} &= ASC_{daml} + \beta_{TT} \times \text{TT} + \beta_{TTR} \times \text{TTV} + \beta_{toll} \times Toll \\
U_{\text{CP-ML}} &= ASC_{cpml} + \beta_{TT} \times \text{TT} + \beta_{TTR} \times \text{TTV}
\end{aligned}
$$

Equation 26

Where *TT* is the travel time*;* β_{TT} is the parameter associated with travel time, *TTV* is the travel time variability; mathematically, it is the difference between the base case travel time and the worst case travel time; β_{TTR} is the parameter associated with travel time variability, β_{Toll} is the parameter associated with toll paid for using the managed lanes; *Toll* is the toll rate for driving alone on the managed lanes, and *ASCs* are the alternative specific coefficients.

Note only the DA-ML (Drive alone on the Managed Lanes) mode has a variable Toll included in the utility function. This is because the DA-ML is the only mode where that traveler has to pay a toll because those who carpool may go on the toll road without paying the toll.

Travelers' willingness-to-pay or their marginal rate of substitution between money and travel time or travel time variability are important areas of research in transportation. Equation 27 provides the formulae for the marginal WTPs of travel time (WTP_{VTTS}) and travel time reliability (WTP_{VOR}) for the conventional ML model. These flow from the marginal rates of substitution, for example, between travel time and tolls.

$$
\begin{aligned}
WTP_{VTTS} &= \frac{\beta_{TT}}{\beta_{Toll}} \\
WTP_{VOR} &= \frac{\beta_{TTR}}{\beta_{Toll}}
\end{aligned}
$$

Equation 27

Table 13 summarizes the results of the conventional MNL models for the D_b-Efficient, Adaptive Random, and combination of the two datasets. For the D_b-Efficient design dataset, this model yields a value of travel time of $15.56/hour and a low value of reliability of $1.75 per hour. For the Adaptive Random dataset, the coefficient associated with toll rate, however, is positive, which is counterintuitive. The combination of respondents from the D_b-Efficient and Adaptive Random designs included 793 observations (All Inclusive), this model yields a value of travel time of $20.80/hour and a low value of reliability of $2.20 per hour. The conventional MNL model (A) of D_b-efficient dataset generates significant parameter estimates of both *Travel Time* and *Toll Rate* with negative signs suggesting that higher values of these variables are less preferred in such associated mode of travel.

Comparing the significant parameter estimates, in particular the coefficients of *Travel Time* for the three datasets, the Adaptive Random and the overall dataset are not generating significant parameter estimates. This may indicate a better performance of the D_b-Efficient design in this case.

Table 13 Multinomial Logit Model for Respondents Presented with SP Question in Format A

Conventional MNL Model			
	Survey Design		
	D_b-Efficient	Adaptive Random	All Inclusive
Number of Observations	390	402	792
Variable			
NonRandom Parameters in the Utility Functions			
ASC-CP-GPL	- 3.17***	- 3.24***	- 3.20***
ASC-DA-ML	- 0.01	- 0.71*	- 0.39
ASC-CP-ML	- 1.84***	- 0.70*	- 1.06***
Travel Time (minutes)	- 0.14***	0.04	- 0.05
Travel Time Variability (minutes)	- 0.02	- 0.10	0.01
Toll Rate ($)	- 0.54***	0.13**	- 0.15***
	Goodness-of-fit		
Log-likelihood for Constants Only Model	- 436.86	- 451.89	- 894.93
Log-likelihood at Convergence	- 415.25	- 452.39	- 889.96
Adjusted ρ_c^2	0.05	0.00	0.01

Note: ***, **, * ==> Significance at 1%, 5%, 10% level. ASC = alternative specific constant coefficient
Adjusted $_c^2 = 1-\frac{LL(\hat{\beta})-K}{LL(C)-Kc}$ where, $LL(\hat{\beta})$ = log-likelihood for the estimated model, K = number of parameters in the estimated model, $LL(C)$ = log-likelihood for the constants only model, K_c = number of parameters in the constants only model

5.2.2 Model estimation with reference point model (survey question format B)

As discussed in the literature review, two important aspects of prospect theory are the incorporation of value functions for gain and loss, and the probability weighting functions for gain and loss in the calculation of utility. PT assumes that people tend to care more about the change of wealth position, such as if it is a gain or loss. PT also posits that people may translate 'objective' probabilities using non-linear weighting rules, resulting in an over- or under-weighting of such probabilities. Therefore, the value function, $v(x)$, in the utility function (see Equation 1) reflects the subjective value of the outcome, measuring the deviations from the RP into gains and losses. A decision weight (ω) is associated with each probability of occurrence (p) through a probability weighting function, and ω measures how travelers actually perceive the impact of p on the overall value of prospect *V*. Distinct functions are associated with positive and negative outcomes, V^+ and V^-, respectively (see Equation 1). This section aims to investigate the significance of the use of travel time difference relative to the travel time of the respondents' most recent trip in a form of travel time gain and loss by including the *Travel Time Difference* only (instead of the *Travel Time*) in the utility functions (see Table 1 and Figure 9). The effect of incorporating the probability weighting and the combination of the two (value function for gain and loss, and the probability weighting for gain and loss) are examined in later sections. The utility functions (for the Reference Point model) for each of the four alternatives are given in Equation 28.

$$
\begin{aligned}
U_{\text{DA-GPL}} &= \beta_{TTDGain} \times \text{TTD}_{\text{gain1}}^{\alpha} + \beta_{TTDLoss} \times \lambda \times \text{TTD}_{\text{loss}}^{\beta} \\
U_{\text{CP-GPL}} &= ASC_{cpgpl} + \beta_{TTDGain} \times \text{TTD}_{\text{gain1}}^{\alpha} + \beta_{TTDLoss} \times \lambda \times \text{TTD}_{\text{loss}}^{\beta} \\
U_{\text{DA-ML}} &= ASC_{daml} + \beta_{TTDGain} \times \text{TTD}_{\text{gain1}}^{\alpha} + \beta_{TTDGain} \times \text{TTD}_{\text{gain2}}^{\alpha} + \beta_{toll} \times Toll \\
U_{\text{CP-ML}} &= ASC_{cpml} + \beta_{TTDGain} \times \text{TTD}_{\text{gain1}}^{\alpha} + \beta_{TTDGain} \times \text{TTD}_{\text{gain2}}^{\alpha}
\end{aligned}
\qquad \textbf{Equation 28}
$$

Where

- TTD_{gain1} and TTD_{gain2} are the gain in travel time by driving in the GPLs/MLs relative to that of the respondent's most recent trip. In this paper a gain is really a reduction in travel time, a shorter trip.
- $\beta_{TTDGain}$ is the parameter associated with gain in travel time,
- α is the diminishing sensitivity parameter associated with a gain in travel time (where the travel time is shorter than the most recent trip),
- TTD_{Loss} is the loss in travel time driving in the GPLs relative to that of the respondent's most recent trip. In this paper a loss is really an increase in travel time, a longer trip,
- $\beta_{TTDLoss}$ is the parameter associated with a loss in travel time,
- β is the diminishing sensitivity parameter associated with a loss in travel time (where the travel time is longer than the most recent trip),
- λ is the loss aversion parameter associated with a loss in travel time (where the travel time is longer than the most recent trip),
- β_{Toll} is the parameter associated with toll paid for using the managed lanes,
- *Toll* is the toll rate for driving alone on the managed lanes,
- *ASCs* are the alternative specific coefficients.

As discussed in Section 4.2.3, the travel speed on MLs were constrained to be higher than on the GPLs in the stated preference questions, and we assumed that there is a non-zero chance that the travel time of a hypothetical trip on GPLs is longer or shorter than the travel time for the respondent's most recent trip. We also assume that driving alone or carpooling on MLs offers a more reliable trip with a shorter travel time than the GPLs. Therefore, in the utility functions of modes DA-GPL and CP-GPL a gain in travel time (TTD_{gain1}) and a loss in travel time are included. The utility functions of modes DA-ML and CP-ML include two gains in travel time (TTD_{gain1} is the smaller gain and TTD_{gain2} is the larger gain) (see Figure 9).

The marginal utility for *Travel Time Difference* (*TTD*) is given by the partial derivatives of the utility function with respect to *TTD* (Equation 29). Equation 30 gives WTP of travel time difference (WTP_{VTTD}) for the Reference Point Model.

$$\frac{\partial U}{\partial TTD} = \frac{\partial(\beta_{TTDGain} \times \mathrm{TTD}^{\alpha}_{\mathrm{gain1}} + \beta_{TTDGain} \times \mathrm{TTD}^{\alpha}_{\mathrm{gain2}})}{\partial TTD} = \beta_{TTDGain} \times (\alpha \times \mathrm{TTD}^{\alpha-1}_{\mathrm{gain1}} + \alpha \times \mathrm{TTD}^{\alpha-1}_{\mathrm{gain}} \quad \textbf{Equation 29}$$

$$WTP_{VTTD} = \frac{\partial U}{\partial TTD} \Big/ \frac{\partial U}{\partial Toll} = \frac{\beta_{TTDGain} \times (\alpha \times \mathrm{TTD}^{\alpha-1}_{\mathrm{gain1}} + \alpha \times \mathrm{TTD}^{\alpha-1}_{\mathrm{gain2}})}{\beta_{Toll}} \quad \textbf{Equation 30}$$

Table 14 summarizes the results of the Reference Point Model for the D_b-Efficient, Adaptive Random, and All Inclusive datasets. The results indicate that the *Toll Rate* parameter and derived standard deviation of *Toll Rate* are significant. The significant parameter estimate for the derived standard deviation of *Toll Rate* indicates that the dispersion around the mean is statistically non-zero, suggesting that the existence of heterogeneity in the parameter estimate over the sampled population around the mean parameter estimate. For example, different individuals may have individual-specific parameter estimates, and this may be different from the mean parameter estimate of a sample population. The coefficient of *Travel Time Difference* for gain (α) for the three datasets are significant and positive (but less than one), suggesting that the marginal utility for savings in travel time of the survey respondents decreases as the difference becomes larger. Similar to the D_b-Efficient design, in the Adaptive Random design the coefficients of Travel Time Difference for loss (β and λ) are not statistically significant. For the dataset combining D_b-efficient and Adaptive Random the coefficients of *Travel Time Difference* for gain and for loss (α, β and λ) are statistically significant.

The given values of α and β indicate decreasing marginal values in both positive and negative domains which suggests diminishing sensitivity. The combination of β (0.17) and λ (0.92) suggests that the marginal disutility for losses in travel time of the survey respondents decreases as the difference becomes larger. Given the values of α, β and λ, the value function curve is concave for gains and convex for loss (see Equation 2). This result also suggests that for an equivalent travel time difference (gain or loss), the impact of loss (travel time difference is presented as loss) looms larger than the impact of an equivalent gain which is presented as travel time savings suggesting that the utility functions are steeper in the losses than in the gains domain. Figure 16 presents a plot of value function for this model. This is consistent with expectations as the negative consequences of being late usually outweigh the benefits of being early.

Table 14 Mixed Logit Model for Respondents Presented with SP Question in Format B

Reference Point Model			
	Survey Design		
	D_b-Efficient	Adaptive Random	All Inclusive
Number of Observations	405	357	762
Variable			
Random Parameters in the Utility Functions			
Travel Time Difference Gain ($\beta_{TTDGain}$)	1.16	- 1.36	2.54
Travel Time Difference Loss ($\beta_{TTDLoss}$)	0.05	3.42	- 4.16
Toll Rate ($)	- 1.99	- 5.60**	- 1.05**
NonRandom Parameters in the Utility Functions			
ASC-CP-GPL	- 2.53***	- 3.49***	- 3.49***
ASC-DA-ML	- 7.08	2.02	- 0.10
ASC-CP-ML	- 16.76	- 5.00	- 6.18
Travel Time Difference Gain-α (minutes)	1.73	- 0.13	0.09**
Travel Time Difference Loss-β (minutes)	0.18	0.11	0.17**
Travel Time Difference Loss-λ (minutes)	- 4.46	- 0.77	0.92**
Derived Standard Deviations of Random Parameters			
Travel Time Difference Gain ($\beta_{TTDGain}$)	0.99	8.18	1.47
Travel Time Difference Loss ($\beta_{TTDLoss}$)	0.03	1.76	45.67
Toll Rate ($)	3.04***	8.25***	8.70***
	Goodness-of-fit		
Log-likelihood for Constants Only Model	- 406.70	- 373.40	- 789.73
Log-likelihood at Convergence	- 301.37	- 300.15	- 628.25
Adjusted ρ_c^2	0.25	0.20	0.20
	Derived Values		
WTP_{VTTD} (Mean)	13.23	11.05	11.56
WTP_{VTTD} (Median)	10.95	10.37	8.67
S.D. WTP_{VTTD}	6.34	2.89	5.68

Note: ***, **, * ==> Significance at 1%, 5%, 10% level. ASC = alternative specific constant coefficient

Adjusted ${}_c^2 = 1-\frac{LL(\hat{\beta})-K}{LL(C)-Kc}$ where, $LL(\hat{\beta})$ = log-likelihood for the estimated model, K = number of parameters in the estimated model, $LL(C)$ = log-likelihood for the constants only model, K_c = number of parameters in the constants only model

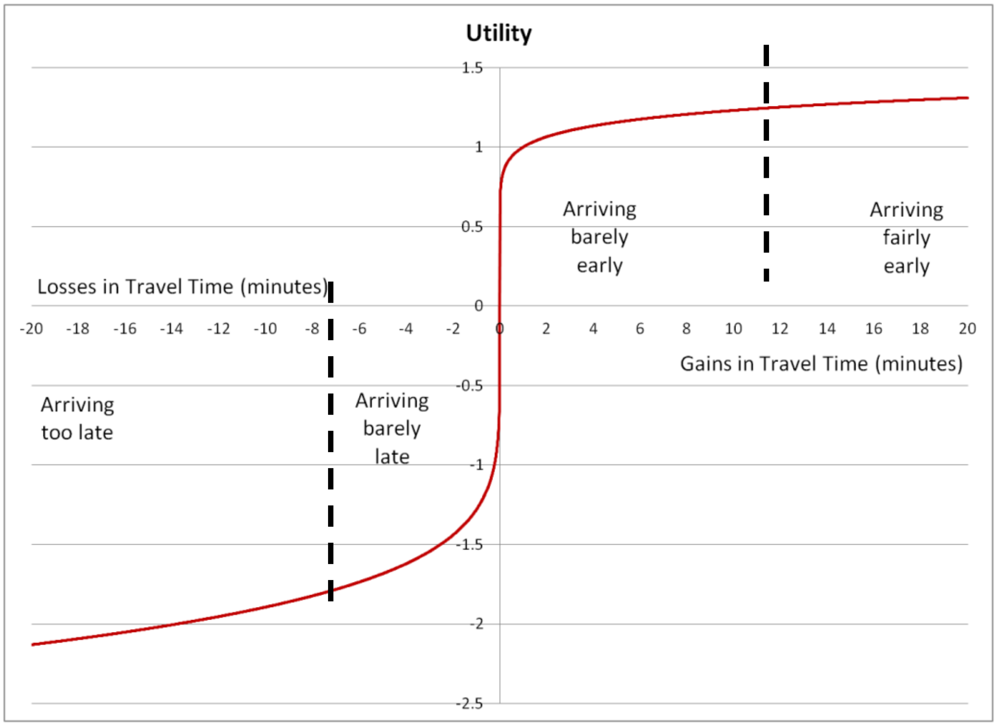


Figure 16 Value Function for Reference Point Model

5.2.3 Model estimation with PT-pwf model (survey question format C)

As mentioned in previous section, one key important development of prospect theory is the incorporation of the probability weighting functions for gain and loss in the calculation of utility. The PT-pwf model (Table 1, Format C) investigates the significance of the inclusion of probability weighing for both gain and loss by including the PT proposed probability weighting functions only in the utility functions. Comparing to survey question Format B, this format uses the travel time (instead of the travel time difference) in the utility calculation (see Table 1 and Figure 10). In this way, the significance of probability weighting may be examined without mixing with the effect of PT proposed value functions. The utility functions (for the PT-pwf model) for each of the four alternatives are given in Equation 31.

$$U_{\text{DA-GPL}} = \beta_{TT} \times \left\{ \left(\frac{\text{Prob}_1^{\delta}}{(\text{Prob}_1^{\delta} + (1-\text{Prob}_1^{\delta})^{\frac{1}{\delta}}} \right) \times \text{TT}_1 + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TT}_2 \right\}$$

$$U_{\text{CP-GPL}} = ASC_{cpgpl} + \beta_{TT} \times \left\{ \left(\frac{\text{Prob}_1^{\delta}}{(\text{Prob}_1^{\delta} + (1-\text{Prob}_1^{\delta})^{\frac{1}{\delta}}} \right) \times \text{TT}_1 + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TT}_2 \right\}$$

$$U_{\text{DA-ML}} = ASC_{daml} + \beta_{TT} \times \left\{ \left(\frac{\text{Prob}_1^{\sigma}}{(\text{Prob}_1^{\sigma} + (1-\text{Prob}_1^{\sigma})^{\frac{1}{\sigma}}} \right) \times \text{TT}_1 + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TT}_2 \right\} + \beta_{toll} \times T$$

$$U_{\text{CP-ML}} = ASC_{cpml} + \beta_{TT} \times \left\{ \left(\frac{\text{Prob}_1^{\sigma}}{(\text{Prob}_1^{\sigma} + (1-\text{Prob}_1^{\sigma})^{\frac{1}{\sigma}}} \right) \times \text{TT}_1 + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TT}_2 \right\}$$

Equation 31

Where

- TT_1 and TT_2 are the two probable travel times for a hypothetical trip,
- $Prob_1$ is the associated probability of occurrence of TT_1,
- γ is the probability weighting parameter for gain,
- $Prob_2$ is the associated probability of occurrence of TT_2,
- δ is the probability weighting parameter for loss,
- *Toll* is the toll rate for driving alone on the managed lanes,
- *ASCs* are the alternative specific coefficients.

The marginal utility for *Travel Time* (*TT*) is given by the partial derivatives of the utility function with respect to *TT* (Equation 32). Equation 33 gives WTP of travel time (WTP_{VTT}) for the PT-pwf model.

$$\frac{\partial U}{\partial TT} = \frac{\partial(\beta_{TT} \times \left\{ \left(\frac{\text{Prob}_1^{\sigma}}{(\text{Prob}_1^{\sigma} + (1-\text{Prob}_1^{\sigma})^{\frac{1}{\sigma}}} \right) \times \text{TT}_1 + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TT}_2 \right\})}{\partial TT}$$

Equation 32

$$= \beta_{TT} \times \left\{ \left(\frac{\text{Prob}_1^{\sigma}}{(\text{Prob}_1^{\sigma} + (1-\text{Prob}_1^{\sigma})^{\frac{1}{\sigma}}} \right) + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}} \right) \right\}$$

$$WTP_{VTT} = \frac{\partial U}{\partial TT} \bigg/ \frac{\partial U}{\partial Toll} = \frac{\beta_{TT} \times \left\{ \left(\frac{\text{Prob}_1^{\sigma}}{(\text{Prob}_1^{\sigma} + (1 - \text{Prob}_1^{\sigma})^{\frac{1}{\sigma}}} \right) + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1 - \text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}} \right) \right\}}{\beta_{Toll}}$$ **Equation 33**

Table 15 shows the results of the PT-pwf models for the D_b-Efficient, Adaptive Random, and combination of the two datasets. The results of the PT-pwf model show that the *Toll Rate* parameter and derived standard deviation of the *Toll Rate* parameter are significant. For the three datasets, the coefficients of both *Probability Weighting for Gain* (γ) and *Probability Weighting for Loss* (δ) are significant at the 1% level. Estimates of γ and δ in the probability weighting functions (see Equation 3) suggest an inverted S-shape which implies that when the function is concave low probabilities are over-weighted and when the function is convex high probabilities are under-weighted. Figure 17 presents the plots of the probability weighting for gain ($\gamma = 0.78$) and loss ($\delta = 0.75$) for the D_b-Efficient design. From this figure, it can be seen that high probabilities for loss are more under-weighted than probabilities for gain, instead low probabilities for loss are more over-weighted than probabilities for gain. This results are consistent with Tversky and Kahneman's (1992) findings ($\gamma = 0.61$ and $\delta = 0.69$) in probability weighting. Figure 18 and Figure 19 present the plots of the probability weighting for the Adaptive Random design gain ($\gamma = 0.69$, $\delta = 0.79$), and the combination ($\gamma = 0.77$, $\delta = 0.81$). From the three figures, particularly Figure 18 and Figure 19, we can see that the probability weighting curves for gain and loss are close and hence we suspect that survey respondents may use one single probability weighting instead of two as initially proposed for gain and loss.

