Variation in the Value of Travel Time Savings
and its Impact on the Benefits of Managed Lanes

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ABSTRACT

This research examines the variation in the value of travel time savings (VTTS) for travelers with a managed lane (ML) option when taking an ordinary trip versus a trip that is unusual in some way. VTTS estimates vary substantially depending on the urgency of the trip made. At the low end, the mean VTTS for a traveler who wants to make extra stops and still arrive on time is approximately 10 percent higher than that for an ordinary trip. At the high end, a traveler running late for an appointment shows a mean VTTS that is approximately 300 percent higher than that for an ordinary trip. These estimates vary widely over the population of travelers. In light of these variations, the value of an uncongested travel alternative (such as MLs) is examined and found to be greatly undervalued if using typical VTTS estimates.
1. INTRODUCTION

Managed lanes (MLs) generally offer travelers a tolled, congestion-free, alternative to a congested, but toll-free, route. Studying travelers’ willingness to pay for this uncongested alternative offers transportation planners a unique opportunity to better understand how travelers value their travel time savings under different circumstances. This research examines the variation in the value of travel time savings (VTTS) for travelers with a ML option when taking an ordinary trip versus a trip that is unusual in some way. We hypothesize that the VTTS for an unusual trip, such as when running late for a meeting, would be much higher than the VTTS on an ordinary trip. If true, the uncongested travel alternatives (such as MLs) would be greatly undervalued if the estimate of VTTS for ordinary trips is used in a cost-benefit analysis.

This variability in VTTS is further supported by previous research indicating that travelers’ VTTS changes depending on the time of day the trip is taken (Small et al., 1999; Tseng and Verhoef, 2008) and whether the traveler was delayed (Tilahun and Levinson, 2008). Additionally, typical stated preference (SP) studies designed for VTTS estimation for MLs travelers tend to underestimate VTTS compared to studies that use the revealed preference approach (see Ghosh, 2001; Brownstone et al., 2003, Brownstone and Small, 2005). Further, many of the studies of existing managed lanes have concluded that the vast majority of travelers use MLs only occasionally, and include travelers from all income groups (Sullivan et al., 2000;  

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1 Revealed preference uses data on actual trips taken and actual tolls paid, if any tolls exist. Conversely, “stated” preference modeling constructs choices of trips as a function of attributes that the investigator designs and builds into the modeling exercise. The stated choice approach allows exploration of responses to tolls that may not exist in the transportation system.
Collier and Goodin, 2002; Burris and Stockton, 2004). These findings indicate that travelers are assigning different values to their travel time savings on different trip occasions and using MLs when those VTTS are in the higher end of the travelers’ range of VTTS.

This research takes advantage of the recently opened Katy Freeway MLs, Houston, Texas, to estimate the range of VTTS, and its impact on the use of MLs. Section 2 describes the implementation of a SP survey of the Katy Freeway travelers, which was undertaken as part of the research. Section 3 describes the analysis technique used to extract the travelers’ range of VTTS in ordinary and unusual trip situations from the survey data. Section 4 includes the VTTS results and a discussion of how these can be used to better understand traveler decisions on MLs facilities and how to measure the true benefits offered by MLs. Section 5 offers conclusions about this research.

2. SURVEY DESIGN AND DATA COLLECTION

2.1 Study Location

Houston, Texas is one of the largest cities in the United States with a 2007 US Census population estimate of over 5.7 million people living in the Houston metropolitan area (USCB, 2007). The city has an extensive network of freeways which includes the Katy Freeway; a 23-mile stretch of Interstate-10 connecting the cities of Katy and Houston (Figure 1). An expansion project for this freeway began in 2003 and the expanded facility first opened in October 2008 (TxDOT, 2009). The new facility also has two Katy Tollway/Managed Lanes (MLs) in each direction between State Highway 6 and Interstate 610 (a distance of 12 miles). METRO buses and high occupancy vehicles (HOV2+ with 2 or more people in a vehicle) and motorcycles can use the MLs for free during peak hours (Monday to Friday 5 a.m. to 11 a.m. and 2 p.m. to 8
Beginning in April 2009, single occupant vehicle drivers willing to pay a toll could also use the MLs while HOVs and motorcycles continue to use the lanes toll-free during the peak hours and pay a toll only during off-peak hours. The toll must be paid electronically, using EZTag or TxTag (HCTRA, 2009), the local electronic tags that allow passage through toll gates without stopping to pay by cash or credit card. Tolls on this new facility vary by the time of day ($4, $2, $1 for peak, shoulder and off-peak times respectively for the 12 mile stretch).

As part of this research, a SP survey of Katy Freeway travelers was conducted just after the Katy Freeway MLs opened in October 2008. This allowed survey respondents to be familiar with the facility and most of the choice alternatives offered in the survey.

### 2.2 Data collection

Survey responses were collected via an internet-based survey the internet. Due to its online nature, the sampling process presents a potential sampling bias as it requires the sample individuals to have at least some temporary, if not permanent, internet access in order to take the survey. We conducted a detailed sampling bias analysis and found that the sample used in the current study is similar to that obtained from a survey of travelers observed using the Katy Freeway. The discussion of sampling issues for internet based surveys in general and the analysis of sampling bias for this study are presented in Patil et al. (forthcoming, 2011) and Burris and Patil (2009).

A total of 6,312 respondents took at least some portion of the online/internet survey. Of these, 3,990 respondents fully completed the survey. We removed 973 responses due to a problem in the implementation of a particular SP design strategy (see Patil et al. 2011 for details), and 119 responses from motorcycle and transit travelers. The final sample considered
for model estimation consists of a total 2,898 respondents who answered the questions as discussed in the next section of this paper.