Table 15 Mixed Logit Model for Respondents Presented with SP Question in Format C

PT-pwf Model			
	Survey Design		
	D_b-Efficient	**Adaptive Random**	**All Inclusive**
Number of Observations	381	312	693
Variable			
Random Parameters in the Utility Functions			
Travel Time (Minutes)	- 0.17**	- 0.35***	- 0.14*
Toll Rate ($)	- 2.18***	- 1.68***	- 1.92**
NonRandom Parameters in the Utility Functions			
ASC-CP-GPL	- 2.32***	- 2.89***	- 2.53***
ASC-DA-ML	2.53***	0.22	1.76***
ASC-CP-ML	- 1.43***	- 3.90***	- 2.72***
Probability Weighting - δ	0.75***	0.79***	0.81***
Probability Weighting - γ	0.78***	0.69***	0.77***
Derived Standard Deviations of Random Parameters			
Travel Time (Minutes)	1.50***	1.49***	2.02***
Toll Rate ($)	7.72***	4.41***	6.50***
	Goodness-of-fit		
Log-likelihood for Constants Only Model	- 528.18	- 432.52	- 960.70
Log-likelihood at Convergence	- 353.10	- 287.77	- 621.65
Adjusted ρ_c^2	0.23	0.29	0.35
	Derived Values		
WTP_{VTTD} (Mean)	12.52	14.60	13.72
WTP_{VTTD} (Median)	13.21	14.91	14.10
S.D. WTP_{VTTD}	1.69	1.41	1.59

Note: ***, **, * ==> Significance at 1%, 5%, 10% level. ASC = alternative specific constant coefficient.
Adjusted $_c^2 = 1-\frac{LL(\hat{\beta})-K}{LL(C)-Kc}$ where, $LL(\hat{\beta})$ = log-likelihood for the estimated model, K = number of parameters in the estimated model, $LL(C)$ = log-likelihood for the constants only model, K_c = number of parameters in the constants only model

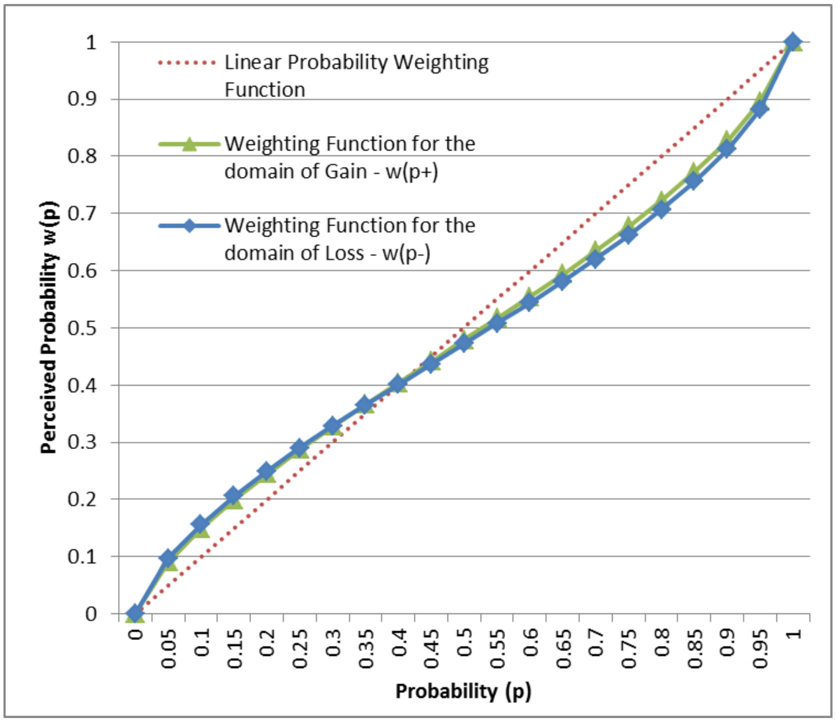


Figure 17 Probability Weighting Curve (Gamma = 0.78, Delta = 0.75)

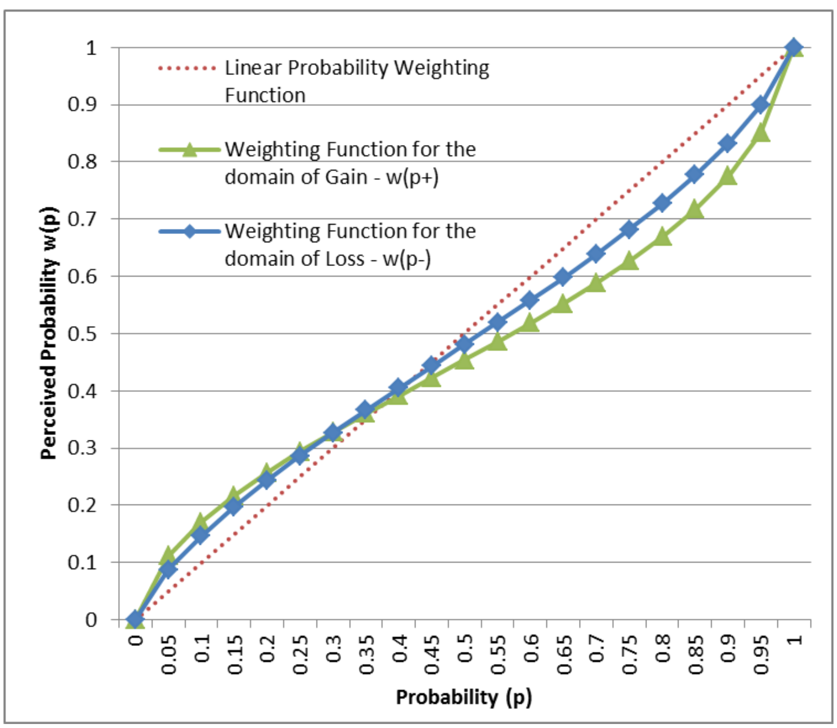


Figure 18 Probability Weighting Curve (Gamma = 0.69, Delta = 0.79)

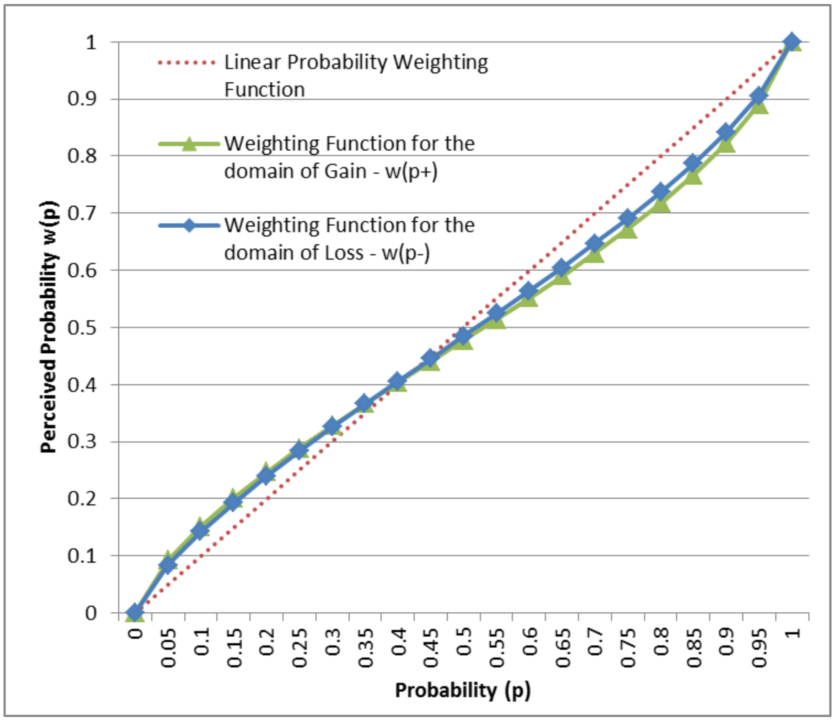


Figure 19 Probability Weighting Curve (Gamma = 0.77, Delta = 0.81)

5.2.4 Model estimation with PT-Full model (survey question format D)

As previously mentioned, two key important aspects of prospect theory are the incorporation of value functions for gain and loss, and the probability weighting functions for gain and loss in the calculation of utility. This section investigates the combined significance of both PT proposed value functions and probability weighting functions in the calculation of utility (see Table 1 and Figure 11). The utility functions (for the PT-Full model) for each of the four alternatives are given in Equation 34.

$$U_{\text{DA-GPL}} = \beta_{TTDGain} \times \left(\frac{\text{Prob}_1^{\gamma}}{(\text{Prob}_1^{\gamma} + (1-\text{Prob}_1^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TTD}_{\text{gain1}}^{\alpha} + \beta_{TTDLoss} \times \left(\frac{\text{Prob}_2^{\delta}}{(\text{Prob}_2^{\delta} + (1-\text{Prob}_2^{\delta})^{\frac{1}{\delta}}} \right) \times \lambda \times \text{TTD}_{\text{loss}}^{\beta}$$

$$U_{\text{CP-GPL}} = ASC_{cpgpl} + \beta_{TTDGain} \times \left(\frac{\text{Prob}_1^{\gamma}}{(\text{Prob}_1^{\gamma} + (1-\text{Prob}_1^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TTD}_{\text{gain1}}^{\alpha} + \beta_{TTDLoss} \times \left(\frac{\text{Prob}_2^{\delta}}{(\text{Prob}_2^{\delta} + (1-\text{Prob}_2^{\delta})^{\frac{1}{\delta}}} \right) \times \lambda \times \text{TTD}_{\text{loss}}^{\beta}$$

Equation 34

$$U_{\text{DA-ML}} = ASC_{daml} + \beta_{TTDGain} \times \left\{ \left(\frac{\text{Prob}_1^{\gamma}}{(\text{Prob}_1^{\gamma} + (1-\text{Prob}_1^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TTD}_{\text{gain1}}^{\alpha} + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TTD}_{\text{gain2}}^{\alpha} \right\} + \beta_{toll} \times$$

$$U_{\text{CP-ML}} = ASC_{cpml} + \beta_{TTDGain} \times \left\{ \left(\frac{\text{Prob}_1^{\gamma}}{(\text{Prob}_1^{\gamma} + (1-\text{Prob}_1^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TTD}_{\text{gain1}}^{\alpha} + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}} \right) \times \text{TTD}_{\text{gain2}}^{\alpha} \right\}$$

Where

- TTD_{gain1} and TTD_{gain2} are the gain in travel time driving in the GPLs/MLs relative to the respondent's most recent trip,
- α is the diminishing sensitivity parameter associated with gain in travel time,
- TTD_{Loss} is the loss in travel time driving in the GPLs relative to that of the respondent's most recent trip,
- β is the diminishing sensitivity parameter associated with loss in travel time
- λ is the loss aversion parameter associated with loss in travel time,
- $Prob_1$ is the associated probability of occurrence of TTD_{gain1} and TTD_{Loss}
- γ is the probability weighting parameter for gain,
- $Prob_2$ is the associated probability of occurrence of TTD_{gain1} and TTD_{gain2}
- δ is the probability weighting parameter for loss,
- *Toll* is the toll rate for driving alone on the managed lanes,
- *ASCs* are the alternative specific coefficients.

The marginal utility for *Travel Time Difference* (*TTD*) is given by the partial derivatives of the utility function with respect to *TTD* (Equation 35). Equation 36 gives WTP of travel time difference (WTP_{VTTD}) for the PT-Full model.

$$\frac{\partial U}{\partial TTD} = \frac{\partial\left(\beta_{TTD} \times \left\{\left(\frac{\text{Prob}_1^{\gamma}}{(\text{Prob}_1^{\gamma} + (1-\text{Prob}_1^{\gamma})^{\frac{1}{\gamma}}}\right) \times \text{TTD}_{\text{gain1}}^{\alpha} + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}}\right) \times \text{TTD}_{\text{gain2}}^{\alpha}\right\}\right)}{\partial TTD}$$
$$= \beta_{TTD} \times \left\{\left(\frac{\text{Prob}_1^{\gamma}}{(\text{Prob}_1^{\gamma} + (1-\text{Prob}_1^{\gamma})^{\frac{1}{\gamma}}}\right) \times \alpha \times \text{TTD}_{\text{gain1}}^{\alpha-1} + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}}\right) \times \alpha \times \text{TTD}_{\text{gain2}}^{\alpha-1}\right\}$$

Equation 35

$$WTP_{VTTD} = \frac{\partial U}{\partial TTD} \Big/ \frac{\partial U}{\partial Toll} = \frac{\beta_{TTD} \times \left\{\left(\frac{\text{Prob}_1^{\gamma}}{(\text{Prob}_1^{\gamma} + (1-\text{Prob}_1^{\gamma})^{\frac{1}{\gamma}}}\right) \times \alpha \times \text{TTD}_{\text{gain1}}^{\alpha-1} + \left(\frac{\text{Prob}_2^{\gamma}}{(\text{Prob}_2^{\gamma} + (1-\text{Prob}_2^{\gamma})^{\frac{1}{\gamma}}}\right) \times \alpha \times \text{TTD}_{\text{gain2}}^{\alpha-1}\right\}}{\beta_{Toll}}$$

Equation 36

Table 16 summarizes the results of the PT-Full models for the D_b-Efficient, Adaptive Random, and the All Inclusive datasets. The results of the PT-Full model (D) investigated the combined significance of both PT proposed value functions and probability weighting functions in the calculation of utility. Besides significant *Toll Rate* parameter and derived standard deviation of *Toll Rate*, other notable results include significant *Travel Time Difference for Gain* (α), and *Probability Weighting for Loss* (δ) and *Probability Weighting for gain* (γ). Similarly to results ($\alpha = 0.09$) in the Reference Point models (see Table 14), a significant and positive α (0.24, 0.30) suggests that the marginal utility for savings in travel time of the survey respondents decreases as the difference becomes larger. Figure 20 presents the plots of the probability weighting for gain ($\gamma = 0.49$) and loss ($\delta = 2.73$). The probability weighting curve for loss shows that the survey respondents extremely under-weight all probability of loss up to 90%.

The estimates of *Probability Weighting for Loss* (δ) and *Probability Weighting for Gain* (γ) from the PT-pwf models (see Table 15) and PT-Full models ($\delta = 2.73$ and $\gamma = 0.49$) confirm the non-linearity in probability weighting. A value smaller than one implies survey respondents overweight small probabilities and underweight high probabilities. For example a value of 0.49 for γ shows that respondents perceive a probability of 0.10 as 0.20, i.e. $\omega^{-}(0.10)$ = 0.20 (Equation 3). Additionally, the big difference between estimates (δ= 0.81 vs. δ= 2.73, γ= 0.77 vs. γ= 0.49) from the two models may indicate a significant difference in the way respondents perceive objective probabilities presented in the two SP question formats (Format C and D). Remember that in the PT-pwf model (Format C), it is the actual travel time (instead of travel time difference) shown to the survey respondent. Instead, in the PT-Full model (Format D), it is the travel time gain/loss shown to the respondents, and in this format the attribute levels were clearly presented as gain or loss and resulted in much more extreme under- and over-weighting.

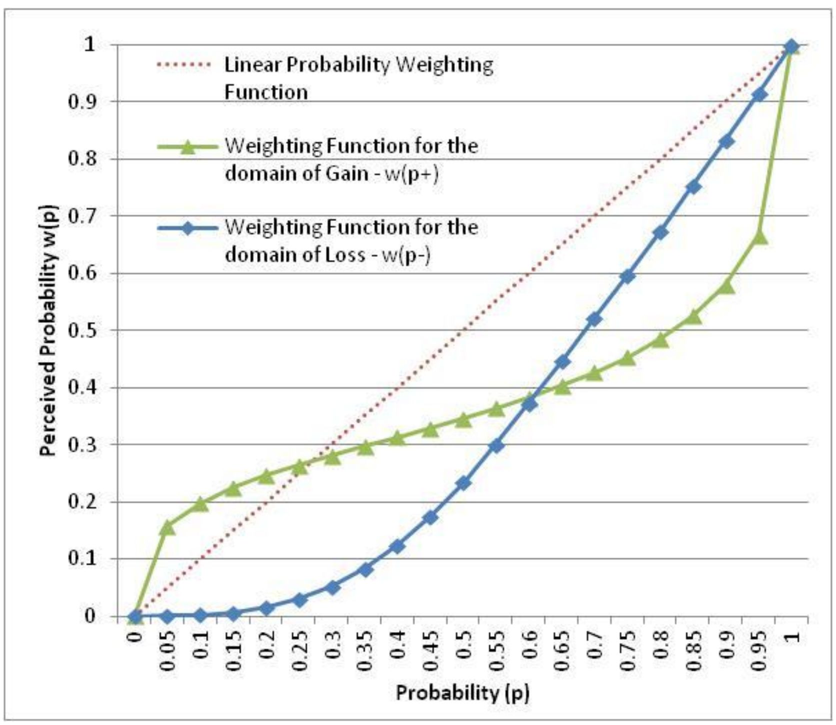


Figure 20 Probability Weighting Curve (Gamma = 0.49, Delta = 2.73)

Table 16 Mixed Logit Model for Respondents Presented with SP Question in Format D

PT-Full Model			
	Survey Design		
	D_b-Efficient	Adaptive Random	All Inclusive
Number of Observations	393	396	789
Variable			
Random Parameters in the Utility Functions			
Travel Time Difference Gain ($\beta_{TTDGain}$)	0.41***	0.45	1.10*
Toll Rate ($)	- 2.88*	0.60	- 1.33***
NonRandom Parameters in the Utility Functions			
ASC-CP-GPL	- 3.02***	- 2.30***	- 2.52***
ASC-DA-ML	1.15	- 2.31***	2.34***
ASC-CP-ML	- 0.88*	- 3.83***	- 1.46***
Travel Time Difference Gain-α (minutes)	0.24***	0.99	0.30***
Travel Time Difference Loss-β (minutes)	0.20	1.23	1.35
Travel Time Difference Loss-λ (minutes)	- 3.42	- 17.79	- 0.72
Probability Weighting Loss - δ	2.66***	0.39***	2.73*
Probability Weighting Gain - γ	0.56***	0.47***	0.49***
Derived Standard Deviations of Random Parameters			
Travel Time Difference Gain ($\beta_{TTDGain}$)	0.48***	2.42	2.59*
Toll Rate ($)	2.17	5.94***	3.04***
	Goodness-of-fit		
Log-likelihood for Constants Only Model	-544.91	-548.28	- 862.01
Log-likelihood at Convergence	-454.81	-358.28	- 722.63
Adjusted ρ_c^2	0.17	0.34	0.17
	Derived Values		
WTP_{VTTD} (Mean)	8.56	13.38	10.66
WTP_{VTTD} (Median)	6.93	12.29	9.91
S.D. WTP_{VTTD}	5.67	6.19	5.36

Note: ***, **, * ==> Significance at 1%, 5%, 10% level. ASC = alternative specific constant coefficient

Adjusted $_c^2 = 1-\frac{LL(\hat{\beta})-K}{LL(C)-Kc}$ where, $LL(\hat{\beta})$ = log-likelihood for the estimated model, K = number of parameters in the estimated model, $LL(C)$ = log-likelihood for the constants only model, K_c = number of parameters in the constants only model

Considering the close estimates for gain and loss probability weighting functions from the PT-pwf model (δ= 0.81 and γ = 0.77), we suspect that in this situation, where an attribute level is not presented in an apparent gain/loss form, respondents may simply use one single probability weighting function, instead of two (one for gain and one for loss), to translate the objective probability of occurrence into subjective weighted probability. However, when the attributes (such as the travel time) are presented in a clear gain/loss format (travel time difference) the respondents are more likely to use different weights for gain and loss as shown in the PT-Full model (δ= 2.73 and γ= 0.49). Fine-tuned empirical experiments specifically examining this issue are needed to further investigate if respondents are using one or two probability weighting values in a context that the attribute is not presented in an obvious gain/loss form.

5.3 Estimation of the Value of Travel Time Savings and the Value of Travel Time Reliability

As shown in Table 17, The conventional MNL model (A) yields a value of travel time savings (VTTS) of \$20.80/hour and a value of travel time reliability of \$2.20 per hour. The mean WTPs of *Travel Time Difference* ($VTTD_{Gain}$) are \$11.56/hour with a standard deviation of \$5.68/hour for the Reference Point model (B), while the mean WTPs of *Travel Time* (VTTS) are \$13.72/hour with a standard deviation of \$1.59/hour for the PT-pwf model (C). For the PT-Full model (D), the mean WTPs of *Travel Time Difference* ($VTTD_{Gain}$) are \$10.66/hour with a standard deviation of \$5.36/hour. Comparing the WTPs of *Travel Time* and *Travel Time Difference* from the four models, we find the values fairly similar and that the travelers have a higher VTTS than $VTTD_{Gain}$. Additionally, these WTP estimates from the Reference Point, PT-pwf, and PT-Full models are half as large as VTTS obtained in a recent study by Devarasetty, Burris et al. (2012) with implied VTTS of \$22/hour by D_b-efficient design from travelers on the same roadway. However, Sikka and Hanley (2012) obtained similar WTP estimates for frequency embedded travel time. In their study, for example, the WTP for mean travel time is $6.98/hour plus a $3.27/hour for travel time reliability to avoid unexpected delays. Using a non-linear logit model embedding probability weighting and risk/ambiguity attitudes, Sikka (2012) derived WTP estimates of $12.18/hour when the chance of delay is 10%, and $11.46/hour if the chance of delay is 90%. Sikka (2012) and our study's WTP estimates may indicate previous projections overestimated VTTS. However, more research on the use of PT models is needed to improve on ML mode prediction. Additionally, the standard deviations associated with the distributed WTP measures are quite large. This is because the cost and travel time difference parameters are distributed and drawing parameter values may lead large values. Note that models presented here in this section included very few preference variables (toll cost, travel time/travel time difference) in the utility equations, which can be considered as the base models. We will include other explanatory variables, such as trip characteristics and socio-economic characteristics, in the models that are presented in Section 5.6.

Table 17 Willingness to Pay Measures Generated from the Four Models

Model Type	WTP Measures	D_b-Efficient	Adaptive Random	All Inclusive
Conventional MNL Model	WTP (Mean)	15.56	N/A	20.80
	WTP (Median)	N/A	N/A	N/A
	S.D. WTP	N/A	N/A	N/A
Reference Point Model	WTP (Mean)	13.23	11.05	11.56
	WTP (Median)	10.95	10.37	8.67
	S.D. WTP	6.34	2.89	5.68
PT-pwf Model	WTP (Mean)	12.52	14.60	13.72
	WTP (Median)	13.21	14.91	14.10
	S.D. WTP	1.69	1.41	1.59
PT-Full Model	WTP (Mean)	8.56	13.38	10.66
	WTP (Median)	6.93	12.29	9.91
	S.D. WTP	5.67	6.19	5.36

5.4 Comparing Survey Designs for Efficiency in Parameter Estimation

The prediction success (the percentage of correct predictions) for the four models were compared to investigate the impact of the two survey design strategies and model types on the prediction capabilities of the models. The percentage of correct predictions for each mode by each design is presented in Table 18. The percent of correct prediction measures for all modes for PT-pwf model is highest followed by the PT-Full model. Excluding the conventional MNL model, Adaptive Random design strategy generates better prediction than the D_b-efficient design strategy. The prediction power of the conventional MNL Model was the lowest among the four models investigated, indicating PT models may prove beneficial for ML mode choice prediction.

Table 18 Percent of Correct Predictions for Each Alternative

Model Type	Mode	Percent of Correct Prediction		
		D_b-Efficient	Adaptive Random	All Inclusive
Conventional MNL Model	DA-GPL	50.00	43.67	46.73
	CP-GPL	0.00	0.00	0.00
	DA-ML	31.58	33.33	31.58
	CP-ML	26.80	22.47	23.65
	All Modes	38.7	34.83	35.43
Reference Point Model	DA-GPL	60.51	73.28	67.69
	CP-GPL	0.00	4.76	3.58
	DA-ML	47.25	63.75	57.25
	CP-ML	20.00	13.33	17.28
	All Modes	48.74	61.27	56.27
PT-pwf Model	DA-GPL	78.07	76.59	79.04
	CP-GPL	5.55	0.00	7.69
	DA-ML	83.49	67.67	75.49
	CP-ML	51.35	76.56	75.19
	All Modes	71.12	71.79	74.60
PT-Full Model	DA-GPL	85.18	76.54	77.93
	CP-GPL	3.57	8.69	5.71
	DA-ML	59.75	60.18	66.51
	CP-ML	46.26	51.28	62.73
	All Modes	67.43	68.98	69.58

5.5 Improvement in Corrective Prediction with Probability Weighting

From the previous results (see Table 18), it seems that incorporating a probability weighting function into utility calculation improves the prediction power with higher correct prediction rate for PT based models (PT-pwf and PT-Full models). Examination of the predictive ability of mode choice of the conventional and PT-based models indicates that the models embedding probability weighting outperform models without such weighting. On average, models with probability weighting result in above 65 percent of all mode choices correctly predicted, while conventional models predict about 35 percent of choices correctly. However, the comparisons of prediction power based on prediction results from those models were not straightforward because these models used different datasets. For example, the prediction results of the conventional models were based on SP question Format A, instead the PT-pwf models were using the Format C. The number of observations as well as the survey respondents in each dataset is different.