2.3 Details of the Survey Questionnaire

Each respondent was presented with the SP survey, which took approximately 12 to 15 minutes to complete. The survey questionnaire was structured to first ask the respondent questions about their most recent trip on the Katy Freeway, followed by an introduction to the managed lanes concept was provided. Next there were questions regarding the respondent’s attitudes towards this ML concept, a set SP questions, and key socio-economic questions that can potentially be used to explain the choices.

In the fifth section of the survey questionnaire respondents were presented with three pairs of SP questions, which were randomly assigned to the respondent based on the prior week trip characteristics provided in the first part of the questionnaire. Each pair of SP questions asked about mode choice under an ordinary situation and an urgent situation. The respondent could choose from among four alternatives that feature different modes of travel, and other key attributes of the alternatives. The specific values of travel time and toll to be presented in the SP questions were calculated using the reported actual trip length for each respondent and using one of the three underlying experimental designs. The designs included random, adaptive random, and D-Efficient design. A detailed discussion regarding how design impacted results is included in Patil et al. (forthcoming, 2011). In each SP question pair, the respondents were presented with four out of following five travel modes as labeled alternatives.

1. Carpool on general purpose lanes (CP-GPL),
2. Drive alone on general purpose lanes (DA-GPL),
3. Drive alone on managed lanes (DA-ML),

4. Carpool with one other person on managed lanes (HOV2-ML),

5. Carpool with three or more people on managed lanes (HOV3+-ML).

A typical presentation of a pair of SP questions presented in the survey questionnaire is shown in Figure 2.

2.4 Details of Urgent Situations Presented

One of the main objectives of this study was to investigate if travelers value their time differently when faced by an urgent travel situation versus an ordinary travel situation. The SP questions were designed to capture the possible difference in VTTS for an individual’s ordinary and urgent trip situations. In all the three SP question pairs, one of six categories was used to describe the urgent trip situation that a traveler can face, while the ordinary trip referred to the typical trip in the week prior to the time the survey was taken. The six urgent reasons and their implications are given in Table 1. The wording of the urgent trip situation categories and descriptions were considered in an attempt to make them:

- applicable to numerous other urgent trip situations that may also fall into that category,
- applicable to either direction of travel (towards/away from downtown),
- applicable to all days of the week (weekday/weekend), and
- applicable to all times of departure (peak/shoulder/off-peak).

Note that not all of the urgent trip situations in Table 1 occur unexpectedly as some of them can be known and planned for in advance. In all six urgent trip situations the hypothesis was that travelers’ VTTS would be higher than it is for travel in ordinary trip situations. In each pair of SP
questions, the travel time and toll values used for the question relating to an urgent trip situation were the same as those corresponding to the ordinary travel situation. A description of the discrete choice model used to analyze these respondent’s mode choices and estimate their VTTS in ordinary and urgent travel situations is presented in the next section.

3. EMPIRICAL DESIGN

The standard conditional multinomial logit model (MNL) is the most popular form of discrete choice model in which the utility of an alternative \( j = 1, \ldots, J \) for an individual \( q = 1, \ldots, Q \) in a choice situation \( t = 1, \ldots, T \) as specified by

\[
U_{q,j,t} = \beta' x_{qjt} + \epsilon_{q,j,t} \tag{1}
\]

where, \( \beta \) = the coefficients to be estimated,

\( x_{qjt} \) = the \((K \times 1)\) vector of \( K \) independent variables which include alternative specific constants, characteristics of the individuals, characteristics of the alternative and other descriptive variables affecting the choice.

\( \epsilon_{q,j,t} \) = the error components which may be due unaccounted measurement error, correlation in the parameters, unobserved individual preferences and other similar unobserved characteristics of the choice making.

The model consists of a deterministic part and a random (error) component, where the randomness is introduced by the investigator rather and not by an individual’s uncertainty about an outcome. The error component \( (\epsilon_{q,j,t}) \) is assumed to be identical and independently distributed (iid) Type 1 extreme value, which gives a closed form multinomial logit model probability (Equation 2). This assumption yields very simple properties, but it makes the MNL
unable to account for individual heterogeneity, a shortcoming stemming from the independence from irrelevant alternatives (IIA) property.

\[
\text{Prob (choice } j \text{ | individual } q, \mathbf{X}_{q,t}, \text{choice setting } t) = \frac{\exp(\beta' r_{aqjt})}{\sum_{q't} \exp(\beta' r_{aqjt})}
\] (2)

To assess these limitations, mixed logit (or random parameter logit- RPL) models are now frequently being used in empirical work (Train, 1998; Revelt and Train, 1998; Train, 2003). Thanks to increased computational power, the mixed logit model has evolved from a basic specification, which allows only the parameters to be distributed randomly, to more sophisticated specifications that can accommodate repeated responses from the same individual (as panel data or autocorrelation), scale differences in data sources, different error structures, heteroscedasticity, and also heterogeneity in preferences, which may arise from various sources (see, Brownstone and Train, 1999; Ben-Akiva et al., 2001; Bhat and Castelar, 2002; Greene et al., 2006; Greene and Hensher, 2007; Hensher et al., 2008). The equations below follow the notation and the specification used for the more flexible models, as discussed in Greene and Hensher (2007) and show the expansion from a basic mixed logit specification to the more advanced one applied in this study is explained next.