Therefore, another evaluation of improvement in predictive power of a PT-pwf and PT-Full model (both include probability weighting functions in the utility estimation) was undertaken. This study examined the difference in prediction results between models with and without probability weighting in the utility estimation for the PT-pwf and PT-Full models. The utility functions for the non-weighted PT-pwf model and non-weighted PT-Full model (both without probability weighting) for each of the four alternatives are given in Equation 37 and Equation 38, respectively. It is the stated probabilities instead of the translated ones were straightly used in the utility estimation. Compare to Equation 31 for PT-pwf and Equation 34 for PT-Full models.

$$
\begin{aligned}
U_{\text{DA-GPL}} &= \beta_{TT} \times (\text{Prob}_1 \times \text{TT}_1 + \text{Prob}_2 \times \text{TT}_2) \\
U_{\text{CP-GPL}} &= ASC_{cpgpl} + \beta_{TT} \times (\text{Prob}_1 \times \text{TT}_1 + \text{Prob}_2 \times \text{TT}_2) \\
U_{\text{DA-ML}} &= ASC_{daml} + \beta_{TT} \times (\text{Prob}_1 \times \text{TT}_1 + \text{Prob}_2 \times \text{TT}_2) + \beta_{toll} \times Toll \\
U_{\text{CP-ML}} &= ASC_{cpml} + \beta_{TT} \times (\text{Prob}_1 \times \text{TT}_1 + \text{Prob}_2 \times \text{TT}_2)
\end{aligned}
\qquad \textbf{Equation 37}
$$

Where TT_1 and TT_2 are the two probable travel times for a hypothetical trip; $Prob_1$ is the associated probability of occurrence of TT_1; $Prob_2$ is the associated probability of occurrence of TT_2; *Toll* is the toll rate for driving alone on the managed lanes; and *ASCs* are the alternative specific coefficients.

$$
\begin{aligned}
U_{\text{DA-GPL}} &= \beta_{TTDGain} \times \text{Prob}_1 \times \text{TTD}^{\alpha}_{\text{gain1}} + \beta_{TTDLoss} \times \text{Prob}_2 \times \lambda \times \text{TTD}^{\beta}_{\text{loss}} \\
U_{\text{CP-GPL}} &= ASC_{cpgpl} + \beta_{TTDGain} \times \text{Prob}_1 \times \text{TTD}^{\alpha}_{\text{gain1}} + \beta_{TTDLoss} \times \text{Prob}_2 \times \lambda \times \text{TTD}^{\beta}_{\text{loss}} \\
U_{\text{DA-ML}} &= ASC_{daml} + \beta_{TTDGain} \times (\text{Prob}_1 \times \text{TTD}^{\alpha}_{\text{gain1}} + \text{Prob}_2 \times \text{TTD}^{\alpha}_{\text{gain2}}) + \beta_{toll} \times \\
U_{\text{CP-ML}} &= ASC_{cpml} + \beta_{TTDGain} \times (\text{Prob}_1 \times \text{TTD}^{\alpha}_{\text{gain1}} + \text{Prob}_2 \times \text{TTD}^{\alpha}_{\text{gain2}})
\end{aligned}
$$

Equation 38

Where TTD_{gain1} and TTD_{gain2} are the gain in travel time driving in the GPLs/MLs relative to that of the respondent's most recent trip; α is the diminishing sensitivity parameter associated with gain in travel time (the travel time is shorter than the most recent trip); TTD_{Loss} is the loss in travel time driving in the GPLs relative to that of the respondent's most recent trip; β is the diminishing sensitivity parameter associated with loss in travel time (the travel time is longer than the most recent trip); λ is the loss aversion parameter associated with loss in travel time (the travel time is longer than the most recent trip); $Prob_1$ is the associated probability of occurrence of TTD_{gain1} and TTD_{Loss}; $Prob_2$ is the associated probability of occurrence of TTD_{gain1} and TTD_{gain2}; *Toll* is the toll rate for driving alone on the managed lanes, and *ASCs* are the alternative specific coefficients.

The percentage of correct predictions for each mode by each design is presented in Table 19. Comparison of the percent of correct prediction measures for all modes for PT-pwf model (see Equation 31) (71% on average) and the PT-pwf model without probability weighting (see Equation 37) (55% on average) indicate that the inclusion of probability weighting in utility function improves the prediction power by 16%. The difference in correct prediction measures for all modes for the PT-Full model (see Equation 34) (68% on average) and the PT-Full model without probability weighting (see Equation 38) (62% on average) is about 6%. Such comparisons indicate that the inclusion of probability weighting in utility estimation is a contributing factor in the improvement in prediction power of PT-pwf and PT-Full models.

Table 19 Comparison of Percent of Correct Prediction for Each Alternative

Mode	Percent of Correct Prediction					
	PT-pwf Model			PT-pwf Model without Probability Weighting		
	D_b-Efficient	Adaptive Random	All Inclusive	D_b-Efficient	Adaptive Random	All Inclusive
DA-GPL	78.07	76.59	79.04	70.26	53.79	65.29
CP-GPL	5.55	0.00	7.69	5.56	0.00	4.17
DA-ML	83.49	67.67	75.49	85.14	53.60	65.89
CP-ML	51.35	76.56	75.19	37.31	27.87	70.97
All Modes	71.12	71.79	74.60	65.35	47.27	64.32
	PT-Full Model			PT-Full Model without Probability Weighting		
	D_b-Efficient	Adaptive Random	All Inclusive	D_b-Efficient	Adaptive Random	All Inclusive
DA-GPL	85.18	76.54	77.93	70.09	73.42	69.00
CP-GPL	3.57	8.69	5.71	4.99	9.09	4.99
DA-ML	59.75	60.18	66.51	57.29	56.36	55.33
CP-ML	46.26	51.28	62.73	50.11	58.53	60.19
All Modes	67.43	68.98	69.58	61.27	63.38	60.96

5.6 Mode Choice Models Including Trip and Socio-Economic Characteristics

In Section 5.2, the parameter estimation of logit models using four survey question formats (A through D) were presented. Results of the models indicate there is significant improvement, in terms of predicative power, in models using PT-based value functions and probability weighting functions. Models presented in the previous sections included very few variables in the utility equations. Variables included Travel Time (TT) or Travel Time Difference (TTD) and/or probability of occurrence (Prob1 or 2). Such models can be considered the base models (see Equation 28, Equation 31, Equation 34). However, other probable explanatory variables, such as trip characteristics, socio-economic characteristics, may also play significant roles in travelers' route choice decision. This section examines the inclusion of explanatory variables (Trip Purpose, Age, Education Level, Income Level, and Gender) in the mixed logit models. A step wise selection procedure was used to identify and select the significant variables. In the step wise selection method, an initial model is fit with no variables and in each step the model is rerun with one additional variable. Each variable is tested in the new model, and the contribution of each added variable to the model is calculated. The model is updated with the most significant variable (maximum contribution) and the process is repeated until no additional remaining variables may help increase the significance of the model. In a forward selection method, a variable is never removed once it is added to the model. However, in the step wise selection method, a variable added in previous steps may be removed at a later rerun. In this method, similarly in the forward selection method, variables are added one at a time to the model and the variables already in the model are also tested and might be removed in each step if found insignificant (Ratner 2003).

5.6.1 Revised conventional MNL model (survey question format A)

Table 20 summarizes the results of the conventional MNL Model with additional trip and socio-economic variables for the D_b-Efficient, Adaptive Random, and All Inclusive datasets. Comparing the results shown in Table 20, except for minor difference in parameter estimates we found that the signs and range of *Toll Rate*, and *Travel Time* parameters are consistent to the estimates in Table 13. The goodness-of-fit of the revised models increased about 3 to 5 percent by including more variables. From the parameter estimates, it can be inferred that male respondents or respondents with postgraduate education are less likely to carpool on the general purpose lanes.

5.6.2 Revised reference point model (survey question format B)

Table 21 summarizes the results of the Reference Point Model with additional trip and socio-economic variables for the D_b-Efficient, Adaptive Random, and All Inclusive datasets. Comparing the results shown in Table 21, except for minor difference in parameter estimates we found that the signs and range of *Toll Rate*, and *Travel Time Difference* parameters (α, β, λ) are consistent to the estimates in Table 14. Note that the number of observations in each dataset for the revised models may not be the same as those for the base models. This is because including additional variables in the revised model results in the removal of a few observations from analysis. For example, because those dummy variables (*Trip Purpose*, *Age*, *Income*, etc.) were added into the model, respondents who didn't answer any of those corresponding questions were then removed. In the following, we will focus on discussion of the results of parameters of interest in this section.

From the parameter estimates, it can be inferred that carpooling on the GPLs is more common for recreational trips. Conversely carpooling on the GPLs is a less preferred mode for commuting or other work related trips. Respondents who are 25 to 44 years old are more likely to choose carpooling on either MLs or GPLs. For the All Inclusive dataset, the coefficients of the dummy variable "*Education*" are negative for the carpooling alternatives. It may imply that respondents with some college education or above are less likely to carpool. The positive sign of coefficient of "Income" indicates that the respondents who belong to the income group ($75,000 to $99,999) are more likely to choose carpooling on the managed lanes. Additionally the overall model fits (Adjusted ρ_c^2) were improved by including additional trip and demographic variables in the logit model.

Table 20 Revised Mixed Logit Model for Respondents Presented with SP Question in Format A

Conventional MNL Model				
		Survey Design		
		D_b-Efficient	Adaptive Random	All Inclusive
Number of Observations		321	349	670
Variable				
NonRandom Parameters in the Utility Functions				
ASC-CP-GPL		- 1.43***	- 1.60***	- 2.92***
ASC-DA-ML		- 0.18	- 0.81	- 0.37
ASC-CP-ML		- 2.34	- 0.70	- 1.14***
Travel Time (minutes)		- 0.16***	0.03	- 0.07*
Travel Time Variability (minutes)		0.01	- 0.10	0.01
Toll Rate ($)		- 0.57	0.14	- 0.18***
Trip and Social-economic characteristics				
NonRandom Parameters	**Alternatives**			
Trip Purpose Commute (dv)	**CP-GPL**	N/A	N/A	- 0.22
Education (College) (dv)	**CP-GPL**	N/A	N/A	0.15
Education (Postgraduate) (dv)	**CP-GPL**	- 36.76***	N/A	- 100
Gender (dv)	**CP-GPL**	N/A	- 1.60***	N/A
		Goodness-of-fit		
Log-likelihood for Constants Only Model		- 366.29	- 454.37	- 804.35
Log-likelihood at Convergence		- 337.06	- 442.94	- 759.87
Adjusted ρ_c^2		0.08	0.03	0.06

Note: ***, **, * ==> Significance at 1%, 5%, 10% level. ASC = alternative specific constant coefficient

Adjusted $_c^2$ = 1-$\frac{LL(\hat{\beta})-K}{LL(C)-Kc}$ where, $LL(\hat{\beta})$ = log-likelihood for the estimated model, K = number of parameters in the estimated model, $LL(C)$ = log-likelihood for the constants only model, K_c = number of parameters in the constants only model

Table 21 Revised Mixed Logit Model for Respondents Presented with SP Question in Format B

Reference Point Model				
		Survey Design		
		D_b-Efficient	Adaptive Random	All Inclusive
Number of Observations		363	309	672
Variable				
Random Parameters in the Utility Functions				
Travel Time Difference Gain ($\beta_{TTDGain}$)		0.74	2.07	5.46
Toll Rate ($)		-7.51***	-1.33**	- 12.24***
NonRandom Parameters in the Utility Functions				
ASC-CP-GPL		- 5.35***	- 3.30***	- 1.25***
ASC-DA-ML		3.76	7.46	- 5.63
ASC-CP-ML		- 6.54	- 15.64	- 22.92
Travel Time Difference Gain-α (minutes)		0.27	0.11	0.14***
Travel Time Difference Loss-β (minutes)		0.17	0.31	0.01
Travel Time Difference Loss-λ (minutes)		- 4.92	- 3.93	- 12.99
Trip and Social-economic characteristics				
NonRandom Parameters	Alternatives			
Trip Purpose Commute (dv)	CP-GPL	N/A	N/A	- 1.45***
Trip Purpose Recreation (dv)	CP-GPL	1.93**	1.20*	N/A
Trip Purpose Work (dv)	CP-GPL	N/A	N/A	- 2.25***
Age (25 – 34) (dv)	CP-GPL	2.68***	N/A	0.96**
Age (25 – 34) (dv)	CP-ML	N/A	2.09***	2.34**
Age (35 – 44) (dv)	CP-GPL	2.20***	N/A	1.07**
Age (35 – 44) (dv)	CP-ML	3.16**	N/A	2.08**
Education (Some College/Vocational) (dv)	CP-GPL	N/A	N/A	- 2.13***
Education (College) (dv)	CP-GPL	N/A	N/A	- 1.77***
Education (College) (dv)	CP-ML	- 4.17***	N/A	N/A
Education (Postgraduate) (dv)	CP-GPL	- 2.12***	N/A	N/A
Education (Postgraduate) (dv)	CP-ML	- 2.85***	N/A	N/A
Income ($75,000 - $99,999) (dv)	CP-ML	N/A	N/A	2.39**

Table 21 Continued

Reference Point Model			
	Survey Design		
	D_b-Efficient	**Adaptive Random**	**All Inclusive**
Number of Observations	363	309	672
Derived Standard Deviations of Random Parameters			
Toll Rate ($)	16.16***	4.19***	28.66***
Travel Time Difference Gain ($\beta_{TTDGain}$)	12.17*	8.49	11.72***
	Goodness-of-fit		
Log-likelihood for Constants Only Model	- 503.22	- 428.36	- 931.59
Log-likelihood at Convergence	- 271.05	- 274.29	- 589.89
Adjusted ρ_c^2	0.46	0.35	0.36
	Derived Values		
WTP_{VTTD} (Mean)	10.11	11.38	10.75
WTP_{VTTD} (Median)	10.25	11.02	10.62
S.D. WTP_{VTTD}	6.41	3.24	5.24

Note: ***, **, * ==> Significance at 1%, 5%, 10% level. ASC = alternative specific constant coefficient

Adjusted $_c^2$ = 1- $\frac{LL(\hat{\beta})-K}{LL(C)-Kc}$ where, $LL(\hat{\beta})$ = log-likelihood for the estimated model, K = number of parameters in the estimated model, $LL(C)$ = log-likelihood for the constants only model, K_c = number of parameters in the constants only model

5.6.3 Revised PT-pwf model (survey question format C)

Table 22 summarizes the results of the PT-pwf Model with additional trip and socio-economic variables for the D_b-Efficient, Adaptive Random, and All Inclusive datasets. Comparing the results shown in Table 15, the signs and range of *Toll Rate*, and *Travel Time* parameters are consistent to the estimates in Table 22. However, some coefficients of both *Probability Weighting for Gain* (γ) and *Probability Weighting for Loss* (δ) are different from previous estimates as shown in Table 15, and this result in very different shapes of probability weighting. For example, for the All Inclusive dataset the *Probability Weighting for Loss* (δ) is 1.93 in the revised model (Table 22) while it is 0.81 in the base model (Table 15). From Equation 3 we can see that δ and γ determine the curvature of the probability weighting function. For values of $0 < \delta$ and $\gamma < 1$, the weighting function has an inverse S-shape with overweighting of low probabilities, and underweighting of high probabilities; for values of $1 < \delta$ and $\gamma < 2$, the weighting function shows a S-shape with underweighting of low probabilities, and overweighting of high probabilities; for values of $2 \leq \delta$ and γ, a convex probability weighting curve will be shown (see Figure 21 for the three curves with δ or γ equal 0.5, 1.5 and 2.5, respectively). The discrepancy of parameter estimates (δ and γ) between the base model (Table 15) and revised model (Table 22) can be attributed to the different number of observations in the two datasets. Note that there are 795 observations in the All Inclusive dataset for the base model while 567 observations in the counterpart for the revised model. The discrepancy of parameter estimates (δ and γ) also suggest that individuals may use very different weights to translate objective probabilities, and this is further verified in Section 5.7.2 where segmentation analysis of survey respondents is presented.

From the parameter estimates, it can be inferred that male respondents are less likely to choose the CP-GPL mode. A negative coefficient estimate of the "*Trip Purpose*" indicates that for recreational or work related trips respondents are less likely to choose carpooling. Respondents who are 25 to 44 years old are more likely to choose carpooling on the managed lanes. Similarly to the Reference Point models, the overall model fits (Adjusted ρ_c^2) were improved by including additional trip and demographic variables in the PT-pwf model.

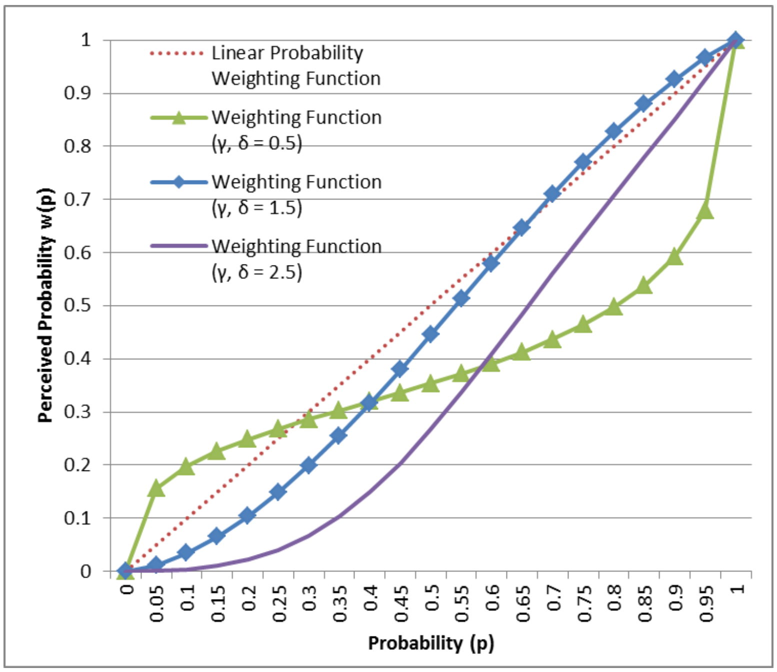


Figure 21 Probability Weighting Curve (Gamma, Delta = 0.5, 1.5, 2.5)

Table 22 Revised Mixed Logit Model for Respondents Presented with SP Question in Format C

PT-pwf Model				
		Survey Design		
		D_b-Efficient	**Adaptive Random**	**All Inclusive**
Number of Observations		303	264	567
Variable				
Random Parameters in the Utility Functions				
Travel Time (Minutes)		- 0.28**	- 0.02	- 0.36***
Toll Rate ($)		- 0.51**	- 1.26	- 7.31***
NonRandom Parameters in the Utility Functions				
ASC-CP-GPL		- 2.81***	- 1.96***	- 2.29***
ASC-DA-ML		0.69	0.01	4.69***
ASC-CP-ML		- 2.47***	- 4.84***	- 2.57***
Probability Weighting - δ		2.45***	0.74***	1.93***
Probability Weighting - γ		0.75***	0.76***	1.10***
Trip and Social-economic characteristics				
NonRandom Parameters	**Alternatives**			
Gender (dv)	**CP-GPL**	N/A	N/A	- 0.62***
Trip Purpose Recreation (dv)	**CP-ML**	N/A	N/A	- 2.85***
Trip Purpose Work (dv)	**CP-ML**	N/A	N/A	- 4.68***
Age (25 – 34) (dv)	**CP-ML**	N/A	N/A	0.92*
Age (35 – 44) (dv)	**CP-ML**	1.48**	1.86	1.07*
Derived Standard Deviations of Random Parameters				
Travel Time (Minutes)		1.69***	2.81***	1.24***
Toll Rate ($)		1.94***	7.06***	17.05***
		Goodness-of-fit		
Log-likelihood for Constants Only Model		- 420.04	- 365.98	- 786.02
Log-likelihood at Convergence		- 262.89	- 237.91	- 533.42
Adjusted ρ_c^2		0.38	0.35	0.32
		Derived Values		
WTP_{VTTD} (Mean)		14.56	15.02	15.12
WTP_{VTTD} (Median)		14.82	15.26	15.09
S.D. WTP_{VTTD}		2.55	2.21	1.36

Note: ***, **, * ==> Significance at 1%, 5%, 10% level. ASC = alternative specific constant coefficient

Adjusted $\rho_c^2 = 1-\frac{LL(\hat{\beta})-K}{LL(C)-Kc}$ where, $LL(\hat{\beta})$ = log-likelihood for the estimated model, K = number of parameters in the estimated model, $LL(C)$ = log-likelihood for the constants only model, K_c = number of parameters in the constants only model only model

5.6.4 Revised PT-Full model (survey question format D)

Table 23 summarizes the results of the PT-Full Model with additional trip and socio-economic variables for the D_b-Efficient, Adaptive Random, and All Inclusive datasets. Comparing the results shown in Table 14 and Table 16, the parameter of *Toll Rate*, *Travel Time Difference* (α, β, λ), and *Probability Weighting* (δ, γ) are close to estimates in this section (Table 23), particularly for the All Inclusive datasets.

From the parameter estimates, it can be inferred that respondents who belong to the age group (25 to 34) are less likely to choose the CP-GPL, and respondents from age group (25 to 34) and (45 to 54) are less likely to choose DA-ML mode. These results are in line with findings from the Reference Point (Table 21) and PT-pwf models (Table 22). Respondents from two income groups ($35,000 to $49,999) and ($75,000 to $99,999) are less likely to choose DA-ML over other modes, while respondents from the highest income group ($200,000 or more) are more likely to choose DA-ML. The results also indicate that the respondents with college education are less likely to choose CP-ML mode.