The simplest specification of the mixed logit allows the parameters to be distributed randomly to account for individuals’ heterogeneity in taste and attributes. The analyst chooses a probability distribution that is assumed to be appropriate for the taste parameter, typically a normal, lognormal, or a triangular distribution. Each estimated parameter can thus be assumed to vary across individuals or

\[
\beta_{qk} = \tilde{\beta}_k + \sigma_k v_{qk}
\] (3)
where, $\bar{\beta}_k$ = the population mean for the $k^{th}$ (random) parameter,

$v_{q,k} = \text{the individual specific unobserved heterogeneity with mean zero and standard deviation (scaled to) one, and}$

$\sigma_k = \text{the standard deviation of the random parameter } \beta_{q,k}.$

The basic specification in Equation (3) can be further extended to account for heterogeneity in the mean and to also control for heteroscedasticity

$$\beta_{q,k} = \bar{\beta}_k + \delta_k' z_q + \gamma_{q,k} v_{q,k} \tag{4}$$

where $\delta_k' z_q = \text{the observed heterogeneity around the mean of the } k^{th} \text{ random parameter (} \delta_k \text{ is to be estimated and } z_q \text{ is a vector of observed variables which may contain data on individual specific characteristics such as the socio-demographic factors)},$

$v_{q,k} = \text{the structural random variable which now accounts for individual and choice specific, unobserved random disturbances with } E[v_{q,k}] = 0 \text{ and } \text{Var}[v_{q,k}] = \sigma_k^2, \text{ a known constant and}$

$$\gamma_{q,k} = \sigma_k \exp[\eta_k' h_q] \text{ with } \exp[\eta_k' h_q] \text{ as the observed heterogeneity in the distribution of } \beta_{q,k} (\eta_k \text{ is to be estimated and } h_q \text{ is a data vector which may contain individual specific characteristics}).$$

Using the probabilities implied by Equation (4) the parameters are now assumed to be randomly distributed over individuals with both means and variances that can depend on the individual characteristics, $z_q$ and $h_q$ (Greene and Hensher, 2007). The specification with
heterogeneity around the mean can be applied to the problem of estimating the VTTS for different groups of individuals.

Following Hensher et al. (2005, p. 660-667), we investigate preference heterogeneity around the mean of travel time and toll parameters for the ordinary and six urgent travel situations. To produce estimation results that are behaviorally meaningful, we assume a constrained triangular distribution for the travel time coefficient ($\beta_{\text{time}}$) with its spread equal to the mean, i.e. $\sqrt{3} \cdot \sigma_{\text{time}} = \bar{\beta}_{\text{time}}$ (see Train (2003) for a discussion of the details of the triangular distribution). However, the toll coefficient ($\beta_c$) is assumed to be fixed (non-random) to facilitate the VTTS estimation. Note that, both the time and toll parameters are estimated in a way that does take into account heterogeneity in preferences that may arise because of the six urgent trip situations. Next, two dummy variables for medium and high household income groups are added to the model specification in order to capture the observable heterogeneity in the toll parameter with respect to three income categories (low, medium and high income). Equations 5 and 6 specify the parameters for the time ($\beta_{\text{time}}$) and toll ($\beta_c$) (shown here without heteroscedasticity and without individual specific notation $q$ for ease of presentation). These equations are essentially marginal utilities with respect to time and cost (i.e. partial derivatives of the utility function with respect to time and cost).

$$
\beta_{\text{time}} = \bar{\beta}_{\text{time}} + \delta_{1t} \times \text{ImpAppt} + \delta_{2t} \times \text{LateAppt} + \delta_{3t} \times \text{WorryTime} + \delta_{4t} \times \text{BadWeather} + \delta_{5t} \times \text{LateML} + \delta_{6t} \times \text{ExtraStops} + \bar{\beta}_{\text{time}} \times t_{\text{time}} \\
$$

$$
\beta_c = \bar{\beta}_c + \delta_{1c} \times \text{ImpAppt} + \delta_{2c} \times \text{LateAppt} + \delta_{3c} \times \text{WorryTime} + \delta_{4c} \times \text{BadWeather} + \delta_{5c} \times \text{LateML} + \delta_{6c} \times \text{ExtraStops} + \delta_{7c} \times \text{IncMed} + \delta_{8c} \times \text{IncHigh}
$$
where, $\bar{\beta}_{\text{time}}$ and $\bar{\beta}_c$ are the estimated population means of the constrained triangular and non-stochastic distributions corresponding to the time and toll parameters respectively.

$\delta_{1t}, \ldots, \delta_{6t}$ and $\delta_{1c}, \ldots, \delta_{6c}$ are heterogeneities in the means of travel time and toll parameters respectively,

$\text{ImpAppt, LateAppt, WorryTime, BadWeather, LateML, and ExtraStops}$ are the dummy variables corresponding the six urgent trip situations (refer Table 1 for details),

$\text{IncMed}$ and $\text{IncHigh}$ are dummy variables for medium ($\$50,000-100,000$) and high (greater than $\$100,000$) annual household income, and

$t_{\text{time}}$ is randomly drawn from a triangular distribution (-1, 1) with mean 0 and is obtained by transforming a continuous uniform distribution with a range between 0 and 1, see Hensher et al. 2005 pp.641 for details.

Using Equations (5) and (6), the implied VTTS distribution for the low household income category identified by $\text{IncMed} = 0$ and $\text{IncHigh} = 0$ can be calculated for the ordinary situations ($\mu_{\text{ord}}$) and six urgent trip situations ($\mu_1, \ldots, \mu_6$) as shown in Equation (7) and (8). Note that the implied VTTS distributions for the medium and high household income categories can be similarly calculated by adding the estimates of $\delta_{7c}$ and $\delta_{8c}$ respectively in the denominator of Equations (7) and (8).

\[
\mu_{\text{ord}} = \frac{\bar{\beta}_{\text{time}} + \bar{\beta}_{\text{time}} \times t_{\text{time}}}{\bar{\beta}_c} \quad (7)
\]

\[
\mu_i = \frac{\bar{\beta}_{\text{time}} + \delta_{1t} + \bar{\beta}_{\text{time}} \times t_{\text{time}}}{\bar{\beta}_c + \delta_{ic}}, \quad i = 1, \ldots, 6 \quad (8)
\]

where, $\mu$ = VTTS for the situation denoted by the subscript of $\mu$.
Further extension of the mixed logit model can account for autocorrelation that may exist in panel data or repeated choice situations. Thus the preferences as estimated by the random parameters are allowed to evolve over time or over sequence of choices (Greene and Hensher, 2007). The underlying structural parameter, $v_{q,k}$ in Equation 4 is then specified for each situation $t$ as

$$v_{q,k,t} = \rho_k v_{q,k,t-1} + w_{q,k,t},$$  \hspace{1cm} (9)$$

where, $\rho_k$ = the autocorrelation parameters that are to be estimated

$w_{q,k,t}$ = the new underlying structural random variable.

While the above extensions (Equations 4 and 8) are related solely to the random parameters (not to the error components), further modifications to the model specification can be made to incorporate additional unobserved heterogeneity through effects that are associated with the preferences within the alternatives. For example, Equation 10 shows the individual’s utility function with an extension yielding the ‘kernel logit’ model (Brownstone and Train, 1999; Ben-Akiva et al., 2001; Greene and Hensher, 2007 for details)

$$U_{q,j,t} = \beta'_{q} x_{q,j,t} + \epsilon_{q,j,t} + \sum_{m=1}^{M} c_{jm} W_{q,m},$$  \hspace{1cm} (10)$$

where $c_{jm} = 1$ if the error component $m$ appears in the utility function of alternative $j$ and

$W_{q,m}$ = the normally distributed effects with zero mean.

The effects, $W_{q,m}$ are associated with individual preferences within the choices (alternatives) and can account for unobserved heterogeneity such that
\[
\text{Var}[W_{mq}] = \left[ \theta_m \times \exp (\tau_m h_q) \right]^2
\] (11)

where \( \theta_m \) = the scale factor for error component \( m \),

\( \tau_m \) = parameters in the heteroscedastic variances of the error components, and

\( h_q \) = the data vector which contains individual choice invariant characteristics that produce heterogeneity in the variances of the error components.

Finally, the conditional choice probability with all of the above extensions to the basic mixed logit model is given by Equation (12).

\[
\text{Prob}_{q,t}(j_t | X_{gt}, \Omega, z_q, h_q, v_q, W_q) = \frac{\exp (\beta x_{q,t} + \sum_{m=1}^{M} \epsilon_{jm} W_{mq})}{\sum_{j=1}^{J} \exp (\beta x_{q,t} + \sum_{m=1}^{M} \epsilon_{jm} W_{mq})}
\] (12)

where, \( \Omega \) = the parameter set which collects all the structural parameters.

The unconditional probability of Equation 12 is estimated using the maximum simulated likelihood method.

4. RESULTS

The mixed logit model with the above extensions is estimated using the software Nlogit 4 (Greene, 2007). A MNL model is also estimated to compare any additional gains obtained by the mixed logit model with the specified error structures. The estimated model coefficients are used to examine travelers’ VTTS in various situations and determine the value of ML travel.

4.1. Model Estimation

Table 2 includes the results of the MNL and mixed logit models. Key explanatory variables including the trip length, trip purpose, traveler’s age, gender, household type, size,
vehicle stock, and vehicle occupancy for the individual’s most recent trip were found to be significant in the basic model (see, Burris and Patil 2009 for a more detailed discussion of all parameters and variables).

The mixed logit model estimation procedure uses 350 Halton draws to minimize simulation variance. The estimation procedure used here utilized 350 Halton draws primarily because use of more draws takes multiple days for estimation of this complex model. Note that previous studies have concluded that the use of Halton sequences rather than random draws decreases the total estimation time, which can be extensive in complex models, and smoothes the simulation (Bhat, 2001, Train, 2003). It is also common to use 200 to 500 Halton draws (Greene et al. 2006, Greene and Hensher, 2007, Hensher et al. 2008). We specify the alternative specific parameters (ASCs) and travel time parameter as random parameters, while the other parameters are assumed fixed, as in the conventional and basic conditional MNL. We assume a normal distribution for the ASCs because we do not have specific information about a particular distribution, and we use a constrained triangular distribution for the travel time parameter. The use of an unconstrained triangular distribution did not provide a behaviorally meaningful sign\(^3\) for the travel time parameter over the full sample. To allow for possibility of different sources of random preferences for different trip situations we use a technique described in Brownstone et al. (2000) and Hensher et al. (2008) to estimate a scale parameter \(\lambda_{qt}\) for the urgent travel

\(^2\) See, Hensher and Greene, 2003 for discussion on required number of Halton draws for stability in estimation

\(^3\) The travel time parameter is expected to be negative as it represents increased disutility for increased travel time. The positive sign will infer that the traveler actually enjoys longer travel, which is counterintuitive for the present study.
situations (the ordinary situations scale parameter is normalized to 1.0). The scale parameter in these models relates to the variance of the error term.

As described in the Section 3, we employ six dummy variables to incorporate observable preference heterogeneity in the means of the travel time and toll parameters, with one dummy variable for each of the six situations (an ordinary situation corresponds to a zero value for all the six urgent situations dummy variables, and is the base case). With the exception of heterogeneity for the variables \textit{ImpAppt}, \textit{BadWeather}, and \textit{Extra Stops} (\(\delta_{1t}, \delta_{4t}\) and \(\delta_{6t}\)) in travel time, all other types of trip situations are statistically significant sources of influence on preference heterogeneity for both travel time and toll parameters (\(p = 0.05\) for all statistical inferences). In other words, the description of the type of urgent trips is relevant in determining the choices that respondents make and thus, their preferences for time and tolls.

The preference heterogeneity variables relating to the medium and high income groups (\(\delta_{7c}\) and \(\delta_{8c}\)) are also found to be significant. We find that observed heterogeneity around the standard deviation of the travel time parameter (\(\eta_k\)) with respect to gender is not statistically significant. This finding indicates that male travelers are not heterogeneous in terms of the marginal disutility associated with the travel time of all the modes when compared with female travelers.