Table 23 Revised Mixed Logit Model for Respondents Presented with SP Question in Format D

PT-Full Model				
		Survey Design		
		D_b-Efficient	**Adaptive Random**	**All Inclusive**
Number of Observations		327	315	642
Variable				
Random Parameters in the Utility Functions				
Travel Time Difference Gain ($\beta_{TTDGain}$)		7.34**	0.19	0.78
Toll Rate ($)		- 2.16**	- 0.33	- 0.85**
NonRandom Parameters in the Utility Functions				
ASC-CP-GPL		- 4.08***	- 1.13*	- 1.93***
ASC-DA-ML		4.34***	- 1.59	3.53***
ASC-CP-ML		0.47	- 2.71**	- 0.63
Travel Time Difference Gain-α (minutes)		0.01	0.89*	0.64**
Travel Time Difference Loss-β (minutes)		0.63	1.03	8.33
Travel Time Difference Loss-λ (minutes)		1.06	2.22	16.45
Probability Weighting Loss - δ		0.37***	0.28***	3.03*
Probability Weighting Gain - γ		0.45**	0.55***	0.66*
Trip and Social-economic characteristics				
NonRandom Parameters	**Alternatives**			
Age (25 – 34) (dv)	**CP-GPL**	N/A	- 1.14*	N/A
Age (25 – 34) (dv)	**DA-ML**	N/A	N/A	- 1.51***
Age (45 – 54) (dv)	**DA-ML**	N/A	- 2.93*	- 2.71***
Income ($35,000 to $49,999) (dv)	**DA-ML**	N/A	N/A	- 2.23***
Income ($75,000 to $99,999) (dv)	**DA-ML**	N/A	- 1.84*	N/A
Income ($200,000 or more) (dv)	**DA-ML**	5.38**	N/A	N/A
Education (College Graduate) (dv)	**CP-ML**	- 2.81***	- 2.63*	- 2.26***
Derived Standard Deviations of Random Parameters				
Travel Time Difference Gain ($\beta_{TTDGain}$)		6.67**	15.06***	1.42*
Toll Rate ($)		5.95***	5.80***	2.77***
		Goodness-of-fit		
Log-likelihood for Constants Only Model		-453.31	-436.68	- 890.00
Log-likelihood at Convergence		-254.13	-276.69	- 565.34
Adjusted ρ_c^2		0.43	0.36	0.37

Note: ***, **, * ==> Significance at 1%, 5%, 10% level. ASC = alternative specific constant coefficient

Adjusted $_c^2 = 1-\frac{LL(\beta)-K}{LL(C)-Kc}$ where, $LL(\hat{\beta})$ = log-likelihood for the estimated model, K = number of parameters in the estimated model, $LL(C)$ = log-likelihood for the constants only model, K_c = number of parameters in the constants only model

5.6.5 Comparison of VTTS obtained from the base and revised models

Comparison of the WTPs (see Table 24) of *Travel Time* and *Travel Time Difference* from the base models and the revised models reveals that the WTP estimates are similar. For the revised conventional MNL models, for example, the WTP of Travel Time Savings is $23.33/hour which is about $1.50 higher than the base model. The mean WTP of *Travel Time Difference* ($VTTD_{Gain}$) is $11.56/hour with a standard deviation of $5.68/hour for the Reference Point model, while the mean WTP of $VTTD_{Gain}$ is $10.75/hour with a standard deviation of $5.24/hour for the revised model. Moreover, similar to the results for the base models, for the revised models we also find that the travelers have a higher VTTS than $VTTD_{Gain}$. Remember in Section 5.3 we found that these WTP estimates from the Reference Point, PT-pwf, and PT-Full models are half as large as VTTS obtained in a recent study (Devarasetty, Burris et al. 2012), similarly the WTP estimates for the revised models in this section are consistent to our findings for the base models as well as a study by Sikka (2012).

Table 24 Comparison of VTTS Generated from the Base Models and Revised Models

Model Type	WTP Measures	D_b-Efficient	Adaptive Random	All Inclusive
Conventional MNL	WTP (Mean)	15.56	N/A	20.80
	WTP (Median)	N/A	N/A	N/A
	S.D. WTP	N/A	N/A	N/A
Revised Conventional MNL	WTP (Mean)	16.84	N/A	23.33
	WTP (Median)	N/A	N/A	N/A
	S.D. WTP	N/A	N/A	N/A
Reference Point Model	WTP (Mean)	13.23	11.05	11.56
	WTP (Median)	10.95	10.37	8.67
	S.D. WTP	6.34	2.89	5.68
Revised Reference Point Model	WTP (Mean)	10.11	11.38	10.75
	WTP (Median)	10.25	11.02	10.62
	S.D. WTP	6.41	3.24	5.24
PT-pwf Model	WTP (Mean)	12.52	14.60	13.72
	WTP (Median)	13.21	14.91	14.10
	S.D. WTP	1.69	1.41	1.59
Revised PT-pwf Model	WTP (Mean)	14.56	15.02	15.12
	WTP (Median)	14.82	15.26	15.09
	S.D. WTP	2.55	2.21	1.36
PT-Full Model	WTP (Mean)	8.56	13.38	10.66
	WTP (Median)	6.93	12.29	9.91
	S.D. WTP	5.67	6.19	5.36
Revised PT-Full Model	WTP (Mean)	8.75	15.01	11.33
	WTP (Median)	7.69	13.79	11.12
	S.D. WTP	4.78	5.39	4.75

5.6.6 Comparison of efficiency in parameter estimation from the base and revised models

The percentage of correct predictions of the base and revised models is presented in Table 25. Comparison of results of the base and revised conventional MNL models shows that the correct prediction was not improved by including additional variables in the utility estimation. However, it can be seen that introducing additional trip and socio-economic variables into the Reference Point models significantly improved the predicative power, particularly for the D_b-efficient design. For the D_b-efficient design, the percent of correct prediction measures for all modes for the Reference Point model is 48.74 while it is 78.85 in the revised model. It is interesting to observe that the improvements in predicative power for the revised PT-pwf and PT-Full models are only minor. This might indicate the significance of embedding probability weighting in utility estimation to make a more accurate mode choice prediction using fewer variables.

Table 25 Percent of Correct Prediction for Each Alternative for the Revised Models

Model Type	Mode	Percent of Correct Prediction		
		D_b-Efficient	Adaptive Random	All Inclusive
Revised Conventional MNL	DA-GPL	50.33	43.93	46.67
	CP-GPL	0.00	0.00	0.00
	DA-ML	35.29	32.80	28.77
	CP-ML	28.57	22.47	23.91
	All Modes	39.88	34.77	35.35
Revised Reference Point Model	DA-GPL	86.73	73.13	87.70
	CP-GPL	30.00	0.00	16.00
	DA-ML	82.86	51.81	88.67
	CP-ML	56.25	68.33	63.41
	All Modes	78.85	65.05	80.80
Revised PT-pwf Model	DA-GPL	78.62	76.67	79.45
	CP-GPL	8.33	14.29	5.56
	DA-ML	74.49	70.73	88.64
	CP-ML	57.45	78.57	61.67
	All Modes	71.19	73.58	76.19
Revised PT-Full Model	DA-GPL	78.36	77.78	78.99
	CP-GPL	0.00	13.64	8.00
	DA-ML	80.22	70.45	68.31
	CP-ML	54.84	68.57	62.50
	All Modes	73.70	70.25	70.72

5.7 Segmentation of Survey Respondents by Demographics and Trip Characteristics

In previous sections, we demonstrated results and comparisons of mixed logit models based on four formats of the SP questions. Predictions of the use of MLs were estimated using conventional utility theory and PT frameworks. From these models the value of travel time savings and/or the value of travel time reliability were estimated. These results were generalized from the whole population of survey respondents for each SP question format. For example, in Table 14 the coefficient of *Travel Time*

Difference for gain (α) for D_b-efficient design is 0.09 which is an estimate from 254 respondents (762 observations). However, this estimate ($\alpha = 0.09$) may be very different for a sub sample, for example, travelers whose trip is for recreational purpose. Using similar segmentation analysis, although for different purpose and methodology, Patil et al. (2011) estimated the VTTS for different situations including one normal and six urgent situations and they found that travelers have a higher value for travel time savings for a trip in urgent situation than in a normal situation. Therefore, it is not unusual that the risk attitude may also depend on the trip characteristics and socio-economic characteristics of the travelers. To further understand travelers' perception of risk and probability weighting, it is necessary to conduct a segmentation analysis of the survey respondents based on their trip characteristics and socio-economic characteristics. Our segmentation analysis is similar to a customer segmentation practice which divide a customer base into several groups of individuals with similar characteristics in specific ways relevant to marketing (DeSarbo, Jedidi et al. 2001). In this section several factors were checked to see how responses varied across various groups of respondents. Factors include *Age*, *Gender*, *Income Level*, and *Trip Purpose*. This section starts with the segmentation analysis on the SP question Format B, followed by Format C, and Format D. Our segmentation analysis reveals that a majority of the parameter estimates (particularly for the Reference Point and PT-Full models) are not statistically significant, hence only significant results are discussed.

5.7.1. Segmented model estimation with reference point model

For the *Age* groups, a majority of the coefficients of *Travel Time Difference* for gain (α) for the All Inclusive dataset are significant and positive (0.10, 0.12, 0.12, and 0.17). Values of α are in a reasonable range comparing with estimates from previous section. A significant and positive α suggests that the marginal utility for savings in travel time of the survey respondents decreases as the difference becomes larger. The close significant estimates of α imply that the survey respondents from the age groups have similar attitude towards risk in the domain of gain (a shorter travel time relative to the most recent trip). For the *Gender* groups, the coefficients of *Travel Time Difference* for gain (α) for the All Inclusive dataset are significant and positive (0.38 for male, and 0.49 for female). The difference here implies that *Gender* might be a factor influencing the risk attitude towards gain in travel time. For the *Income* groups, the coefficients of *Travel Time Difference* for gain (α) for the All Inclusive dataset are significant and positive (0.23, 0.29 and 0.30).

5.7.2. Segmented model estimation with PT-pwf model

Table 26 summarizes the results of the PT-pwf Model using grouped data by *Age*, *Gender*, *Income Level*, and *Trip Purpose*. For a straightforward comparison of the response of different group respondents, only parameter estimates of interest (δ and γ for the PT-pwf Model) are presented.

For the *Age* groups, the coefficients of both *Probability Weighting for Gain* (γ) and *Probability Weighting for Loss* (δ) for the three datasets are statistically significant. The parameter estimates indicate that the four age groups used four different but similar weights to translate the objective occurrence of probability into perceived probability. For the three age groups (35 to 44, 45 to 54, and 55 to 64), significant estimates of γ and δ in the probability weighting functions suggest an inverted S-shape which implies that when the function is concave low probabilities are over-weighted and when the function is convex high probabilities are under-weighted. The change of parameter estimates of γ and δ as people ages may imply a gradual adjustment of travelers' attitude towards risk and objective probability (see Figure 22). It is also worth noting that for the age group (25 to 34), estimate of $\gamma(1.23)$ and $\delta(1.53)$ in the probability weighting functions suggest a S-shaped curve which implies that when the function is convex low probabilities are under-weighted and when the function is concave high probabilities are over-weighted. This might suggest that respondents may use different weights in probability weighting as they age. For example, respondents who are between 25 and 34 years old overestimate high probabilities and underweight low probabilities while older respondents generally underestimate high probabilities and overestimate low probabilities. Similar effect of age on probability weighting has been observed in a previous study investigating whether individuals attach psychological weight on an outcome while choosing risky alternatives. Eckel and Holovchenko (2011) observed strong non-linear relationship between probability weighing and subjects' age. They found that the age has an inverted U-shape effect on the parameter estimates of the subjective probability weighting function. They also found that as age increases, individuals in the beginning (younger phase) would have a tendency to underweight and then switch to overweight the probabilities. Their findings also indicate that age is non-linearly related to the risk coefficients (α, β) as shown in the Reference Point models. As peoples' age increase, individuals is risk-loving in some age, however at certain age (a turning point), individuals might switch from risk-loving to risk-averse –which suggests a U-shaped relationship this time. Our findings imply significant effect of age on travelers' psychological weight and risk sensitivity, though it is not conclusive because some parameter estimates for the D_b-Efficient dataset is not statistically significant.

For the *Gender* groups, the coefficients of *Travel Time* (δ and γ) for the three datasets (D_b-Efficient, Adaptive Random and All Inclusive) are statistically significant. Our results indicate that regardless of gender survey respondents generally over-weight low probabilities and under-weight high probabilities. The results also imply that gender as a factor may play a role to different content how the objective probabilities were translated into subjective probability using different weights. For example, coefficient estimates of δ (0.87, 0.91, and 0.81) for male are higher than δ (2.12, 0.68, and 0.70) for female. This difference suggests that female may generally use more weights in translating probabilities.

For the *Income* groups, the coefficient estimates for the two relatively higher-income groups (More than \$50,000) are statistically significant. The coefficient estimates for the low-income group (Less than \$50,000) are not statistically significant. For the middle-income group (\$50,000 to \$10,0000), the coefficient estimates of δ and γ

for the three datasets are not consistent. For example, for the D_b-Efficient the probability weighting function for the gain is an inverted S-shape while it is S-shaped for the Adaptive Random dataset. Such inconsistency could be attributed to the heterogeneity in preferences, risk attitude and beliefs. In a study investigating decision making in risky travel choices in the presence of travel time variability, Li and Hensher (2013) found that unobserved between-individual heterogeneity in preferences, risk attitude and beliefs in a single Rank-Dependent Utility model, and the resulting distribution of the cumulative probability weighting parameter (symbolizing belief) has an empirical range of 0.4317 to 1.8805. Such a range generates two types of probability weighting curvatures: inverted S-shaped and S-shaped curvature.

Table 26 Segmentation of Survey Respondents Presented with SP Question in Format C

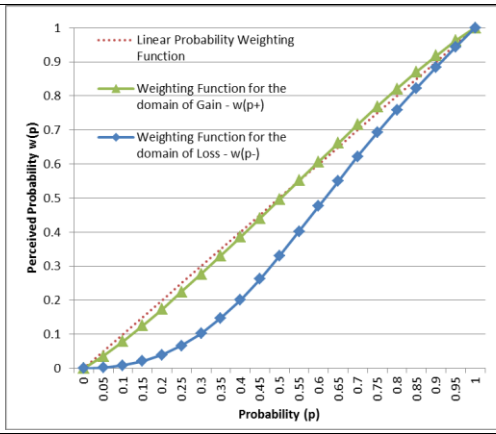
PT-pwf Model							
Characteristics	Variable	Survey Design					
		D_b-Efficient		Adaptive Random		All Inclusive	
		Number of Observations	Parameter	Number of Observations	Parameter	Number of Observations	Parameter
Age							
25 to 34	δ	114	2.13**	93	1.60**	207	1.53***
	γ		1.12**		1.16***		1.23***
35 to 44	δ	105	0.61*	87	0.38***	192	0.60***
	γ		0.84**		0.55***		0.76***
45 to 54	δ	72	0.63	66	0.46***	138	1.72
	γ		1.30		0.55***		0.90***
55 to 64	δ	57	1.98	63	0.78***	120	0.64***
	γ		1.03		0.68***		0.56***
65 or older	δ	24	N/A	24	N/A	48	1.19
	γ						0.59
Gender							
Male	δ	225	0.87*	189	0.91***	414	0.81***
	γ		0.82**		0.75***		0.65***
Female	δ	141	2.12***	117	0.68***	258	0.70***
	γ		0.97***		1.01*		0.70***
Income							
Less than $50,000	δ	30	N/A	30	0.87	60	0.72
	γ				0.74		0.58
$50,000 to $10,0000	δ	120	2.82*	81	0.90***	201	0.67***
	γ		0.70***		1.74***		0.47***
More than $10,0000	δ	174	2.98***	168	0.85***	342	2.67***
	γ		0.95***		0.73***		0.91***
	γ		0.93		0.58***		0.57***

Table 26 Continued

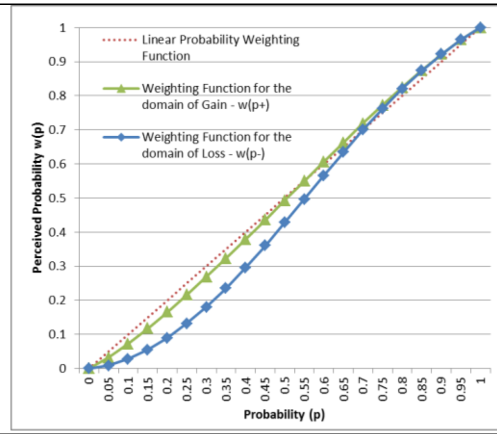
PT-pwf Model							
Characteristics	Variable	Survey Design					
		D_b-Efficient		Adaptive Random		All Inclusive	
		Number of Observations	Parameter	Number of Observations	Parameter	Number of Observations	Parameter
Trip Purpose							
Commuting	δ	222	1.85***	198	0.62***	420	0.84***
	γ		0.89***		0.79***		0.77***
Recreational	δ	93	0.79	66	0.59***	159	0.74***
	γ		0.73		0.46***		0.83*
Work related	δ	90	0.59	63	0.77***	153	0.73***
	γ		0.93		0.58***		0.57***

Note: a) estimates not available (N/A) is due to either no enough observations to run the model or the estimated variance matrix of estimates is singular;

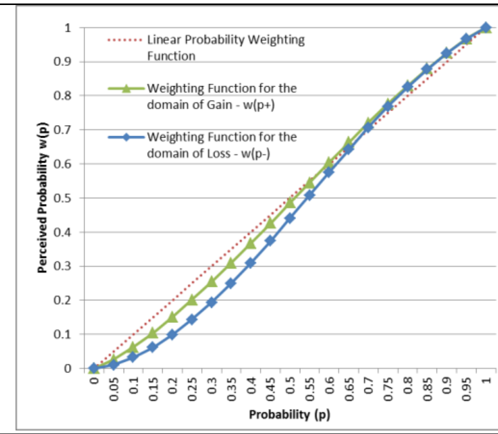
b) ***, **, * ==> Significance at 1%, 5%, 10% level.



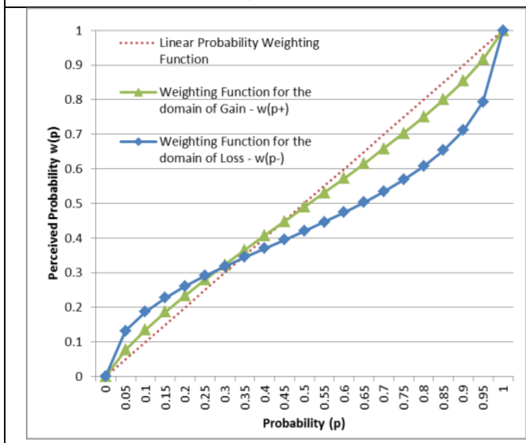
Delta = 2.13***, **Gamma** = 1.12***



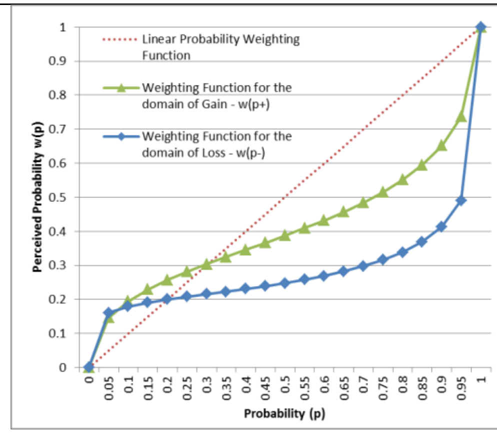
Delta = 1.60***, **Gamma** = 1.16***



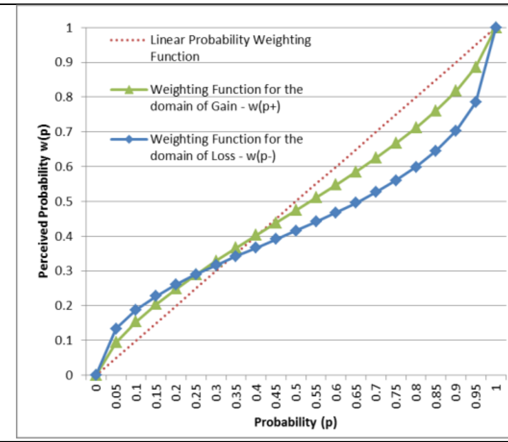
Delta = 1.53***, **Gamma** = 1.23***



Delta = 0.61*, **Gamma** = 0.84**

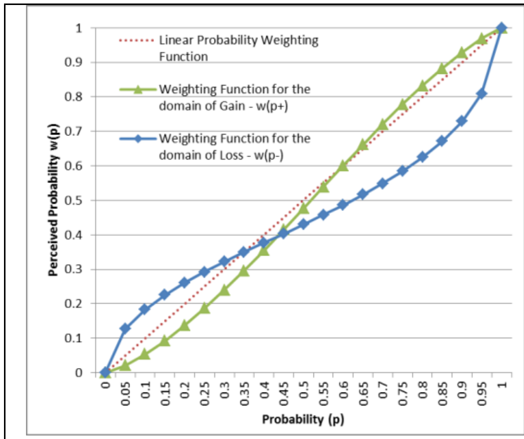


Delta = 0.38***, **Gamma** = 0.55***

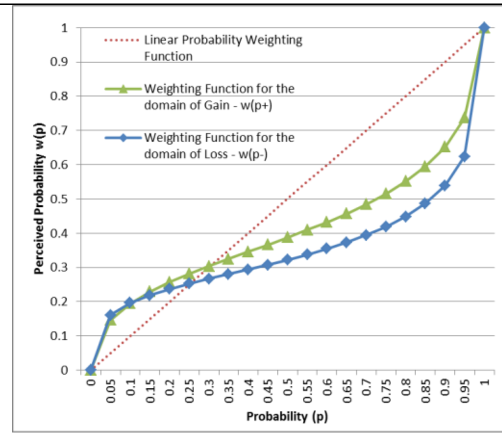


Delta = 0.60***, **Gamma** = 0.76***

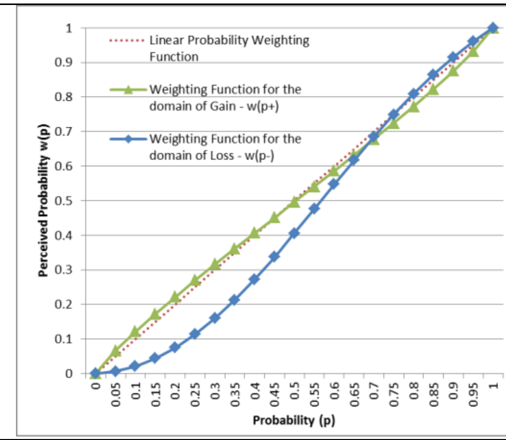
Figure 22 Segmentation Analysis by Age Groups (Probability Weighting Function)



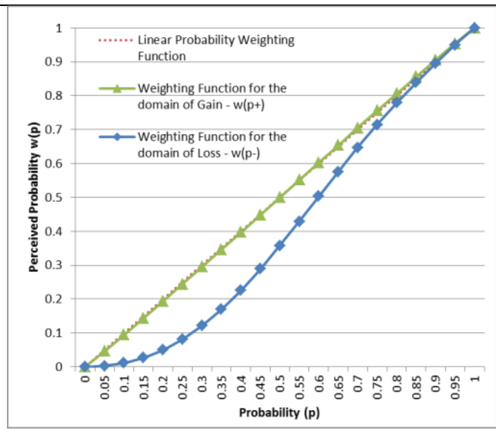
Delta = 0.63, **Gamma** = 1.30



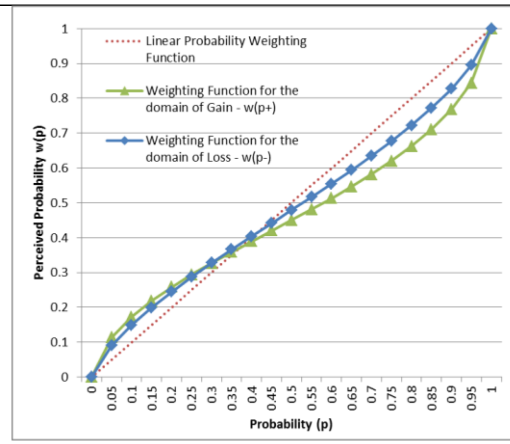
Delta = 0.46***, **Gamma** = 0.55***



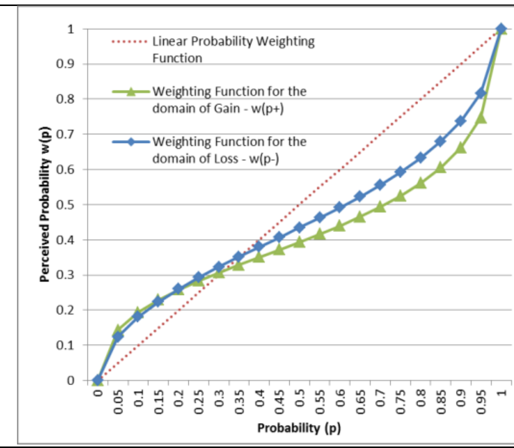
Delta = 1.72, **Gamma** = 0.90***



Delta = 1.98, **Gamma** = 1.03



Delta = 0.78***, **Gamma** = 0.68***



Delta = 0.64***, **Gamma** = 0.56***

Figure 22 Continued

For the *Trip Purpose* groups, the coefficients of *Travel Time* (δ and γ) for the All Inclusive dataset are statistically significant. Our results indicate that regardless of trip purpose survey respondents generally over-weight low probabilities and under-weight high probabilities. Additionally, the results also imply that respondents may use different weights in probability weighting in different trip purpose situations. For example, among the three trip purposes (Commuting, Recreation, and Other Work Related), respondents would use the least weight in probability weighting for commuting trips and largest weight for other work related trips. This might be so because for commuting trips travelers are very familiar with the daily commuting routes and have enough knowledge about the approximate commuting time. Therefore, they don't use much weighting in this situation. However, they might not be familiar with the routes associated with other work related trips, but it is related to their work which might be of more importance than trips with other purposes, the respondents may not have much belief in the travel time and hence may use more weighting for work related trips other than commuting. This may help explain the difference in probability weighting for trips with different trip purposes.

5.7.3. Segmented model estimation with PT-Full model (survey question format D)

For the *Gender* groups, the coefficients of α for the All Inclusive dataset are 0.45 for male group and 0.55 for female group. This indicates that in the domain of gain the marginal increase in utility for female is greater than for male, and this is also consistent with results from the revised PT-Full models (see Table 23). This is particularly true for the D_b-Efficient dataset ($\alpha = 0.15$ for male, 0.57 for female). For the All Inclusive dataset, the estimate of γ for gender groups are close ($\gamma = 0.55$ for male, 0.56 for female) and this may suggest that male and female respondents might use similar probability weighting strategies. However, for the D_b-Efficient dataset, the estimate of γ for gender groups is 0.61 for male and 0.68 for female, while it is 0.43 for male and 0.65 for female for the Adaptive Random dataset. The three datasets are generating different results (all below unity though). Such varying results are largely attributable to the individual heterogeneity. For example, Gonzalez and Wu (1999) found their study subjects could either predominantly overweight or underweight objective probabilities relative to the identity line.

For the *Income* groups, the coefficient estimates of γ for the All Inclusive dataset suggest that middle-income group ($\gamma = 0.30$) underweight middle to high probabilities more than the high-income group ($\gamma = 0.62$).

For the *Trip Purpose* groups, among the three trip purposes (Commuting, Recreation, and Other Work Related), statistical significant estimates of γ for the other work related trips are 0.26 (D_b-Efficient) and 0.37 (Adaptive Random). Such results might imply that the respondents may use probability weighting particularly for other work related trips. Remember that in the PT-pwf models respondents would use the least weight in probability weighting for commuting trips and largest weight for other work related trips. This finding suggests that probability weighting associated with work related trips deserves special consideration and further exploration.

5.7.4. Summary of the segmented model estimation

Segmentation analysis on the survey respondents' attitude towards risk and probability weighting grouped by their trip and socio-economic characteristics reveals interesting findings, particularly for the PT-pwf models. Results of the PT-pwf models (Table 26) indicate that variables, *Age*, *Gender*, *Income Level*, and *Trip Purpose*, played significant influence on the respondents' probability weighting. In particular respondents may use different weights in probability weighting as they age, and this findings is consistent with findings from previous study in the field of behavior economics (Eckel and Holovchenko 2011) because similar phenomena has been observed in their empirical experiments. Grouping data by respondent characteristic within each model design resulted in a much smaller sample, and this may help explain the many results that are not statistically significant we obtained in the segmented models.

6. CONCLUSION & RECOMMENDATION FOR FUTURE RESEARCH

This study presents models that estimate Katy Freeway travelers' route choice predictions using a conventional expected utility theory (EUT) framework versus a prospect theory approach which allows for departures from the strict assumptions EUT makes. The primary purpose of this research is to determine if PT is superior to EUT when predicting and understanding travelers' behavior in the case of MLs. To achieve the objectives of this study, a stated preference survey and conducted with design using two different survey design methods with four SP question formats for each design strategy. The responses from the survey were examined using advanced discrete choice models. Significant and interesting general findings resemble those in previous studies that use PT, including the fact that individuals weight probabilities (e.g. Tversky and Kahneman (1992)).

6.1 Parameter Estimates of the PT Proposed Value Function and Probability Weighting Function

The results of the Reference Point Model (B) indicate that the marginal utility for savings in travel time of the survey respondents decreases as the difference from the reference point (status quo) becomes larger - diminishing sensitivity. The combination of a positive β and a negative λ suggests that the marginal disutility for losses in travel time of the survey respondents decreases as the difference from the reference point becomes larger. Given the values of α, β and λ, the value function curve is concave for gains and convex for loss. This result also suggests that for an equivalent travel time difference (gain or loss), the impact of a loss (travel time difference is presented as a loss) looms larger than the impact of an equivalent gain (which is presented as travel time savings) suggesting that the utility functions are steeper in the losses than in the gains domain. For example for the Reference Point Model (B), the estimates of *Travel Time Difference* for a gain ($\alpha = 0.09$) and the combination of *Travel Time Difference* for loss ($\beta = 0.17$)

and λ (0.92) suggests that the disutility of an additional 10 minutes spent in travel (perceived as a loss) is about twice the utility of a 10 minutes savings in travel time (a gain). The policy implications of this study are that Katy Freeway travelers are more concerned with the damage/disutility caused by being late for work from choosing a route than they are with potential savings in travel time. This is consistent with expectations as the negative consequences of being late usually outweigh the benefits of being early. Our results from the RP models are in line with previous study by Masiero and Hensher (2010; 2011). Our study and theirs both found significant improvement in the goodness of fit of the model if preferences are specified as asymmetric. Masiero and Hensher (2010) indicated that the asymmetry specification produced a steeper utility function for losses than for gains for the punctuality attribute, while ours is for the travel time attribute (shorter or longer travel time relative to respondents' most recent trip). Their models suggest nonlinearity and diminishing sensitivity in terms of the marginal disutility of punctuality and ours is for travel time difference. Their WTPs for travel time savings are \$6.02 and \$9.50 for the unrestricted models, respectively. We also obtained relatively low WTPs for travel time savings from the RP models. However, there are three key differences between our models and theirs: (1) their study investigated loss aversion and diminishing sensitivity in a freight transport framework, while ours is for travelers route choice between MLs and GPLs; (2) Masiero and Hensher (2010; 2011) used a piecewise linear approximation in the utility estimation to model the nonlinearity, and our RP models used two power functions (with loss aversion and risk attitude parameters) for the value function specifications in the domain of gain and losses, respectively; (3) our study examined the efficiency of two survey design methods (D_b-efficient and Adaptive Random) while theirs used a random generation strategy to maintain experiment orthogonality. Additionally, the levels of attributes in their study varied by either 5 or 10 percent, which may not truthfully mimic the actual variation of transport cost and time in the real freight transport industry. Therefore, Masiero and Hensher (2010) indicated that a broader domain (smaller or larger level ranges) of attribute levels are needed to establish the validity of the diminishing sensitivity in choice experiments.

The PT-pwf model investigates the significance of the inclusion of probability weighing for both gain and loss by including only the PT proposed probability weighting functions in the utility functions. The results of the PT-pwf model show that when the function is concave low probabilities are over-weighted and when the function is convex high probabilities are under-weighted, which means high probabilities for loss are more under-weighted than probabilities for gain, while low probabilities for loss are more over-weighted than probabilities for gain. This results (γ= 0.77 and δ= 0.81) are close to Tversky and Kahneman's (1992) findings (γ= 0.61 and δ= 0.69) in probability weighting. The parameter estimates of the probability weighting function for the PT-Full Model (D) (γ= 2.73 and δ= 0.49) indicate that on average, the travelers demonstrate a sense of optimism when the chances of having a longer travel time are high. Parameter estimates (δ= 1.93, and γ= 1.10) for the revised PT-pwf models, however, suggest S-shaped probability weighting curves (see Figure 21 for an example), while the estimates of the base model (γ= 0.77 and δ= 0.81) imply inverted S-shaped curves. The difference between parameter estimates of the base and revised models is primarily because the revised models use smaller samples than the base models and this difference suggests the mix of pessimistic and optimistic beliefs of the sampled respondents. Our results also indicated that when there is a transformation of probabilities (either smaller or larger than 1), medium probabilities (approximately 40 to 60%) always tend to be underweighted. This suggests that for a given trip the travel time with a medium level of probability would be underweighted, which in turn implies stronger conservative beliefs.

The estimates of *Probability Weighting for Loss* (δ) and *Probability Weighting for Gain* (γ) from the PT-pwf (γ= 0.77 and δ= 0.81) and PT-Full (γ= 2.73 and δ= 0.49) models confirm the non-linearity in probability weighting. A value smaller than one implies survey respondents overweight small probabilities and underweight high probabilities. For example a value of 0.49 for δ, shows that respondents perceive a probability of 0.10 as 0.20, i.e. $\omega^{-}(0.10) = 0.20$ (Equation 3). Additionally, the difference between estimates (δ= 0.81 vs. δ= 0.49, γ= 0.77 vs. $\boldsymbol{\gamma}$= 2.73) from the two models (PT-pwf vs. PT-Full) may indicate a significant difference in the way that respondents may perceive objective probabilities presented in the two SP question formats (Format C and D). Remember that in the PT-pwf model, it is the actual travel time (instead of travel time difference) shown to the survey respondent, while in the PT-Full model it is the travel time difference shown to the respondents, and in this format the attribute levels were clearly presented as gain or loss and resulted in much more extreme under- and over-weighting. Considering the close estimates from the PT-pwf model (δ= 0.81 and γ= 0.77), we then suspect that in this situation respondents may simply use one single probability weighting function, instead of two (one for gain and the other for loss), to translate probability. However, when the attributes are presented in a clear gain/loss format (such as travel time difference instead of travel time) the respondents are more likely to weight the gain and loss differently (γ= 2.73 and δ= 0.49 in the PT-Full model).

6.2 The Value of Travel Time Savings and Travel Time Reliability and Comparison of WTPs with Estimates from Previous Surveys

The WTP measures (for *Travel Time* and *Travel Time Difference*) calculated in this study are lower than many previously available route choice studies. The conventional MNL model (A) yields a value of travel time savings (VTTS) of \$20.80/hour and a low value of travel time reliability of \$2.20 per hour. The VTTS (\$20.80/hour) is close to results from previous surveys (Patil, Burris et al. 2011; Devarasetty, Burris et al. 2012). The mean WTPs of *Travel Time Difference* ($\text{VTTD}_{\text{Gain}}$) are \$11.56/hour with a standard deviation of \$5.68/hour for the Reference Point model (B), while the mean WTPs of *Travel Time* (VTTS) are \$13.72/hour with a standard deviation of \$1.59/hour for the PT-pwf model (C). For the PT-Full model (D), the mean WTPs of *Travel Time Difference* ($\text{VTTD}_{\text{Gain}}$) are \$10.66/hour with a standard deviation of \$5.36/hour. Comparing the WTPs of *Travel Time* and *Travel Time Difference* from the four models, it is obvious that the travelers value travel time savings more than $VTTD_{Gain}$. The concepts of VTTS and $VTTD_{Gain}$ may appear to be the same or close. However, in essence there is a basic distinction between the two: the calculation of VTTS is based on a one-way substitution of time and cost, while the estimation of $VTTD_{Gain/Loss}$ is essentially a two-way exchange/substitution. For example, a \$10 VTTS suggests that the travelers' value of travel time is \$10 per hour. Mathematically, it means that the traveler is willing to pay \$10 for saving one hour in travel time, but it also suggests that the traveler is ready to tolerate one hour delay by receiving compensation at the value of \$10. Instead, a \$10 $VTTD_{Gain}$ only suggests that a traveler is willing to pay \$10 for saving one hour in travel time. How much a traveler values a one-hour delay (or longer travel time) will need the estimation of $VTTD_{Loss}$, which might be higher than the $VTTD_{Gain}$ as shown in a typical value function (Figure 15). Because a managed lane is assumed to offer faster travel, only scenarios of shorter travel time on the managed lanes are included in the SP questions. Therefore, in this study it is not possible to estimate a $VTTD_{Loss}$, which could be a topic deserving exploration in the future.

Additionally, these WTP estimates are half as large as VTTS obtained in a recent study by Devarasetty et al. (2012) with implied VTTS of \$22/hour by D_b-efficient design. In a similar survey for Katy Freeway travelers, using similar modeling techniques Patil et al. (2011) estimated the VTTS as 55 percent, 52 percent, and 40 percent of the hourly wage by different design strategies. Their estimates are close to that of Devarasetty et al. (2012).

However, Sikka and Hanley (2012) obtained similar WTP estimates for frequency embedded travel time. In their study, for example, the WTP for mean travel time is \$6.98/hour plus a \$3.27/hour for travel time reliability to avoid unexpected delays. Using a non-linear logit model embedding probability weighting and risk/ambiguity attitudes, Sikka and Hanley (2012) derived WTP estimates of \$12.18/hour when the chance of delay is 10%, and \$11.46/hour if the chance of delay is

90%. This study's WTP estimates may indicate previous projections overestimated VTTS. However, more research on the use of PT models is needed to improve on ML mode prediction. Additionally, the standard deviations associated with the distributed WTP measures are quite large. This is because the cost and travel time difference parameters are distributed and drawing parameter values may lead large values.

The relatively low WTP measures from our study might be partly explained by the risk attitude of the survey respondents. Remember that our respondents for the PT-based models (particular the RP models) are risk averse in both domains (gain and loss), and a risk averse person would require a risk premium to participate in any given risky gamble. This means that a risk adverse person will be worse off in terms of utility in a gamble, even such a gamble might be perceived as a fair game by a risk neutral person. The risk premium is the difference between the expected value of the gamble and the certainty equivalent. Note that the risk premium for a risk neutral individual will be zero, and the risk premium demanded for given risky gamble will increase as the risk aversion of an individual increase. Put another way, how travelers deal with risk will depend upon how large they perceive the impact of the risk to be. This may help explain the lower WTPs from our study because respondents might consider route choice decision-making as a gamble, particular in circumstances (the PT-based models) that the travel time are presented as saving or loss associated with probability of occurrence.

6.3 Comparison of Prediction Power for Models from Different Approaches

The prediction success rates (the percentage of correct predictions) for the four models were compared to examine the impact of survey design strategies and model types on the models' prediction capabilities. Excluding the conventional MNL model, Adaptive Random design strategy generates better prediction than the D_b-efficient design strategy. Note that the percent of correct prediction measures for PT-pwf model is highest followed by the PT-Full model. The prediction power of the conventional MNL

Model is the lowest among the four models investigated, indicating PT models hold promises for MLs choice prediction.

6.4 Improvement of Incorporating Probability Weighting

The percent of correct prediction measures for all modes for PT-pwf model and the PT-pwf model were compared to the percent of correct prediction for the PT-Full model and the PT-Full model without probability weighting. The inclusion of probability weighting in utility function improves the prediction power. Such comparisons indicate that the improvement in prediction power of PT-pwf and PT-Full models is the contribution of probability weighting in utility estimation.

6.5 Parameter Estimation in Logit Model with Trip and Socio-Economic Variables

A step wise selection procedure was used to identify trip and socio-economic characteristics that were significant variables in explaining mode choice of the respondents. Apart from the variables *Toll Rate*, *Travel Time*, *Travel Time Difference*, the mixed logit models for this analysis include other explanatory variables, such as *Trip Purpose*, *Age*, *Education Level*, *Income Level*, and *Gender*. Our results indicate that carpooling on the GPLs is more common for recreational trips, and instead for commuting or other work related trips, carpooling on the GPLs is a less preferred option. Respondents who are 25 to 44 year old are more likely to choose carpooling on either MLs or GPLs. Respondents with some college education or above are less likely to carpooling. Respondents who are between 25 and 44 are more likely to choose carpooling on the managed lanes. Respondents from two income groups ($35,000 to $49,999) and ($75,000 to $99,999) are less likely to choose DA-ML over other modes, while respondents from the highest income group ($200,000 or more) are more likely to choose DA-ML.

Introducing additional trip and socio-economic variables into the Reference Point models significantly improved the predicative power, particularly for the D_b-efficient design. For the D_b-efficient design, the percent of correct prediction measures for all modes for the Reference Point model is 48.74 while it is 78.85 in the revised model with additional explanatory variables. It is interesting to observe that the improvement in predicative power for the revised PT-pwf and PT-Full models is only minor. This might indicate the significance of embedding probability weighting in utility estimation to make a more accurate mode choice prediction.

Comparison of the WTPs of *Travel Time* and *Travel Time Difference* from the base models and the revised models reveals that the WTP estimates are similar. Similar to the results for the base models, results of the revised models indicate that the travelers have a higher VTTS than $VTTD_{Gain}$. In the base models, we found that these WTP estimates from the Reference Point, PT-pwf, and PT-Full models are half as large as VTTS obtained in a recent study (Devarasetty, Burris et al. 2012), and WTP estimates for the revised models are consistent to our findings for the base models as well as a study by Sikka (2012).

6.6 Segmentation Analysis of Risk Attitude and Probability Weighting

To further understand different groups of travelers' perception of risk and probability weighting, we conducted a segmentation analysis of the survey respondents. Our segmentation analysis is similar to a customer segmentation practice which divides a customer base into several groups of individuals with similar characteristics in specific ways relevant to marketing. Several factors were checked to see how responses varied across various groups of respondents. Respondents were segmented by *Age*, *Gender*, *Income Level*, and *Trip Purpose*.

From the PT-pwf models, our results indicate that *Age* plays a role in influencing respondents' probability weighting. It is observed that respondents may use different weights in probability weighting as they age. Our results indicate that regardless of gender, survey respondents generally over-weight low probabilities and under-weight high probabilities. The results also imply that gender as a factor may play a role how the objective probabilities were translated into subjective probability using different weights. For the *Trip Purpose* groups, our results indicate that regardless of trip purpose, survey respondents generally over-weight low probabilities and under-weight high probabilities. Additionally, the results also imply that respondents may use different weights in probability weighting for different trip purposes.

6.7 Recommendations for Future Research

This study collected data on stated preference responses and we obtained 1027 valid responses for analysis. Due to the limited time that an online survey respondent might be willing to spend, for each respondent only three SP questions were presented. Therefore, the parameter estimates associated with the probability weighting function are a mixture/average of all the sample respondents involved. However, for a more accurate fitting of a probability weighting function, more data points for each individual respondent may be necessary. In future data collection efforts, we may garner more data points for each individual respondent by asking more questions with regard to probability of occurrence. This may help yield more accurate estimates of probability weighting functions, and subsequently the value of travel time savings from a prospect theory approach.

Comparing parameter estimates (γ and δ) of the probability weighting for loss and gain for the three datasets, the results are consistent and comparable. However, because it is the *Travel Time* instead of *Travel Time Difference* was used in the survey question for this format (see Table 1 and Figure 10), survey respondents may not perceive if they were in a gain or loss context, and hence may simply use a single probability weighting function (instead of two) to translate objective probabilities. Therefore, future study may examine if the survey respondent was essentially using just one single probability weighting function (for both gain and loss) instead of two (one for gain and the other for loss) to "translate" probability.

The patronage of toll facility and MLs largely depends on the potential benefits (more reliable travel time and/or travel time savings) offered by such a facility. How the travelers actually perceive the potential benefits may have a significant influence on the use of MLs. This is about the belief that the travelers have on the facility. In lieu of the significant improvement in predicative power of the models embedding probability weighting functions, as well as the stochastic nature of travel times, in future survey efforts it might be helpful to collect information regarding Katy Freeway travelers' actual belief on the benefits from using the MLs, and compare their 'belief' with the actual probability of reliable travel time and savings. Such comparison might help verify the accuracy of the probability weighting obtained in this study.