The estimate of urgent situations to ordinary situations scale parameter is statistically significant (significantly different from 1) and less than one (0.64) suggesting a higher variance on the unobserved effects associated with the urgent situations. Overall, the mixed logit model provides an improvement in the model fit over the simple MNL model as indicated by the higher adjusted \(\rho_c^2\) and the improved log-likelihood value. A likelihood ratio test to determine if the
improvement obtained by the mixed logit specification over the MNL model is statistically
significant (p-value = 0.00000). Hence, only the mixed logit model and the corresponding
parameters for it are used for the estimation of the individual’s VTTS in the remainder of this
paper.

4.2. VTTS Estimation and Policy Implications

The parameter estimates for the mixed logit model are used to estimate the implied VTTS
for ordinary and urgent situations for the three income groups (Table 3). The implied mean
VTTS is estimated as the ratio of the travel time to the estimated toll parameter using the
heterogeneity in mean corresponding to each urgent situation and to each income group
(Equations 6 and 7). For example, for a low income group traveler facing the situation LateAppt
the implied VTTS distribution is given by

\[
\mu_2 = \frac{\bar{\beta}_{\text{time}} + \delta_{2t} + \bar{\beta}_{\text{time}} \times t_{\text{time}}}{\bar{\beta}_c + \delta_{2c}} = 60 \times \frac{-0.24 - 0.07 - 0.24 \times t_{\text{time}}}{-1.81 + 1.28} = 35.2 - 27.17 \times t_{\text{time}}
\]  

(13)

where, \( t_{\text{time}} \) = randomly drawn value from a triangular distribution (-1, 1) as described in
Equation 5.

Similarly, for a high income group traveler facing the same situation (LateAppt), the
implied VTTS distribution will be given by

\[
\mu_2 = \frac{\bar{\beta}_{\text{time}} + \delta_{2t} + \bar{\beta}_{\text{time}} \times t_{\text{time}}}{\bar{\beta}_c + \delta_{2c} + \delta_{bc}} = 60 \times \frac{-0.24 - 0.07 - 0.24 \times t_{\text{time}}}{-1.81 + 1.28 + 0.14} = 47.5 - 27.17 \times t_{\text{time}}
\]  

(14)

Table 3 illustrates that the estimated VTTS is much higher for all of the six urgent
situations than for non-urgent situations. The maximum estimate of the mean of VTTS is
observed when the traveler is running late for an important appointment or meeting (LateAppt).
The mean VTTS for LateApp is 3.8 to 5.5 times greater than the mean of the implied VTTS corresponding to an ordinary situation. The estimates of the mean of VTTS for all other urgent situations, except for the ExtraStop situation, are also relatively high as compared to the mean of VTTS corresponding to the ordinary situation. This suggests that travelers do not value travel time savings very highly (in comparison to the ordinary situation scenario) when they need to make extra stops on the trip, but still need to arrive on schedule. They may be depending more on the possibility of making an early departure, and less on paying or engaging in carpooling to use the managed lanes in order to make up for the extra time needed.

Implied means of the VTTS are also significantly different for different income groups; the low and high income groups have higher VTTS estimates compared to the medium income group. The higher estimate for low income group in comparison to the medium income group might be attributed to the fixed-schedule constraints associated with lower paying jobs or a possible sampling bias related to low income travelers.

To further illustrate and compare the distributions of the implied VTTS corresponding to all these situations we take a draw of 1000 sample points from the triangular distribution (the distribution used for the travel time parameter) and estimate the VTTS values for the low income group. Note that although the standard deviation of the distribution for the travel time parameter is set to be equal to the mean, the heterogeneity in the means of travel time and toll parameters results in different shapes to the distributions of VTTS corresponding to different situations. Figure 3 shows that the VTTS for the LateApp situation does not only have a large mean, but it also has a large spread as compared to the ordinary and other urgent situations, indicating the large variability of the VTTS for different travelers.
The preceding analysis clearly indicates a significant difference between a travelers’ typical VTTS on a ML and their VTTS in urgent situations. It is the VTTS based on typical travel which generally serves as the basis to calculate travelers’ willingness to pay for a ML. Therefore, engineers and planners are missing the added value that MLs have for travelers on urgent trips. Based on previous studies and anecdotal evidence and information provided by ML travelers we know that many individuals only use the MLs in urgent situations. This added value is therefore unmeasured and the true value of MLs is underestimated. The following scenarios illustrate this underestimation.

Assumptions:

- Total travelers in one direction on the freeway = 8000 veh/hr,
- Percent of travelers facing an urgent situation= 0, 10, 20 and 30. Of these
  - 25 percent face urgent situation- ImpAppt,
  - 25 percent face urgent situation- LateAppt,
  - 12.5 percent face urgent situation- WorryTime,
  - 12.5 percent face urgent situation- BadWeather,
  - 12.5 percent face urgent situation- LateML,
  - 12.5 percent face urgent situation- ExtraStops,
- Percent of ML travelers with low incomes (less than $50,000) = 25 %,
- Percent of ML travelers with medium incomes ($50,000 to $100,000) = 37%,
- Percent of ML travelers with low incomes (greater than $100,000) = 38%.

Using the above assumptions and the VTTS estimates we can evaluate the travel time saving benefits offered by the managed lanes. We estimate these benefits for an increasing
number of toll paying vehicles, which is the number of vehicles that can fit on the managed lanes aside from toll-free HOVs (see Figure 4).