The attributes used in the four SP question formats were presented as *Travel Time* and *Travel Time Difference*. This presentation might result in different perception of the travelers. For example, the given travel time which is longer than the most recent trip or even it is presented as a travel time difference (a longer travel time) might not be perceived as an equivalent delay. Subsequently, the interpretation of the WTPs from models using *Travel Time* and *Travel Time Difference* might be different from WTP estimates of avoiding a delay. Therefore, in future endeavors, attributes can be presented as arriving X minutes early, arriving on time, and arriving X minutes late. Then it is possible to measure the WTPs that a traveler might want pay to avoid a delay.

A majority of parameter estimates in our segmentation analysis were not statistically significant, and this can be largely attributed to the fact that segmenting respondents for each model design resulted in much less data points for each segmented model. Segmentation analysis is important because strong non-linear relationship between probability weighting and subjects' age has been observed in previous study (Eckel and Holovchenko 2011). Modeling based on segmentation may yield more accurate mode choice prediction and WTP estimates. Additionally, it is interesting to see that the chance obtaining significant results for the All Inclusive dataset are higher than for the other two datasets. In light of this observation, future studies in this regard may require more data collection effort to generate more useful and significant results.

To increase the survey sample, economic incentives, such as gift cards, may be offered to encourage participation. This survey obtained 1067 complete survey without any economic incentives. Instead, 3990 and 3325 respondents participated in the two similar surveys in 2008 and 2010, respectively. The higher participation might be partly because participants were offered a chance to win an award of $250 gas cards selected by a lottery in the previous studies.

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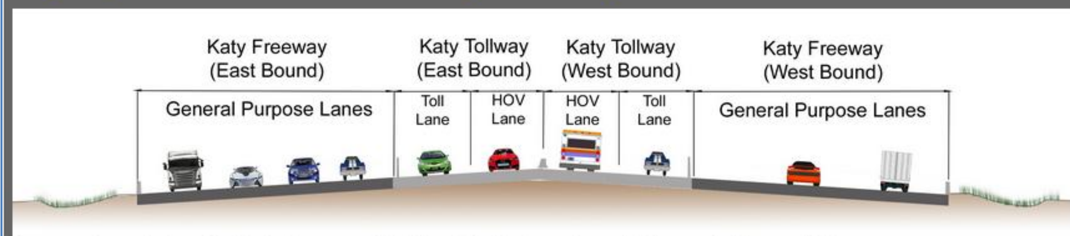
APPENDIX A. SURVEY QUESTIONNAIRE

Katy Freeway Managed Lane Survey

A. Introduction to the New Managed Lanes

*The Katy Tollway begins west of SH 6 and ends at the I-10/I-610 interchange. The Tollway has 2 toll lanes in each direction and is operated by the Harris County Toll Road Authority (HCTRA) (See figure below). During the rush hour the toll is higher and during other times the toll is lower. Drivers have multiple entrances and exit locations to get on the managed lanes. The facility is an EZ or TX Tag only facility. Qualifying high-occupancy vehicles can travel for free during the peak hours. Metro buses will not be charged a toll at anytime.



Have you traveled on the Katy Freeway (I-10) or Katy Tollway lanes in the past six months?

Choose one of the following answers

- Yes
- No

B. Details of Respondent's Most Recent Trip

Please tell us about your most recent trip on the Katy Freeway (I-10) traveling towards downtown Houston during the work week (Monday through Friday). A "trip" is any time you traveled on Katy Freeway.

What was the purpose of your most recent trip?

Choose one of the following answers

- Recreational / Social / Shopping / Entertainment / Personal Errands
- Commuting to or from my place of work (going to or from work)
- Work related (other than to or from home to work)
- To attend class at school or educational institute
- Other

?

Where did you get ON and OFF the Katy Freeway (I-10)?

	ON	OFF
An exit west of FM 1463 (Katy Road)		
FM 1463 (Katy Road)		
Pin Oak Road		
Katy Mills Blvd./Highway Blvd.		
Katy-Fort Bend Road		
Peek Road/Grand Parkway		
Mason Road		
Westgreen Blvd.		
Fry Road		
Greenhouse Road/Baker Road		
Barker Cypress Road		
Park Row/Park 10		
Highway 6		
Eldridge Parkway		
Dairy Ashford		
Kirkwood Road		
Sam Houston Parkway/Wilcrest Drive		
Gessner Road		
Bunker Hill Road		
Blalock Road/Echo Lane		
Bingle Road/Campbell		
Wirt Road		
Antoine Drive/Chimney Rock		
Silber Road/N. Post Oak Road		
Loop 610		
Washington Avenue/Westcott St.		
TC Jester Blvd.		
Durham Dr./Shepherd Dr./Patterson St.		
Studemont St./Heights Blvd.		
Taylor St.		
I-45 Downtown Houston		
An exit east of I-45 Downtown Houston		

Where did you Enter and Exit the Katy Tollway?

	ON	OFF
State Highway 6 (SH 6)		
Addicks Park and Ride		
Between Dairy Ashford and Kirkwood		
Between Gessner and Bunker Hill		
Between Chimney Rock and Antoine		
Between Antoine and Silber		
East of Loop 610		

Have you ever changed where you entered or exited the Katy Freeway in order to have an easier path to or from the Tollway?

Choose one of the following answers

- Yes
- No

On your most recent trip away from downtown Houston did you travel in the general purpose lanes or the Tollway lanes?

Choose one of the following answers

- General Purpose Lanes
- Tollway lanes (toll lanes or HOV lanes)

On what day of the week was your most recent trip away from downtown Houston?

Choose one of the following answers

- Sunday
- Monday
- Tuesday
- Wednesday
- Thursday
- Friday
- Saturday

You previously indicated your most recent trip away from downtown Houston was Commuting to or from my place of work (going to or from work). What time of day did that trip start? (for example, when did you leave your origin)

Choose one of the following answers

Please choose...

What kind of vehicle did you use for your most recent trip?

Choose one of the following answers

- Motorcycle
- Passenger car, SUV, or pick-up truck
- Bus

How much did you pay to ride the bus? Choose one:

Check any that apply

- $ per trip
- $ per day
- $ per week
- $ per month

How many people, including you, were in the Passenger Car/ SUV/Pick-up Truck?

Choose one of the following answers

- 1
- 2
- 3
- 4
- 5 or more

Were you the driver or a passenger on this recent trip?

Choose one of the following answers

- Driver
- Passenger

How much extra time did it take to pick up and drop off the passenger(s)? (minutes)

Only numbers may be entered in these fields

Minutes [ ]

Who did you travel with on this recent trip?

Check any that apply

- [ ] Co-worker / person in the same, or a nearby, office building
- [ ] Neighbor
- [ ] Another commuter in a casual carpool (also known as slugging)
- [ ] Child
- [ ] Adult family member
- [ ] Other: [ ]

What was your travel time on your last trip?

Only numbers may be entered in these fields

minutes [ ]

Have you ever used the Katy Tollway lanes?

- (•) Yes
- ( ) No

What are the main reasons you use the Tollway?

Check any that apply

- [ ] Access to/from to the Tollway lanes is convenient for my trips
- [ ] The Tollway saves time
- [ ] During the peak hours the Tollway will not be congested
- [ ] The Tollway lanes are less stressful than the general purpose lanes
- [ ] Trucks and large vehicles are not allowed on the Tollway
- [ ] Someone else pays my tolls
- [ ] Travel times on the Tollway lanes are consistent and predictable
- [ ] Being able to use the lanes for free as a carpool
- [ ] The Tollway lanes are safer than the general purpose lanes
- [ ] Other: [ ]

What are the primary reasons you do NOT use the Katy Tollway?
Check any that apply

- [ ] It is too complicated/confusing to use the Tollway
- [ ] I do not feel safe traveling on the Tollway lanes
- [ ] I don't have anyone to carpool with
- [ ] The toll is too expensive for me
- [ ] I don't want to have a toll transponder in my vehicle
- [ ] I don't have a credit card needed to setup a toll transponder account
- [ ] I don't like that the toll changes based on the time of day
- [ ] I have the flexibility to travel at less congested times
- [ ] I avoid toll roads whenever possible
- [ ] Access to/from to the Katy Tollway lanes is not convenient for my trips
- [ ] The Tollway does not offer me enough time savings
- [ ] I can easily use routes other than the Katy Freeway, so I'll just avoid Katy Freeway if I think there is a lot of traffic
- [ ] Other:

Do you believe that law enforcement agencies are:
Choose one of the following answers

- ○ Providing the right level of enforcement on the Katy Tollway?
- ○ Providing too little enforcement on the Katy Tollway?
- ○ Providing too much enforcement on the Katy Tollway?

Thinking about the last work week (Monday through Friday), how many trips did you make on the Katy Freeway general purpose lanes, each direction counts as one trip?

Only numbers may be entered in these fields

Trips per week:

Thinking about the last work week (Monday through Friday), how many trips did you make on the Katy Tollway lanes, each direction counts as one trip?

Only numbers may be entered in these fields

Trips per week:

?

Did you have to pay to park in Houston?
Choose one of the following answers

- ◉ Yes
- ○ No

How much does parking cost per day (in $)?

Only numbers may be entered in these fields

per day $

?

C. Stated Preference Questions

Each of the following questions will ask you to choose between three potential travel choices on the Katy Freeway (I-10). For your most recent trip, please click on the one option that you would be most likely to choose if faced with these specific options. Note that carpooling may require added travel time to pick up or drop off your passenger(s).

You described your most recent trip away from downtown Houston on Katy Freeway . If you had the options below for that trip during the afternoon rush hour, which would you have chosen?

Choose one of the following answers

Option A	Option B
Drive alone on the **Main freeway lanes** during afternoon rush hour	**Carpool** with others on the **Main freeway lanes** during afternoon rush hour
No toll	No toll
Average travel time of **23** minute(s) but can be anywhere from **18** to **28** minute(s)	Average travel time of **23** minute(s) but can be anywhere from **18** to **28** minute(s)

Option C	Option D
Drive alone on the **Tollway lanes** during afternoon rush hour	**Carpool** with others on the **Tollway lanes** during afternoon rush hour
Pay $**1.95** toll	No toll
Average travel time of **13** minute(s) but can be anywhere from **12** to **14** minute(s)	Average travel time of **13** minute(s) but can be anywhere from **12** to **14** minute(s)

Typical Scenarios of Survey Design (Conventional MNL Model, Format A)

Each of the following questions will ask you to choose between three potential travel choices on the Katy Freeway (I-10). For your most recent trip, please click on the one option that you would be most likely to choose if faced with these specific options. Note that carpooling may require added travel time to pick up or drop off your passenger(s).

You described your most recent trip away from downtown Houston on Katy Freeway . If the travel time of your most recent trip on the Katy Freeway was 15 minutes, and if you had the options below for that trip during the afternoon rush hour, which would you have chosen?

Choose one of the following answers

Option A	Option B
Drive alone on the **Main freeway lanes** during afternoon rush hour	**Carpool** with others on the **Main freeway lanes** during afternoon rush hour
No toll	No toll
The travel time of this trip may take **4** minute(s) **more** or **less** than your most recent trip	The travel time of this trip may take **4** minute(s) **more** or **less** than your most recent trip

Option C	Option D
Drive alone on the **Tollway lanes** during afternoon rush hour	**Carpool** with others on the **Tollway lanes** during afternoon rush hour
Pay $ **3.50** toll	No toll
The travel time of this trip may take **5** to **7** minute(s) **less than** your most recent trip	The travel time of this trip may take **5** to **7** minute(s) **less than** your most recent trip

Typical Scenarios of Survey Design (Reference Point Model, Format B)

Each of the following questions will ask you to choose between three potential travel choices on the Katy Freeway (I-10). For your most recent trip, please click on the one option that you would be most likely to choose if faced with these specific options. Note that carpooling may require added travel time to pick up or drop off your passenger(s).

You described your most recent trip away from downtown Houston on Katy Freeway . If you had the options below for that trip during the afternoon rush hour, which would you have chosen?

Choose one of the following answers

Option A	Option B
Drive alone on the **Main freeway lanes** during afternoon rush hour	**Carpool** with others on the **Main freeway lanes** during afternoon rush hour
No toll	No toll
5 time(s) out of 10 the trip takes **28** minute(s) **5** time(s) out of 10 the trip takes **17** minute(s)	**5** time(s) out of 10 the trip takes **28** minute(s) **5** time(s) out of 10 the trip takes **17** minute(s)

Option C	Option D
Drive alone on the **Tollway lanes** during afternoon rush hour	**Carpool** with others on the **Tollway lanes** during afternoon rush hour
Pay $ **3.70** toll	No toll
1 time(s) out of 10 the trip takes **11** minute(s) **9** time(s) out of 10 the trip takes **16** minute(s)	**1** time(s) out of 10 the trip takes **11** minute(s) **9** time(s) out of 10 the trip takes **16** minute(s)

Typical Scenarios of Survey Design (PT-pwf Model, Format C)

You described your most recent trip away from downtown Houston on Katy Freeway . If the travel time of your most recent trip on the Katy Freeway was 15 minutes, and if you had the options below for that trip during the afternoon rush hour, which would you have chosen?

Choose one of the following answers

Option A	Option B
Drive alone on the **Main freeway lanes** during afternoon rush hour	**Carpool** with others on the **Main freeway lanes** during afternoon rush hour
No toll	No toll
3 time(s) out of 10 the trip takes **4** minute(s) **more than** your most recent trip **7** time(s) out of 10 the trip takes **2** minute(s) **less than** your most recent trip	**3** time(s) out of 10 the trip takes **4** minute(s) **more than** your most recent trip **7** time(s) out of 10 the trip takes **2** minute(s) **less than** your most recent trip

Option C	Option D
Drive alone on the **Tollway lanes** during afternoon rush hour	**Carpool** with others on the **Tollway lanes** during afternoon rush hour
Pay $ **3.05** toll	No toll
2 time(s) out of 10 the trip takes **7** minute(s) **less than** your most recent trip **8** time(s) out of 10 the trip takes **4** minute(s) **less than** your most recent trip	**2** time(s) out of 10 the trip takes **7** minute(s) **less than** your most recent trip **8** time(s) out of 10 the trip takes **4** minute(s) **less than** your most recent trip

Typical Scenarios of Survey Design (PT-Full Model, Format D)

D. Demographics of Respondents

The following questions will be used for statistical purposes only and answers will remain confidential. All of your answers are very important to us and in no way will they be used to identify you or released to any other person outside the research team.

What is the ZIP Code of that recent trip's Origin?

Only numbers may be entered in this field

What is the ZIP Code of that recent trip's Destination?

Only numbers may be entered in this field

Are you…

- Female
- Male

Which of the following age categories best represents your age?
Choose one of the following answers

- 18 to 24
- 25 to 34
- 35 to 44
- 45 to 54
- 55 to 64
- 65 and over
- Refused

What is your race/ethnicity?
Choose one of the following answers

- White/Caucasian
- Hispanic/Latino
- African American
- Asian American
- Native American
- Refused

What is your highest level of education?
Choose one of the following answers

- Less than high school
- High school graduate
- Some college or vocational school
- College Graduate
- Postgraduate degree
- Refused

What was your gross annual HOUSEHOLD income before taxes in 2011?
Choose one of the following answers

- Less than $10,000
- $10,000 to $14,999
- $15,000 to $24,999
- $25,000 to $34,999
- $35,000 to $49,999
- $50,000 to $74,999
- $75,000 to $99,999
- $100,000 to $199,999
- $200,000 or more
- Its easier to tell my hourly wage rate:
- Other

Feel free to provide any comments or suggestions related to transportation and travel here:

APPENDIX B. N-GENE CODE FOR GENERATING Db-EFFICIENT DESIGN

(1) N-Gene Code for Generating D_b-Efficient Design (Deterministic Models)

```
;Design
;alts=gplda,gplcp,mlda,mlcp
;rows=15
;block=5
;eff=(rppanel,d)
;rep=1000
;rdraws=halton(400)
;cond:
if(mlcp.ttlvl_m <> mlda.ttlvl_m , mlcp.ttlvl_m = mlda.ttlvl_m)
,if(mlcp.var_minute_ml <>mlda.var_minute_ml, mlcp.var_minute_ml =
mlda.var_minute_ml)
,if(gplda.ttlvl_g <> gplcp.ttlvl_g , gplda.ttlvl_g = gplcp.ttlvl_g)
,if(gplcp.var_minute_gl <>gplda.var_minute_gl, gplcp.var_minute_gl =
gplda.var_minute_gl)
;model:
U(mlda)=c2[-2.11]+tt[n,-0.05,0.3]*ttlvl_m[13.09,13.71,14.40] + toll[n,-
0.10,0.1]*tlvl[16.67,33.33,50] + var[n,-0.06,0.5]*var_minute_ml[1.37,1.92,2.47]
/
U(mlcp)=c3[-3.53]+tt*ttlvl_m + var*var_minute_ml
/
U(gplcp)=c4[-
3.72]+tt*ttlvl_g[20.57,22.15,24.00]+var*var_minute_gl[3.10,5.09,7.31]
/
U(gplda)=tt*ttlvl_g+var*var_minute_gl
$
```

(2) N-Gene Code for Generating D_b-Efficient Design

```
;Design
;alts=gplda,gplcp,mlda,mlcp
;rows=21
;block=7
;eff=(rppanel,d)
;rep=1000
;rdraws=random(400)
;cond:
if(mlcp.tt1lvl_m <> mlda.tt1lvl_m , mlcp.tt1lvl_m = mlda.tt1lvl_m)
```

```
,if(mlcp.pbtt1ml<> mlda.pbtt1ml, mlcp.pbtt1ml= mlda.pbtt1ml)
,if(gplcp.tt1lvl_gl <> gplda.tt1lvl_gl , gplcp.tt1lvl_gl = gplda.tt1lvl_gl)
,if(gplcp.pbtt1gl<> gplda.pbtt1gl, gplcp.pbtt1gl= gplda.pbtt1gl)
;model:
U(mlda)=c2[-2.11]+tt1[n,-
0.05,0.3]*pbtt1ml[0,0.10,0.20,0.50,0.80,0.90,1]*tt1lvl_m[11.08,12,13.09]+tt2[n,
-0.05,0.3]*pbtt2ml[fcn(1-mlda.pbtt1ml)]*tt2lvl_m[16]+toll[n,-
0.10,0.1]*t2lvl[16.67,33.33,50]
/
U(mlcp)=c3[-3.53]+tt1*pbtt1ml*tt1lvl_m+tt2*pbtt2ml[fcn(1-
mlcp.pbtt1ml)]*tt2lvl_m
/
U(gplcp)=c4[-
3.72]+tt1*pbtt1gl[0,0.10,0.20,0.50,0.80,0.90,1]*tt1lvl_gl[24,28,36]+tt2*pbtt2gl[f
cn(1-gplcp.pbtt1gl)]*tt2lvl_gl[18]
/
U(gplda)=tt1*pbtt1gl*tt1lvl_gl+tt2*pbtt2gl[fcn(1-gplda.pbtt1gl)]*tt2lvl_gl
$
```

APPENDIX C. NLogit CODES FOR THE MIXED LOGIT MODELS

Format 1 & 5 (Conventional MNL Models Codes)
Design Format 1 – D_b-effcient Design
Design Format 5 - Adaptive Random

```
?*******Codes below for converting raw data from the 6688 survey data into useful
data for DSGNFRMT = 1 and 5 *******
? *** Create variable SPTT (SP question assigned Travel Time) for each SP question
using design Format 1 and 5

CREATE;if(DSGNFrmt=1&SP=1&ALT=1)SPTT = Q11TTG$
CREATE;if(DSGNFrmt=5&SP=1&ALT=1)SPTT = Q11TTG$
CREATE;if(DSGNFrmt=1&SP=1&ALT=2)SPTT = Q11TTG$
CREATE;if(DSGNFrmt=5&SP=1&ALT=2)SPTT = Q11TTG$
CREATE;if(DSGNFrmt=1&SP=1&ALT=3)SPTT = Q11TTM$
CREATE;if(DSGNFrmt=5&SP=1&ALT=3)SPTT = Q11TTM$
CREATE;if(DSGNFrmt=1&SP=1&ALT=4)SPTT = Q11TTM$
CREATE;if(DSGNFrmt=5&SP=1&ALT=4)SPTT = Q11TTM$

CREATE;if(DSGNFrmt=1&SP=2&ALT=1)SPTT = Q21TTG$
CREATE;if(DSGNFrmt=5&SP=2&ALT=1)SPTT = Q21TTG$
CREATE;if(DSGNFrmt=1&SP=2&ALT=2)SPTT = Q21TTG$
CREATE;if(DSGNFrmt=5&SP=2&ALT=2)SPTT = Q21TTG$
CREATE;if(DSGNFrmt=1&SP=2&ALT=3)SPTT = Q21TTM$
CREATE;if(DSGNFrmt=5&SP=2&ALT=3)SPTT = Q21TTM$
CREATE;if(DSGNFrmt=1&SP=2&ALT=4)SPTT = Q21TTM$
CREATE;if(DSGNFrmt=5&SP=2&ALT=4)SPTT = Q21TTM$

CREATE;if(DSGNFrmt=1&SP=3&ALT=1)SPTT = Q31TTG$
CREATE;if(DSGNFrmt=5&SP=3&ALT=1)SPTT = Q31TTG$
CREATE;if(DSGNFrmt=1&SP=3&ALT=2)SPTT = Q31TTG$
CREATE;if(DSGNFrmt=5&SP=3&ALT=2)SPTT = Q31TTG$
CREATE;if(DSGNFrmt=1&SP=3&ALT=3)SPTT = Q31TTM$
CREATE;if(DSGNFrmt=5&SP=3&ALT=3)SPTT = Q31TTM$
CREATE;if(DSGNFrmt=1&SP=3&ALT=4)SPTT = Q31TTM$
CREATE;if(DSGNFrmt=5&SP=3&ALT=4)SPTT = Q31TTM$

? *** Create variable SPToll (SP question assigned Toll for Option C the DA-ML mode)
for each SP question using design Format 1 and 5
```

```
CREATE;if(DSGNFrmt=1&SP=1&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=5&SP=1&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=1&SP=1&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=5&SP=1&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=1&SP=1&ALT=3)SPToll = Q11Toll$
CREATE;if(DSGNFrmt=5&SP=1&ALT=3)SPToll = Q11Toll$
CREATE;if(DSGNFrmt=1&SP=1&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=5&SP=1&ALT=4)SPToll = 0$

CREATE;if(DSGNFrmt=1&SP=2&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=5&SP=2&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=1&SP=2&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=5&SP=2&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=1&SP=2&ALT=3)SPToll = Q21Toll$
CREATE;if(DSGNFrmt=5&SP=2&ALT=3)SPToll = Q21Toll$
CREATE;if(DSGNFrmt=1&SP=2&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=5&SP=2&ALT=4)SPToll = 0$

CREATE;if(DSGNFrmt=1&SP=3&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=5&SP=3&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=1&SP=3&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=5&SP=3&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=1&SP=3&ALT=3)SPToll = Q31Toll$
CREATE;if(DSGNFrmt=5&SP=3&ALT=3)SPToll = Q31Toll$
CREATE;if(DSGNFrmt=1&SP=3&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=5&SP=3&ALT=4)SPToll = 0$

? *** Create variable SPTTV (SP question assigned Travel Time Variability) for each SP question using design Format 1 and 5

CREATE;if(DSGNFrmt=1&SP=1&ALT=1)SPTTV = Q11VarG$
CREATE;if(DSGNFrmt=5&SP=1&ALT=1)SPTTV = Q11VarG$
CREATE;if(DSGNFrmt=1&SP=1&ALT=2)SPTTV = Q11VarG$
CREATE;if(DSGNFrmt=5&SP=1&ALT=2)SPTTV = Q11VarG$
CREATE;if(DSGNFrmt=1&SP=1&ALT=3)SPTTV = Q1VarM$
CREATE;if(DSGNFrmt=5&SP=1&ALT=3)SPTTV = Q1VarM$
CREATE;if(DSGNFrmt=1&SP=1&ALT=4)SPTTV = Q1VarM$
CREATE;if(DSGNFrmt=5&SP=1&ALT=4)SPTTV = Q1VarM$

CREATE;if(DSGNFrmt=1&SP=2&ALT=1)SPTTV = Q21VarG$
CREATE;if(DSGNFrmt=5&SP=2&ALT=1)SPTTV = Q21VarG$
```

```
CREATE;if(DSGNFrmt=1&SP=2&ALT=2)SPTTV = Q21VarG$
CREATE;if(DSGNFrmt=5&SP=2&ALT=2)SPTTV = Q21VarG$
CREATE;if(DSGNFrmt=1&SP=2&ALT=3)SPTTV = Q2VarM$
CREATE;if(DSGNFrmt=5&SP=2&ALT=3)SPTTV = Q2VarM$
CREATE;if(DSGNFrmt=1&SP=2&ALT=4)SPTTV = Q2VarM$
CREATE;if(DSGNFrmt=5&SP=2&ALT=4)SPTTV = Q2VarM$

CREATE;if(DSGNFrmt=1&SP=3&ALT=1)SPTTV = Q31VarG$
CREATE;if(DSGNFrmt=5&SP=3&ALT=1)SPTTV = Q31VarG$
CREATE;if(DSGNFrmt=1&SP=3&ALT=2)SPTTV = Q31VarG$
CREATE;if(DSGNFrmt=5&SP=3&ALT=2)SPTTV = Q31VarG$
CREATE;if(DSGNFrmt=1&SP=3&ALT=3)SPTTV = Q3VarM$
CREATE;if(DSGNFrmt=5&SP=3&ALT=3)SPTTV = Q3VarM$
CREATE;if(DSGNFrmt=1&SP=3&ALT=4)SPTTV = Q3VarM$
CREATE;if(DSGNFrmt=5&SP=3&ALT=4)SPTTV = Q3VarM$

sample;all$

?Model with Constant Only

NLOGIT ; lhs = DECISION,NALTS,alt ;
        Choices = A,B,C,D ;
        Crosstab ;

        Model:
                U(A) = 0/
                U(B) = asccpg/
                U(C) = ascdam/
                U(D) = asccpm$

?Model with TT and Toll

NLOGIT ; lhs = DECISION,NALTS,alt ;

        Choices = A,B,C,D ;
        Crosstab ;

        Model:
                U(A) = c_TT*SPTT + c_TTv*SPTTV/
                U(B) = asccpg + c_TT*SPTT + c_TTV*SPTTV/
                U(C) = ascdam + c_TT*SPTT + c_TTV*SPTTV + c_toll*SPToll/
```

U(D) = asccpm + c_TT*SPTT + c_TTV*SPTTV$

Format 2 & 6 (Reference Point Models Codes)
Design Format 2 - D_b-effcient Design
Design Format 6 - Adaptive Random

?*******Codes below for converting raw data from the 6688 survey data into useful data for DSGNFRMT = 2 and 6 *******
? *** Create variable SPToll (SP question assigned Toll for Option C the DA-ML mode) for each SP question using design Format 2 and 6

```
CREATE;if(DSGNFrmt=2&SP=1&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=6&SP=1&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=2&SP=1&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=6&SP=1&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=2&SP=1&ALT=3)SPToll = Q11Toll$
CREATE;if(DSGNFrmt=6&SP=1&ALT=3)SPToll = Q11Toll$
CREATE;if(DSGNFrmt=2&SP=1&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=6&SP=1&ALT=4)SPToll = 0$

CREATE;if(DSGNFrmt=2&SP=2&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=6&SP=2&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=2&SP=2&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=6&SP=2&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=2&SP=2&ALT=3)SPToll = Q21Toll$
CREATE;if(DSGNFrmt=6&SP=2&ALT=3)SPToll = Q21Toll$
CREATE;if(DSGNFrmt=2&SP=2&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=6&SP=2&ALT=4)SPToll = 0$

CREATE;if(DSGNFrmt=2&SP=3&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=6&SP=3&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=2&SP=3&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=6&SP=3&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=2&SP=3&ALT=3)SPToll = Q31Toll$
CREATE;if(DSGNFrmt=6&SP=3&ALT=3)SPToll = Q31Toll$
CREATE;if(DSGNFrmt=2&SP=3&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=6&SP=3&ALT=4)SPToll = 0$
```

? *** Create variable SPTTD1 and SPTTD2 (SP question assigned Trave Time Difference) for each SP question using design Format 2 and 6

?** Create SPTTD1 and SPTTD2 for SP1

```
CREATE;if(DSGNFrmt=2&SP=1&ALT=1)sptTd1 = Q11VarG$
CREATE;if(DSGNFrmt=6&SP=1&ALT=1)sptTd1 = Q11VarG$
CREATE;if(DSGNFrmt=2&SP=1&ALT=2)sptTd1 = Q11VarG$
CREATE;if(DSGNFrmt=6&SP=1&ALT=2)sptTd1 = Q11VarG$

CREATE;if(DSGNFrmt=2&SP=1&ALT=1)sptTd2 = Q11VarG$
CREATE;if(DSGNFrmt=6&SP=1&ALT=1)sptTd2 = Q11VarG$
CREATE;if(DSGNFrmt=2&SP=1&ALT=2)sptTd2 = Q11VarG$
CREATE;if(DSGNFrmt=6&SP=1&ALT=2)sptTd2 = Q11VarG$

CREATE;if(DSGNFrmt=2&SP=1&ALT=3)sptTd1 = Q11MxDif$
CREATE;if(DSGNFrmt=6&SP=1&ALT=3)sptTd1 = Q11MxDif$
CREATE;if(DSGNFrmt=2&SP=1&ALT=4)sptTd1 = Q11MxDif$
CREATE;if(DSGNFrmt=6&SP=1&ALT=4)sptTd1 = Q11MxDif$

CREATE;if(DSGNFrmt=2&SP=1&ALT=3)sptTd2 = Q11MnDif$
CREATE;if(DSGNFrmt=6&SP=1&ALT=3)sptTd2 = Q11MnDif$
CREATE;if(DSGNFrmt=2&SP=1&ALT=4)sptTd2 = Q11MnDif$
CREATE;if(DSGNFrmt=6&SP=1&ALT=4)sptTd2 = Q11MnDif$
```

?** Create SPTTD1 and SPTTD1 and SPTTD2 for SP2

```
CREATE;if(DSGNFrmt=2&SP=2&ALT=1)sptTd1 = Q21VarG$
CREATE;if(DSGNFrmt=6&SP=2&ALT=1)sptTd1 = Q21VarG$
CREATE;if(DSGNFrmt=2&SP=2&ALT=2)sptTd1 = Q21VarG$
CREATE;if(DSGNFrmt=6&SP=2&ALT=2)sptTd1 = Q21VarG$

CREATE;if(DSGNFrmt=2&SP=2&ALT=1)sptTd2 = Q21VarG$
CREATE;if(DSGNFrmt=6&SP=2&ALT=1)sptTd2 = Q21VarG$
CREATE;if(DSGNFrmt=2&SP=2&ALT=2)sptTd2 = Q21VarG$
CREATE;if(DSGNFrmt=6&SP=2&ALT=2)sptTd2 = Q21VarG$

CREATE;if(DSGNFrmt=2&SP=2&ALT=3)sptTd1 = Q21MxDif$
CREATE;if(DSGNFrmt=6&SP=2&ALT=3)sptTd1 = Q21MxDif$
CREATE;if(DSGNFrmt=2&SP=2&ALT=4)sptTd1 = Q21MxDif$
CREATE;if(DSGNFrmt=6&SP=2&ALT=4)sptTd1 = Q21MxDif$

CREATE;if(DSGNFrmt=2&SP=2&ALT=3)sptTd2 = Q21MnDif$
CREATE;if(DSGNFrmt=6&SP=2&ALT=3)sptTd2 = Q21MnDif$
```

```
CREATE;if(DSGNFrmt=2&SP=2&ALT=4)sptd2 = Q21MnDif$
CREATE;if(DSGNFrmt=6&SP=2&ALT=4)sptd2 = Q21MnDif$

?** Create SPTTD1 and SPTTD1 and SPTTD2 for SP3

CREATE;if(DSGNFrmt=2&SP=3&ALT=1)sptd1 = Q31VarG$
CREATE;if(DSGNFrmt=6&SP=3&ALT=1)sptd1 = Q31VarG$
CREATE;if(DSGNFrmt=2&SP=3&ALT=2)sptd1 = Q31VarG$
CREATE;if(DSGNFrmt=6&SP=3&ALT=2)sptd1 = Q31VarG$

CREATE;if(DSGNFrmt=2&SP=3&ALT=1)sptd2 = Q31VarG$
CREATE;if(DSGNFrmt=6&SP=3&ALT=1)sptd2 = Q31VarG$
CREATE;if(DSGNFrmt=2&SP=3&ALT=2)sptd2 = Q31VarG$
CREATE;if(DSGNFrmt=6&SP=3&ALT=2)sptd2 = Q31VarG$

CREATE;if(DSGNFrmt=2&SP=3&ALT=3)sptd1 = Q31MxDif$
CREATE;if(DSGNFrmt=6&SP=3&ALT=3)sptd1 = Q31MxDif$
CREATE;if(DSGNFrmt=2&SP=3&ALT=4)sptd1 = Q31MxDif$
CREATE;if(DSGNFrmt=6&SP=3&ALT=4)sptd1 = Q31MxDif$

CREATE;if(DSGNFrmt=2&SP=3&ALT=3)sptd2 = Q31MnDif$
CREATE;if(DSGNFrmt=6&SP=3&ALT=3)sptd2 = Q31MnDif$
CREATE;if(DSGNFrmt=2&SP=3&ALT=4)sptd2 = Q31MnDif$
CREATE;if(DSGNFrmt=6&SP=3&ALT=4)sptd2 = Q31MnDif$

sample;all $
REJECT; decision=-999$
REJECT; ID = 1778$
REJECT; ID = 1823$
CREATE ; zrpl = Rnu(0,1) $
NLRPLOGIT
   ; Lhs = DECISION
   ; Choices = A,B,C,D
   ; Check Data
   ; Crosstab
   ; Pds = 3
   ; Labels = B1, B2, asccpg,ascdam,asccpm, Alpha, Beta, Lamda, c_toll
   ; Start -.3, .3,-3.20,-.39,-1.06,-.12,-.12,-2.25,-.15
   ; Fcn = B1(n), B2(n),c_toll(t)
   ; Halton
   ; Draws = 200
```

```
; Correlated
; RPL = zrpl
; Fn1 = valgain1 = B1*spttd1^(exp(Alpha))
; Fn2 = valgain2 = B1*spttd2^(exp(Alpha))
; Fn3 = valloss = B2*Lamda*(spttd2)^(exp(Beta))
; Fn4 = OPTA = Fn1 + Fn3
; Fn5 = OPTB = asccpg + Fn1 + Fn3
; Fn6 = OPTC = ascdam + Fn1 + Fn2 + c_toll*SPToll
; Fn7 = OPTD = asccpm + Fn1 + Fn2
        ; Model:
                U(A) = OPTA/
                U(B) = OPTB/
                U(C) = OPTC/
                U(D) = OPTD
$
```

Format 3 & 7 (PT-pwf Models Codes)
Design Format 3 - D_b-effcient Design
Design Format 7 - Adaptive Random

```
?*******Codes below for converting raw data from the 6688 survey data into useful
data for DSGNFRMT = 3 and 7 *******
? *** Create variable SPToll (SP question assigned Toll for Option C the DA-ML mode)
for each SP question using design Format 3 and 7

CREATE;if(DSGNFrmt=3&SP=1&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=7&SP=1&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=3&SP=1&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=7&SP=1&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=3&SP=1&ALT=3)SPToll = Q12Toll$
CREATE;if(DSGNFrmt=7&SP=1&ALT=3)SPToll = Q12Toll$
CREATE;if(DSGNFrmt=3&SP=1&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=7&SP=1&ALT=4)SPToll = 0$

CREATE;if(DSGNFrmt=3&SP=2&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=7&SP=2&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=3&SP=2&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=7&SP=2&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=3&SP=2&ALT=3)SPToll = Q22Toll$
CREATE;if(DSGNFrmt=7&SP=2&ALT=3)SPToll = Q22Toll$
CREATE;if(DSGNFrmt=3&SP=2&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=7&SP=2&ALT=4)SPToll = 0$
```

```
CREATE;if(DSGNFrmt=3&SP=3&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=7&SP=3&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=3&SP=3&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=7&SP=3&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=3&SP=3&ALT=3)SPToll = Q32Toll$
CREATE;if(DSGNFrmt=7&SP=3&ALT=3)SPToll = Q32Toll$
CREATE;if(DSGNFrmt=3&SP=3&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=7&SP=3&ALT=4)SPToll = 0$

? ** Create variable SPTT1 and SPTT2 (SP question assigned Travel Time) for each SP
question using design Format 3 and 7

CREATE;if(DSGNFrmt=3&SP=1&ALT=1)SPTT1 = Q12TTG1$
CREATE;if(DSGNFrmt=7&SP=1&ALT=1)SPTT1 = Q12TTG1$
CREATE;if(DSGNFrmt=3&SP=1&ALT=1)SPTT2 = Q12TTG2$
CREATE;if(DSGNFrmt=7&SP=1&ALT=1)SPTT2 = Q12TTG2$

CREATE;if(DSGNFrmt=3&SP=1&ALT=2)SPTT1 = Q12TTG1$
CREATE;if(DSGNFrmt=7&SP=1&ALT=2)SPTT1 = Q12TTG1$
CREATE;if(DSGNFrmt=3&SP=1&ALT=2)SPTT2 = Q12TTG2$
CREATE;if(DSGNFrmt=7&SP=1&ALT=2)SPTT2 = Q12TTG2$

CREATE;if(DSGNFrmt=3&SP=1&ALT=3)SPTT1 = Q12TTM1$
CREATE;if(DSGNFrmt=7&SP=1&ALT=3)SPTT1 = Q12TTM1$
CREATE;if(DSGNFrmt=3&SP=1&ALT=3)SPTT2 = Q12TTM2$
CREATE;if(DSGNFrmt=7&SP=1&ALT=3)SPTT2 = Q12TTM2$

CREATE;if(DSGNFrmt=3&SP=1&ALT=4)SPTT1 = Q12TTM1$
CREATE;if(DSGNFrmt=7&SP=1&ALT=4)SPTT1 = Q12TTM1$
CREATE;if(DSGNFrmt=3&SP=1&ALT=4)SPTT2 = Q12TTM2$
CREATE;if(DSGNFrmt=7&SP=1&ALT=4)SPTT2 = Q12TTM2$

CREATE;if(DSGNFrmt=3&SP=2&ALT=1)SPTT1 = Q22TTG1$
CREATE;if(DSGNFrmt=7&SP=2&ALT=1)SPTT1 = Q22TTG1$
CREATE;if(DSGNFrmt=3&SP=2&ALT=1)SPTT2 = Q22TTG2$
CREATE;if(DSGNFrmt=7&SP=2&ALT=1)SPTT2 = Q22TTG2$

CREATE;if(DSGNFrmt=3&SP=2&ALT=2)SPTT1 = Q22TTG1$
CREATE;if(DSGNFrmt=7&SP=2&ALT=2)SPTT1 = Q22TTG1$
CREATE;if(DSGNFrmt=3&SP=2&ALT=2)SPTT2 = Q22TTG2$
CREATE;if(DSGNFrmt=7&SP=2&ALT=2)SPTT2 = Q22TTG2$
```

```
CREATE;if(DSGNFrmt=3&SP=2&ALT=3)SPTT1 = Q22TTM1$
CREATE;if(DSGNFrmt=7&SP=2&ALT=3)SPTT1 = Q22TTM1$
CREATE;if(DSGNFrmt=3&SP=2&ALT=3)SPTT2 = Q22TTM2$
CREATE;if(DSGNFrmt=7&SP=2&ALT=3)SPTT2 = Q22TTM2$

CREATE;if(DSGNFrmt=3&SP=2&ALT=4)SPTT1 = Q22TTM1$
CREATE;if(DSGNFrmt=7&SP=2&ALT=4)SPTT1 = Q22TTM1$
CREATE;if(DSGNFrmt=3&SP=2&ALT=4)SPTT2 = Q22TTM2$
CREATE;if(DSGNFrmt=7&SP=2&ALT=4)SPTT2 = Q22TTM2$

CREATE;if(DSGNFrmt=3&SP=3&ALT=1)SPTT1 = Q32TTG1$
CREATE;if(DSGNFrmt=7&SP=3&ALT=1)SPTT1 = Q32TTG1$
CREATE;if(DSGNFrmt=3&SP=3&ALT=1)SPTT2 = Q32TTG2$
CREATE;if(DSGNFrmt=7&SP=3&ALT=1)SPTT2 = Q32TTG2$

CREATE;if(DSGNFrmt=3&SP=3&ALT=2)SPTT1 = Q32TTG1$
CREATE;if(DSGNFrmt=7&SP=3&ALT=2)SPTT1 = Q32TTG1$
CREATE;if(DSGNFrmt=3&SP=3&ALT=2)SPTT2 = Q32TTG2$
CREATE;if(DSGNFrmt=7&SP=3&ALT=2)SPTT2 = Q32TTG2$

CREATE;if(DSGNFrmt=3&SP=3&ALT=3)SPTT1 = Q32TTM1$
CREATE;if(DSGNFrmt=7&SP=3&ALT=3)SPTT1 = Q32TTM1$
CREATE;if(DSGNFrmt=3&SP=3&ALT=3)SPTT2 = Q32TTM2$
CREATE;if(DSGNFrmt=7&SP=3&ALT=3)SPTT2 = Q32TTM2$

CREATE;if(DSGNFrmt=3&SP=3&ALT=4)SPTT1 = Q32TTM1$
CREATE;if(DSGNFrmt=7&SP=3&ALT=4)SPTT1 = Q32TTM1$
CREATE;if(DSGNFrmt=3&SP=3&ALT=4)SPTT2 = Q32TTM2$
CREATE;if(DSGNFrmt=7&SP=3&ALT=4)SPTT2 = Q32TTM2$

? *** Create variable PRB1 and PRB2 (SP question assigned Probability of Trave Time
Difference) for each SP question using design Format 3 and 7

?** Create PRB1 and PRB2 for SP1

CREATE;if(DSGNFrmt=3&SP=1&ALT=1)PRB1 = Q12PBG1$
CREATE;if(DSGNFrmt=7&SP=1&ALT=1)PRB1 = Q12PBG1$
CREATE;if(DSGNFrmt=3&SP=1&ALT=2)PRB1 = Q12PBG1$
CREATE;if(DSGNFrmt=7&SP=1&ALT=2)PRB1 = Q12PBG1$

CREATE;if(DSGNFrmt=3&SP=1&ALT=3)PRB1 = Q12PBM1$
```

```
CREATE;if(DSGNFrmt=7&SP=1&ALT=3)PRB1 = Q12PBM1$
CREATE;if(DSGNFrmt=3&SP=1&ALT=4)PRB1 = Q12PBM1$
CREATE;if(DSGNFrmt=7&SP=1&ALT=4)PRB1 = Q12PBM1$

CREATE;if(DSGNFrmt=3&SP=1&ALT=1)PRB2 = Q12PBG2$
CREATE;if(DSGNFrmt=7&SP=1&ALT=1)PRB2 = Q12PBG2$
CREATE;if(DSGNFrmt=3&SP=1&ALT=2)PRB2 = Q12PBG2$
CREATE;if(DSGNFrmt=7&SP=1&ALT=2)PRB2 = Q12PBG2$

CREATE;if(DSGNFrmt=3&SP=1&ALT=3)PRB2 = Q12PBM2$
CREATE;if(DSGNFrmt=7&SP=1&ALT=3)PRB2 = Q12PBM2$
CREATE;if(DSGNFrmt=3&SP=1&ALT=4)PRB2 = Q12PBM2$
CREATE;if(DSGNFrmt=7&SP=1&ALT=4)PRB2 = Q12PBM2$

?** Create PRB1 and PRB2 for SP2

CREATE;if(DSGNFrmt=3&SP=2&ALT=1)PRB1 = Q22PBG1$
CREATE;if(DSGNFrmt=7&SP=2&ALT=1)PRB1 = Q22PBG1$
CREATE;if(DSGNFrmt=3&SP=2&ALT=2)PRB1 = Q22PBG1$
CREATE;if(DSGNFrmt=7&SP=2&ALT=2)PRB1 = Q22PBG1$

CREATE;if(DSGNFrmt=3&SP=2&ALT=3)PRB1 = Q22PBM1$
CREATE;if(DSGNFrmt=7&SP=2&ALT=3)PRB1 = Q22PBM1$
CREATE;if(DSGNFrmt=3&SP=2&ALT=4)PRB1 = Q22PBM1$
CREATE;if(DSGNFrmt=7&SP=2&ALT=4)PRB1 = Q22PBM1$

CREATE;if(DSGNFrmt=3&SP=2&ALT=1)PRB2 = Q22PBG2$
CREATE;if(DSGNFrmt=7&SP=2&ALT=1)PRB2 = Q22PBG2$
CREATE;if(DSGNFrmt=3&SP=2&ALT=2)PRB2 = Q22PBG2$
CREATE;if(DSGNFrmt=7&SP=2&ALT=2)PRB2 = Q22PBG2$

CREATE;if(DSGNFrmt=3&SP=2&ALT=3)PRB2 = Q22PBM2$
CREATE;if(DSGNFrmt=7&SP=2&ALT=3)PRB2 = Q22PBM2$
CREATE;if(DSGNFrmt=3&SP=2&ALT=4)PRB2 = Q22PBM2$
CREATE;if(DSGNFrmt=7&SP=2&ALT=4)PRB2 = Q22PBM2$

?** Create PRB1 and PRB2 for SP3

CREATE;if(DSGNFrmt=3&SP=3&ALT=1)PRB1 = Q32PBG1$
CREATE;if(DSGNFrmt=7&SP=3&ALT=1)PRB1 = Q32PBG1$
CREATE;if(DSGNFrmt=3&SP=3&ALT=2)PRB1 = Q32PBG1$
```

```
CREATE;if(DSGNFrmt=7&SP=3&ALT=2)PRB1 = Q32PBG1$

CREATE;if(DSGNFrmt=3&SP=3&ALT=3)PRB1 = Q32PBM1$
CREATE;if(DSGNFrmt=7&SP=3&ALT=3)PRB1 = Q32PBM1$
CREATE;if(DSGNFrmt=3&SP=3&ALT=4)PRB1 = Q32PBM1$
CREATE;if(DSGNFrmt=7&SP=3&ALT=4)PRB1 = Q32PBM1$

CREATE;if(DSGNFrmt=3&SP=3&ALT=1)PRB2 = Q32PBG2$
CREATE;if(DSGNFrmt=7&SP=3&ALT=1)PRB2 = Q32PBG2$
CREATE;if(DSGNFrmt=3&SP=3&ALT=2)PRB2 = Q32PBG2$
CREATE;if(DSGNFrmt=7&SP=3&ALT=2)PRB2 = Q32PBG2$

CREATE;if(DSGNFrmt=3&SP=3&ALT=3)PRB2 = Q32PBM2$
CREATE;if(DSGNFrmt=7&SP=3&ALT=3)PRB2 = Q32PBM2$
CREATE;if(DSGNFrmt=3&SP=3&ALT=4)PRB2 = Q32PBM2$
CREATE;if(DSGNFrmt=7&SP=3&ALT=4)PRB2 = Q32PBM2$

sample;all$
REJECT; VEHTYPE = 1$
REJECT; VEHTYPE = 3$
REJECT; VEHTYPE = 4$
REJECT; decision=-999$
REJECT; SPAnswer = 1$
REJECT; SPAnswer = 2$
NLRPLOGIT
  ; Lhs = DECISION,NALTS,alt
  ; Choices = A,B,C,D
  ; Crosstab
  ; List
  ; Check Data
  ; Pds = 3
  ; Labels = B1, asccpg,ascdam,asccpm, Delta, Gamma, c_toll
  ; Start -.2, -3.20,-.39,-1.06,.61,.69,-.15
  ; Fcn = B1(t), C_Toll(t)
  ; Halton
  ; Draws = 200
  ; Maxit = 50
  ; Correlated
  ; Fn1 = pwf1 = ((prb1)^Gamma)/(((prb1)^Gamma+(1-prb1)^Gamma)^(1/Gamma))
  ; Fn2 = pwf2 = ((prb2)^Delta)/(((prb2)^Delta+(1-prb2)^Delta)^(1/Delta))
  ; Fn3 = OPTA = B1*Fn1*(-SPTT1) + B1*Fn2*(-SPTT2)
```

```
; Fn4 = OPTB = asccpg + B1*Fn1*(-SPTT1) + B1*Fn2*(-SPTT2)
; Fn5 = OPTC = ascdam + B1*Fn1*(-SPTT1) + B1*Fn2*(-SPTT2) + c_toll*SPToll
; Fn6 = OPTD = asccpm + B1*Fn1*(-SPTT1) + B1*Fn2*(-SPTT2)
; Model:
            U(A) = OPTA/
            U(B) = OPTB/
            U(C) = OPTC/
            U(D) = OPTD
     $
```