Figure 4 shows that by assuming all travelers are facing ordinary trips there is the potential for significant underestimation of the value of travel time savings benefits obtained from the managed lanes. For example, assume there is room for 100 more vehicles on the MLs and that all 100 are on ordinary trips. This corresponds to results in hourly benefits identified by the area $a$ below the curve in Figure 5, which corresponds to the ordinary trip situations. This area is approximately $1,635 \ (15.1\times100+ (17.6\times15.1)\times100/2)$. However, if we assume just 10 percent of all 8,000 travelers are facing urgent, and not ordinary trips, the hourly benefits increase to the area identified in Figure 5 by ‘$a + b + c + d$’ (c and d approximated as a triangle for ease of calculation), which is approximated by $5,300.65 \ [(37.8\times100 + (50-37.8)\times39+(50-37.8)\times(100-39)/2+(84.5-50)\times39/2)]$. Hence, the average value of MLs without urgent trips is approximately equal to $16.35 \ (1635/100)$ and the average value of MLs with 10-percent urgent trips is equal to $53.01 \ (5300.65/100)$. Though these are approximations, the indication is that if managed lanes save 10 minutes of travel time, considering all 100 trips to be ordinary trips will yield $272.5 \ (100\times16.35\times10/60)$ in traveler benefits. However, with 10 percent of all trips being urgent trips, the benefits will be $883.4 \ (100\times53.01\times10/60)$. Hence, mistakenly classifying the 10 percent of urgent trips as ordinary trips would underestimate the approximate value of travel time savings benefits by 224 percent ($883.4-272.5\times100$) for those 100 travelers.

These approximations demonstrate that the assumed percentage of urgent trips affects the value of these benefits; hence it calls for accurate estimation of the percentage of travelers facing urgent trips and the percentage of urgent trips of each type using the traveler surveys. This is shown by Figure 6 which plot the results for a case when there is additional room for 100 more
toll paying travelers on the MLs and when the there are approximately 10 minutes of travel time savings offered by the MLs.

Note that the plots in Figure 4 are actually demand curves corresponding to each scenario and these can also be used to set the toll rates on the MLs. When setting the toll rate for MLs it is the travelers with the highest VTTS who are most likely to use the MLs and therefore the ones by which the ML toll could be set. Using the model estimation results, it can be shown that the high end of the high income group travelers in an ordinary situation will have VTTS equal to $16.72/hr. Many low income travelers under different travel situations exceed this $16.72, including:

- 60% facing the urgent situation-\textit{ImpAppt},
- 95% facing the urgent situation-\textit{LateAppt},
- 87% facing the urgent situation-\textit{WorryTime},
- 32% facing the urgent situation-\textit{BadWeather},
- 52% facing the urgent situation-\textit{LateML}, and
- 1% facing the urgent situation-\textit{ExtraStops}, (all represented by shaded area in Figure 7).

Similarly, many medium and high income travelers in urgent travel situations have VTTS greater than the highest VTTS of the high income group travelers in an ordinary situation (that is $16.72/hr) (see Figure 8 and Figure 9). Thus, many of the travelers from the medium and low income groups who are on urgent trips will have VTTS greater than that of the travelers from the high income group on ordinary trips. Hence, depending on the room for toll paying travelers on the managed lanes, the entire group of toll paying travelers could be on urgent trips. Note that
these results depend on the assumed distribution of the VTTS used in this research. However, similar results would be obtained using other reasonable assumptions regarding the distribution of VTTS.

5. CONCLUSIONS

This research focused on estimates of the values of travel time savings (VTTS) for ordinary situations as compared to six different urgent trip situations commonly faced by travelers with an option of using managed lanes. An ordinary situation was defined as a typical trip in the week prior to the survey. Urgent trip situations were represented by expected and unexpected events potentially affecting an ordinary trip which is characterized by budget and schedule constraints (such as business meetings and medical appointments). VTTS are estimated using stated preference data collected via an internet survey of Katy Freeway travelers.

The findings indicate that travelers place a much higher value on their travel time when faced by most of the urgent situations considered in this study. The mean of VTTS corresponding to these urgent situations ranged from $8 to $47.5 per hour as compared to the estimate of $7.4 to $8.6 per hour for the ordinary situations. Further, the study finds that the implied means of VTTS for low and medium income group travelers facing most urgent situations were higher than the high income traveler with the highest VTTS in an ordinary situation (given our assumptions regarding the distribution of VTTS among travelers).

Due to this significant increase in the VTTS for travelers on urgent trips it is possible that the majority of ML travelers are on urgent trips. This includes travelers from all income levels as even low income travelers on urgent trips value their time more than many high income
travelers on regular trips. Thus travelers on MLs are likely to be from all income categories as their need for (and value of) MLs varies mostly by trip urgency.

The second objective of the study was to better understand and estimate the value of managed lanes. The results show that classifying urgent trips as ordinary trips can greatly underestimate the total benefits of managed lanes to travelers. The example in section 4.2 assumes that only 10 percent of travelers take urgent trips and only 10 minutes of travel time savings on a managed lane that could accommodate 100 toll paying vehicles. Under these assumptions, the benefits of managed lanes for those 100 travelers would be more than three times as much as predicted assuming only ordinary trips.

Therefore, using average VTTS for all travelers has the potential to greatly underestimate the value of these MLs to travelers. This has significant policy implications since the benefits of MLs (and of most transportation investments) are primarily derived from travel time savings. Underestimating the value of ML travel time savings underestimates the benefits of MLs, thereby reducing the likelihood of funding such facilities when investment decisions are based on benefit-cost analysis. This study provides an important first step in the estimation of these benefits using modified SP surveys and calls for identification of the proportion of travelers who are taking a trip in an urgent situation such as the ones considered here.

The limitations of this study include a possible sampling bias (particularly with respect to under-sampling low income travelers), possible measurement error in the income variable, restrictive assumptions regarding the assumed distributions for the random parameters and omitting the effects of variables other than travel time savings (such as travel time reliability or penalty for late arrival) in the estimated VTTS. Incorporating these variables, and then
estimating the value of these other variables would be another way that engineers, economists
and planners may be able to estimate the true value of ML travel. Either method will require
continued research into the decision making process of travelers.

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Scientist at Texas Transportation Institute at the time of this research and now with Parsons
Brinkerhoff, for all the support he provided in hosting the survey website. Additionally we would
like to thank HCTRA for helping with the collection of data for this study.