Format 4 & 8 (PT-Full Models Codes)
Design Format 4 - D_b-effcient Design
Design Format 8 - Adaptive Random

```
?*******Codes below for converting raw data from the 6688 survey data into useful
data for DSGNFRMT = 4 and 8 *******
? *** Create variable SPToll (SP question assigned Toll for Option C the DA-ML mode)
for each SP question using design Format 4 and 8

CREATE;if(DSGNFrmt=4&SP=1&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=8&SP=1&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=4&SP=1&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=8&SP=1&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=4&SP=1&ALT=3)SPToll = Q12Toll$
CREATE;if(DSGNFrmt=8&SP=1&ALT=3)SPToll = Q12Toll$
CREATE;if(DSGNFrmt=4&SP=1&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=8&SP=1&ALT=4)SPToll = 0$

CREATE;if(DSGNFrmt=4&SP=2&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=8&SP=2&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=4&SP=2&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=8&SP=2&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=4&SP=2&ALT=3)SPToll = Q22Toll$
CREATE;if(DSGNFrmt=8&SP=2&ALT=3)SPToll = Q22Toll$
CREATE;if(DSGNFrmt=4&SP=2&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=8&SP=2&ALT=4)SPToll = 0$

CREATE;if(DSGNFrmt=4&SP=3&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=8&SP=3&ALT=1)SPToll = 0$
CREATE;if(DSGNFrmt=4&SP=3&ALT=2)SPToll = 0$
CREATE;if(DSGNFrmt=8&SP=3&ALT=2)SPToll = 0$
```

CREATE;if(DSGNFrmt=4&SP=3&ALT=3)SPToll = Q32Toll$
CREATE;if(DSGNFrmt=8&SP=3&ALT=3)SPToll = Q32Toll$
CREATE;if(DSGNFrmt=4&SP=3&ALT=4)SPToll = 0$
CREATE;if(DSGNFrmt=8&SP=3&ALT=4)SPToll = 0$

? *** Create variable SPTTD1 and SPTTD2 (SP question assigned Trave Time Difference) for each SP question using design Format 4 and 8

?** Create SPTTD1 and SPTTD2 for SP1

CREATE;if(DSGNFrmt=4&SP=1&ALT=1&Q12LSG1=2)spttd1 = -Q12TDGG1$
CREATE;if(DSGNFrmt=4&SP=1&ALT=1&Q12LSG1=1)spttd1 = Q12TDGG1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=1&Q12LSG1=2)spttd1 = -Q12TDGG1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=1&Q12LSG1=1)spttd1 = Q12TDGG1$
CREATE;if(DSGNFrmt=4&SP=1&ALT=2&Q12LSG1=2)spttd1 = -Q12TDGG1$
CREATE;if(DSGNFrmt=4&SP=1&ALT=2&Q12LSG1=1)spttd1 = Q12TDGG1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=2&Q12LSG1=2)spttd1 = -Q12TDGG1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=2&Q12LSG1=1)spttd1 = Q12TDGG1$

CREATE;if(DSGNFrmt=4&SP=1&ALT=1&Q12LSG2=2)spttd2 = -Q12TDGG2$
CREATE;if(DSGNFrmt=4&SP=1&ALT=1&Q12LSG2=1)spttd2 = Q12TDGG2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=1&Q12LSG2=2)spttd2 = -Q12TDGG2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=1&Q12LSG2=1)spttd2 = Q12TDGG2$
CREATE;if(DSGNFrmt=4&SP=1&ALT=2&Q12LSG2=2)spttd2 = -Q12TDGG2$
CREATE;if(DSGNFrmt=4&SP=1&ALT=2&Q12LSG2=1)spttd2 = Q12TDGG2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=2&Q12LSG2=2)spttd2 = -Q12TDGG2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=2&Q12LSG2=1)spttd2 = Q12TDGG2$

CREATE;if(DSGNFrmt=4&SP=1&ALT=3&Q12LSM1=2)spttd1 = -Q12TDMG1$
CREATE;if(DSGNFrmt=4&SP=1&ALT=3&Q12LSM1=1)spttd1 = Q12TDMG1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=3&Q12LSM1=2)spttd1 = -Q12TDMG1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=3&Q12LSM1=1)spttd1 = Q12TDMG1$
CREATE;if(DSGNFrmt=4&SP=1&ALT=4&Q12LSM1=2)spttd1 = -Q12TDMG1$
CREATE;if(DSGNFrmt=4&SP=1&ALT=4&Q12LSM1=1)spttd1 = Q12TDMG1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=4&Q12LSM1=2)spttd1 = -Q12TDMG1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=4&Q12LSM1=1)spttd1 = Q12TDMG1$

CREATE;if(DSGNFrmt=4&SP=1&ALT=3&Q12LSM2=2)spttd2 = -Q12TDMG2$
CREATE;if(DSGNFrmt=4&SP=1&ALT=3&Q12LSM2=1)spttd2 = Q12TDMG2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=3&Q12LSM2=2)spttd2 = -Q12TDMG2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=3&Q12LSM2=1)spttd2 = Q12TDMG2$

```
CREATE;if(DSGNFrmt=4&SP=1&ALT=4&Q12LSM2=2)spttd2 = -Q12TDMG2$
CREATE;if(DSGNFrmt=4&SP=1&ALT=4&Q12LSM2=1)spttd2 = Q12TDMG2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=4&Q12LSM2=2)spttd2 = -Q12TDMG2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=4&Q12LSM2=1)spttd2 = Q12TDMG2$

?** Create SPTTD1 and SPTTD1 and SPTTD2 for SP2

CREATE;if(DSGNFrmt=4&SP=2&ALT=1&Q22LSG1=2)spttd1 = -Q22TDGG1$
CREATE;if(DSGNFrmt=4&SP=2&ALT=1&Q22LSG1=1)spttd1 = Q22TDGG1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=1&Q22LSG1=2)spttd1 = -Q22TDGG1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=1&Q22LSG1=1)spttd1 = Q22TDGG1$
CREATE;if(DSGNFrmt=4&SP=2&ALT=2&Q22LSG1=2)spttd1 = -Q22TDGG1$
CREATE;if(DSGNFrmt=4&SP=2&ALT=2&Q22LSG1=1)spttd1 = Q22TDGG1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=2&Q22LSG1=2)spttd1 = -Q22TDGG1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=2&Q22LSG1=1)spttd1 = Q22TDGG1$

CREATE;if(DSGNFrmt=4&SP=2&ALT=1&Q22LSG2=2)spttd2 = -Q22TDGG2$
CREATE;if(DSGNFrmt=4&SP=2&ALT=1&Q22LSG2=1)spttd2 = Q22TDGG2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=1&Q22LSG2=2)spttd2 = -Q22TDGG2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=1&Q22LSG2=1)spttd2 = Q22TDGG2$
CREATE;if(DSGNFrmt=4&SP=2&ALT=2&Q22LSG2=2)spttd2 = -Q22TDGG2$
CREATE;if(DSGNFrmt=4&SP=2&ALT=2&Q22LSG2=1)spttd2 = Q22TDGG2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=2&Q22LSG2=2)spttd2 = -Q22TDGG2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=2&Q22LSG2=1)spttd2 = Q22TDGG2$

CREATE;if(DSGNFrmt=4&SP=2&ALT=3&Q22LSM1=2)spttd1 = -Q22TDMG1$
CREATE;if(DSGNFrmt=4&SP=2&ALT=3&Q22LSM1=1)spttd1 = Q22TDMG1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=3&Q22LSM1=2)spttd1 = -Q22TDMG1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=3&Q22LSM1=1)spttd1 = Q22TDMG1$
CREATE;if(DSGNFrmt=4&SP=2&ALT=4&Q22LSM1=2)spttd1 = -Q22TDMG1$
CREATE;if(DSGNFrmt=4&SP=2&ALT=4&Q22LSM1=1)spttd1 = Q22TDMG1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=4&Q22LSM1=2)spttd1 = -Q22TDMG1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=4&Q22LSM1=1)spttd1 = Q22TDMG1$

CREATE;if(DSGNFrmt=4&SP=2&ALT=3&Q22LSM2=2)spttd2 = -Q22TDMG2$
CREATE;if(DSGNFrmt=4&SP=2&ALT=3&Q22LSM2=1)spttd2 = Q22TDMG2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=3&Q22LSM2=2)spttd2 = -Q22TDMG2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=3&Q22LSM2=1)spttd2 = Q22TDMG2$
CREATE;if(DSGNFrmt=4&SP=2&ALT=4&Q22LSM2=2)spttd2 = -Q22TDMG2$
CREATE;if(DSGNFrmt=4&SP=2&ALT=4&Q22LSM2=1)spttd2 = Q22TDMG2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=4&Q22LSM2=2)spttd2 = -Q22TDMG2$
```

```
CREATE;if(DSGNFrmt=8&SP=2&ALT=4&Q22LSM2=1)spttd2 = Q22TDMG2$

?** Create SPTTD1 and SPTTD1 and SPTTD2 for SP3

CREATE;if(DSGNFrmt=4&SP=3&ALT=1&Q32LSG1=2)spttd1 = -Q32TDGG1$
CREATE;if(DSGNFrmt=4&SP=3&ALT=1&Q32LSG1=1)spttd1 = Q32TDGG1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=1&Q32LSG1=2)spttd1 = -Q32TDGG1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=1&Q32LSG1=1)spttd1 = Q32TDGG1$
CREATE;if(DSGNFrmt=4&SP=3&ALT=2&Q32LSG1=2)spttd1 = -Q32TDGG1$
CREATE;if(DSGNFrmt=4&SP=3&ALT=2&Q32LSG1=1)spttd1 = Q32TDGG1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=2&Q32LSG1=2)spttd1 = -Q32TDGG1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=2&Q32LSG1=1)spttd1 = Q32TDGG1$

CREATE;if(DSGNFrmt=4&SP=3&ALT=1&Q32LSG2=2)spttd2 = -Q32TDGG2$
CREATE;if(DSGNFrmt=4&SP=3&ALT=1&Q32LSG2=1)spttd2 = Q32TDGG2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=1&Q32LSG2=2)spttd2 = -Q32TDGG2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=1&Q32LSG2=1)spttd2 = Q32TDGG2$
CREATE;if(DSGNFrmt=4&SP=3&ALT=2&Q32LSG2=2)spttd2 = -Q32TDGG2$
CREATE;if(DSGNFrmt=4&SP=3&ALT=2&Q32LSG2=1)spttd2 = Q32TDGG2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=2&Q32LSG2=2)spttd2 = -Q32TDGG2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=2&Q32LSG2=1)spttd2 = Q32TDGG2$

CREATE;if(DSGNFrmt=4&SP=3&ALT=3&Q32LSM1=2)spttd1 = -Q32TDMG1$
CREATE;if(DSGNFrmt=4&SP=3&ALT=3&Q32LSM1=1)spttd1 = Q32TDMG1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=3&Q32LSM1=2)spttd1 = -Q32TDMG1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=3&Q32LSM1=1)spttd1 = Q32TDMG1$
CREATE;if(DSGNFrmt=4&SP=3&ALT=4&Q32LSM1=2)spttd1 = -Q32TDMG1$
CREATE;if(DSGNFrmt=4&SP=3&ALT=4&Q32LSM1=1)spttd1 = Q32TDMG1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=4&Q32LSM1=2)spttd1 = -Q32TDMG1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=4&Q32LSM1=1)spttd1 = Q32TDMG1$

CREATE;if(DSGNFrmt=4&SP=3&ALT=3&Q32LSM2=2)spttd2 = -Q32TDMG2$
CREATE;if(DSGNFrmt=4&SP=3&ALT=3&Q32LSM2=1)spttd2 = Q32TDMG2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=3&Q32LSM2=2)spttd2 = -Q32TDMG2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=3&Q32LSM2=1)spttd2 = Q32TDMG2$
CREATE;if(DSGNFrmt=4&SP=3&ALT=4&Q32LSM2=2)spttd2 = -Q32TDMG2$
CREATE;if(DSGNFrmt=4&SP=3&ALT=4&Q32LSM2=1)spttd2 = Q32TDMG2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=4&Q32LSM2=2)spttd2 = -Q32TDMG2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=4&Q32LSM2=1)spttd2 = Q32TDMG2$
```

? *** Create variable PRB1 and PRB2 (SP question assigned Probability of Trave Time Difference) for each SP question using design Format 4 and 8

?** Create PRB1 and PRB2 for SP1

```
CREATE;if(DSGNFrmt=4&SP=1&ALT=1)PRB1 = Q12PBG1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=1)PRB1 = Q12PBG1$
CREATE;if(DSGNFrmt=4&SP=1&ALT=2)PRB1 = Q12PBG1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=2)PRB1 = Q12PBG1$

CREATE;if(DSGNFrmt=4&SP=1&ALT=3)PRB1 = Q12PBM1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=3)PRB1 = Q12PBM1$
CREATE;if(DSGNFrmt=4&SP=1&ALT=4)PRB1 = Q12PBM1$
CREATE;if(DSGNFrmt=8&SP=1&ALT=4)PRB1 = Q12PBM1$

CREATE;if(DSGNFrmt=4&SP=1&ALT=1)PRB2 = Q12PBG2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=1)PRB2 = Q12PBG2$
CREATE;if(DSGNFrmt=4&SP=1&ALT=2)PRB2 = Q12PBG2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=2)PRB2 = Q12PBG2$

CREATE;if(DSGNFrmt=4&SP=1&ALT=3)PRB2 = Q12PBM2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=3)PRB2 = Q12PBM2$
CREATE;if(DSGNFrmt=4&SP=1&ALT=4)PRB2 = Q12PBM2$
CREATE;if(DSGNFrmt=8&SP=1&ALT=4)PRB2 = Q12PBM2$
```

?** Create PRB1 and PRB2 for SP2

```
CREATE;if(DSGNFrmt=4&SP=2&ALT=1)PRB1 = Q22PBG1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=1)PRB1 = Q22PBG1$
CREATE;if(DSGNFrmt=4&SP=2&ALT=2)PRB1 = Q22PBG1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=2)PRB1 = Q22PBG1$

CREATE;if(DSGNFrmt=4&SP=2&ALT=3)PRB1 = Q22PBM1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=3)PRB1 = Q22PBM1$
CREATE;if(DSGNFrmt=4&SP=2&ALT=4)PRB1 = Q22PBM1$
CREATE;if(DSGNFrmt=8&SP=2&ALT=4)PRB1 = Q22PBM1$

CREATE;if(DSGNFrmt=4&SP=2&ALT=1)PRB2 = Q22PBG2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=1)PRB2 = Q22PBG2$
CREATE;if(DSGNFrmt=4&SP=2&ALT=2)PRB2 = Q22PBG2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=2)PRB2 = Q22PBG2$
```

```
CREATE;if(DSGNFrmt=4&SP=2&ALT=3)PRB2 = Q22PBM2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=3)PRB2 = Q22PBM2$
CREATE;if(DSGNFrmt=4&SP=2&ALT=4)PRB2 = Q22PBM2$
CREATE;if(DSGNFrmt=8&SP=2&ALT=4)PRB2 = Q22PBM2$

?** Create PRB1 and PRB2 for SP3

CREATE;if(DSGNFrmt=4&SP=3&ALT=1)PRB1 = Q32PBG1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=1)PRB1 = Q32PBG1$
CREATE;if(DSGNFrmt=4&SP=3&ALT=2)PRB1 = Q32PBG1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=2)PRB1 = Q32PBG1$

CREATE;if(DSGNFrmt=4&SP=3&ALT=3)PRB1 = Q32PBM1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=3)PRB1 = Q32PBM1$
CREATE;if(DSGNFrmt=4&SP=3&ALT=4)PRB1 = Q32PBM1$
CREATE;if(DSGNFrmt=8&SP=3&ALT=4)PRB1 = Q32PBM1$

CREATE;if(DSGNFrmt=4&SP=3&ALT=1)PRB2 = Q32PBG2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=1)PRB2 = Q32PBG2$
CREATE;if(DSGNFrmt=4&SP=3&ALT=2)PRB2 = Q32PBG2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=2)PRB2 = Q32PBG2$

CREATE;if(DSGNFrmt=4&SP=3&ALT=3)PRB2 = Q32PBM2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=3)PRB2 = Q32PBM2$
CREATE;if(DSGNFrmt=4&SP=3&ALT=4)PRB2 = Q32PBM2$
CREATE;if(DSGNFrmt=8&SP=3&ALT=4)PRB2 = Q32PBM2$

sample;all $
REJECT; decision=-999$
CREATE ; zrpl = Rnu(0,1) $
NLRPLOGIT
  ; Lhs = DECISION,NALTS,alt
  ; Choices = A,B,C,D
  ; rpl
  ; Crosstab
  ; List
  ; Check Data
  ; Pds = 3
  ; Pts = 1000
  ; Labels =asccpg,ascdam,asccpm, Alpha, Beta, lamda, Delta, Gamma, c_toll, B1, B2
  ; Start -3.20,-.39,-1.06,.88,.88,-2.25,.61,.69,-.15,-.20, .20
```

```
   ; Fcn = B1(t),B2(t), c_toll(t)
   ; Halton
   ; Draws = 200
   ; Maxit = 50
   ; Correlated
   ; RPL = zrpl
   ; Fn1 = val1 = (sptd1T)^(exp(Alpha))
   ; Fn2 = val2 = (sptd2T)^(exp(Alpha))
   ; Fn3 = val3 = (exp(lamda))*(spttd1T)^(exp(Beta))
   ; Fn4 = pwf1 = ((prb1)^(exp(Delta)))/(((prb1)^(exp(Delta))+(1-
prb1)^(exp(Delta)))^(1/(exp(Delta))))
   ; Fn5 = pwf2 = ((prb1)^(exp(Gamma)))/(((prb1)^(exp(Gamma))+(1-
prb1)^(exp(Gamma)))^(1/(exp(Gamma))))
   ; Fn6 = pwf3 = ((prb2)^(exp(Gamma)))/(((prb2)^(exp(Gamma))+(1-
prb2)^(exp(Gamma)))^(1/(exp(Gamma))))
   ; Fn7 = OPTA = B1*Fn4*Fn3 + B2*Fn6*Fn2
   ; Fn8 = OPTB = asccpg + B1*Fn4*Fn3 + B2*Fn6*Fn2
   ; Fn9 = OPTC = ascdam + B2*Fn5*Fn1 + B2*Fn6*Fn2 + c_toll*SPToll
   ; Fn10 = OPTD = asccpm + B2*Fn5*Fn1 + B2*Fn6*Fn2
   ; Model:
                 U(A) = OPTA/
                 U(B) = OPTB/
                 U(C) = OPTC/
                 U(D) = OPTD
   $
```