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FIGURE 1 Freeway Network in and Around City of Houston, Texas
FIGURE 2 Typical Stated Preference Question in the Survey
FIGURE 3 Distribution of Implied VTTS for the Low Household Income (less than $50,000) Group

FIGURE 4 Estimated Toll Rates for Required Number of Vehicles on MLs
FIGURE 5 Benefits of the Managed Lanes

FIGURE 6 Benefits of Managed Lanes for 100 Toll Paying Vehicles
FIGURE 7 Percent of Low Income Group Travelers with VTTS Greater Than $16.72/hr

FIGURE 8 Percent of Medium Income Group Travelers with VTTS Greater Than $16.72/hr
FIGURE 9 Percent of High Income Group Travelers with VTTS Greater Than $16.72/hr
TABLE 1 Urgent Situations Categories Presented in the SP Survey

<table>
<thead>
<tr>
<th>Urgent Situations</th>
<th>Survey Wording</th>
<th>Description/Implication</th>
</tr>
</thead>
<tbody>
<tr>
<td>Situation 1</td>
<td>You are headed to an important appointment/meeting/event</td>
<td>The traveler may not necessarily have started late; however he/she especially needs to arrive on time.</td>
</tr>
<tr>
<td>ImpAppt</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation 2</td>
<td>You are running late for an appointment or meeting</td>
<td>The traveler knows that he/she is already late and hence is in need of the fastest travel alternative.</td>
</tr>
<tr>
<td>LateAppt</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation 3</td>
<td>You are worried about arriving on time</td>
<td>The traveler needs to arrive on time (as in Situation-1); however now we have added the word worry in the description to analyze if the behavior is any different due to the underlined urgency. People worried might leave earlier than normal or they may plan to use the managed lanes. Also, this situation may or may not include an important appointment/meeting/event.</td>
</tr>
<tr>
<td>WorryTime</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation 4</td>
<td>You expect potential traffic problems due to bad weather</td>
<td>The travel times may be longer than usual (for both GPLs and MLs) with possible additional unreliability in the travel time on the GPLs.</td>
</tr>
<tr>
<td>BadWeather</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation 5</td>
<td>You left late knowing you could take advantage of the toll lanes</td>
<td>Even though similar to situation-2 the traveler in this situation is expected to have higher value of travel time savings than that presented by the usual toll rates. Additionally, analysis of this Situation may provide an interesting insight into travel behavior with respect to a dynamically priced facility and may help us understand how the traveler reacts when faced by tolls which are higher or lower than the usual.</td>
</tr>
<tr>
<td>LateML</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Situation 6</td>
<td>You need to make extra stops on the trip but still need to arrive on schedule</td>
<td>The traveler could make up the time using the MLs or leave earlier depending on flexibility of schedule.</td>
</tr>
<tr>
<td>ExtraStops</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Attribute</td>
<td>Alternative(s)</td>
<td>MNL Model</td>
</tr>
<tr>
<td>-----------</td>
<td>----------------</td>
<td>-----------</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Coeff.</td>
</tr>
<tr>
<td>ASC:CP-GPL</td>
<td>CP-GPL</td>
<td>-0.66</td>
</tr>
<tr>
<td>ASC:DA-ML</td>
<td>DA-ML</td>
<td>-1.04</td>
</tr>
<tr>
<td>ASC:HOV2-ML</td>
<td>HOV2-ML</td>
<td>-0.58</td>
</tr>
<tr>
<td>ASC:HOV3-ML</td>
<td>HOV3-ML</td>
<td>-1.95</td>
</tr>
<tr>
<td>Travel Time (minutes)</td>
<td>All</td>
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</tr>
<tr>
<td>Toll ($)</td>
<td>All</td>
<td>-0.90</td>
</tr>
<tr>
<td>Drove alone for last trip (dv)</td>
<td>CP-GPL</td>
<td>-2.99</td>
</tr>
<tr>
<td>Trip purpose commute/work (dv)</td>
<td>CP-GPL</td>
<td>0.14</td>
</tr>
<tr>
<td>Male (dv) (male =1, female=0)</td>
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</tr>
<tr>
<td>Age between 25 and 54 (dv)</td>
<td>CP-GPL</td>
<td>0.53</td>
</tr>
<tr>
<td>Drove alone for last trip (dv)</td>
<td>DA-ML</td>
<td>-0.27</td>
</tr>
<tr>
<td>Trip Length (miles)</td>
<td>DA-ML</td>
<td>0.01</td>
</tr>
<tr>
<td>Toll tag subscriber (dv) (1= owns a toll tag)</td>
<td>DA-ML</td>
<td>0.57</td>
</tr>
<tr>
<td>Drove alone for last trip (dv)</td>
<td>HOV2-ML</td>
<td>-2.41</td>
</tr>
<tr>
<td>Trip purpose commute/work (dv)</td>
<td>HOV2-ML</td>
<td>0.22</td>
</tr>
<tr>
<td>Trip Length (miles)</td>
<td>HOV2-ML</td>
<td>0.02</td>
</tr>
<tr>
<td>Number of people in household</td>
<td>HOV2-ML</td>
<td>-0.28</td>
</tr>
<tr>
<td>Age between 25 and 54 (dv)</td>
<td>HOV2-ML</td>
<td>0.08</td>
</tr>
<tr>
<td>Male (dv) (male =1, female=0)</td>
<td>HOV2-ML</td>
<td>-0.49</td>
</tr>
<tr>
<td>Single Adult Household (dv)</td>
<td>HOV2-ML</td>
<td>-0.36</td>
</tr>
<tr>
<td>Number of vehicles in the household</td>
<td>HOV2-ML</td>
<td>-0.08</td>
</tr>
<tr>
<td>Drove alone for last trip (dv)</td>
<td>HOV3-ML</td>
<td>-2.88</td>
</tr>
<tr>
<td>Trip Length (miles)</td>
<td>HOV3-ML</td>
<td>0.01</td>
</tr>
<tr>
<td>Male (dv) (male =1, female=0)</td>
<td>HOV3-ML</td>
<td>-0.22</td>
</tr>
<tr>
<td>Age between 25 and 54 (dv)</td>
<td>HOV3-ML</td>
<td>0.32</td>
</tr>
</tbody>
</table>

**Standard deviation of Random Parameters(σ)**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Alternative(s)</th>
<th>Coeff.</th>
<th>t-ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASC:CP-GPL</td>
<td>CP-GPL</td>
<td>3.35</td>
<td>30.08</td>
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<tr>
<td>ASC:DA-ML</td>
<td>DA-ML</td>
<td>1.92</td>
<td>25.74</td>
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<td>ASC:HOV2-ML</td>
<td>HOV2-ML</td>
<td>2.37</td>
<td>24.54</td>
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<tr>
<td>ASC:HOV3-ML</td>
<td>HOV3-ML</td>
<td>3.61</td>
<td>20.71</td>
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<tr>
<td>Travel Time (minutes)</td>
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<td>0.24</td>
<td>31.41</td>
</tr>
<tr>
<td>Urgent to ordinary situations Scale parameter</td>
<td>All</td>
<td>0.64</td>
<td>6.68</td>
</tr>
</tbody>
</table>
TABLE 2- Continued

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Alternative(s)</th>
<th>MNL Model</th>
<th>Mixed Logit Model</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Coeff.</td>
<td>Coeff.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>t-ratio</td>
<td>t-ratio</td>
</tr>
<tr>
<td><strong>Interactions in MNL/Heterogeneity (δ)</strong> in mean in mixed logit**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Travel Time* ImpAppt</td>
<td>All</td>
<td>0.00</td>
<td>-0.40</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Travel Time* LateAppt</td>
<td>All</td>
<td>-0.02</td>
<td>-1.72</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Travel Time* WorryTime</td>
<td>All</td>
<td>-0.07</td>
<td>-5.22</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Travel Time* BadWeather</td>
<td>All</td>
<td>-0.03</td>
<td>-2.19</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Travel Time* LateML</td>
<td>All</td>
<td>-0.02</td>
<td>-2.04</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Travel Time* ExtraStops</td>
<td>All</td>
<td>0.00</td>
<td>-0.39</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toll ($)* ImpAppt</td>
<td>All</td>
<td>0.54</td>
<td>10.14</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toll ($)* LateAppt</td>
<td>All</td>
<td>0.72</td>
<td>15.29</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toll ($)* WorryTime</td>
<td>All</td>
<td>0.47</td>
<td>9.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toll ($)* BadWeather</td>
<td>All</td>
<td>0.36</td>
<td>6.32</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Toll ($)* LateML</td>
<td>All</td>
<td>0.44</td>
<td>8.06</td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Toll ($)* ExtraStops</td>
<td>All</td>
<td>0.13</td>
<td>1.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toll ($)* Medium Household Income ($50,000-100,000)</td>
<td>All</td>
<td>0.01</td>
<td>0.33</td>
</tr>
<tr>
<td>(dv)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toll ($)* High Household Income($&gt;100,000) (dv)</td>
<td>All</td>
<td>0.16</td>
<td>3.87</td>
</tr>
</tbody>
</table>

**Error Components for alternatives and nests of alternatives parameters (θ)**

<table>
<thead>
<tr>
<th>Standard deviation , θ₁</th>
<th>GPL alts.</th>
<th>0.27</th>
<th>3.42</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard deviation , θ₂</td>
<td>ML alts.</td>
<td>2.10</td>
<td>7.27</td>
</tr>
</tbody>
</table>

**Heterogeneity around standard deviation of error components effect (τ)**

<table>
<thead>
<tr>
<th>Male (dv) (male=1, female=0)</th>
<th>GPL alts</th>
<th>1.63</th>
<th>6.03</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of vehicles in the household</td>
<td>GPL alts</td>
<td>0.16</td>
<td>3.93</td>
</tr>
<tr>
<td>Male (dv) (male=1, female=0)</td>
<td>ML alts</td>
<td>-1.06</td>
<td>-5.99</td>
</tr>
<tr>
<td>Number of vehicles in the household</td>
<td>ML alts</td>
<td>-0.06</td>
<td>-1.10</td>
</tr>
<tr>
<td>Log-likelihood at convergence</td>
<td>-13467.43</td>
<td>-10722.10</td>
<td></td>
</tr>
<tr>
<td>Adjusted ρ²</td>
<td>0.28</td>
<td>0.42</td>
<td></td>
</tr>
</tbody>
</table>

Notes dv=dummy variable, R: Mean of the random parameter estimates, Adjusted ρ² = 1 - \frac{LL(\hat{\beta}) - K}{LL(C) - K_c} 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, \( \hat{\beta} \) = Represents spread of the distribution (std. dev.= spread/\sqrt{6}), ASC= Alternative Specific Coefficient
# TABLE 3 Implied Mean VTTS for Ordinary and Urgent Situations

<table>
<thead>
<tr>
<th>Situation</th>
<th>Mean VTTS ($/hr) for Categories of Household Income ($/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low-&lt; 50,000</td>
</tr>
<tr>
<td>Ordinary</td>
<td>7.9</td>
</tr>
<tr>
<td>Headed to an important appointment/meeting/event (ImpAppt)</td>
<td>18.7</td>
</tr>
<tr>
<td>Running late for an appointment or meeting (LateAppt)</td>
<td>35.2</td>
</tr>
<tr>
<td>Worried about arriving on time (WorryTime)</td>
<td>25.0</td>
</tr>
<tr>
<td>Expecting potential traffic problems due to bad weather (BadWeather)</td>
<td>13.9</td>
</tr>
<tr>
<td>Left late knowing you could take advantage of the toll lanes (LateML)</td>
<td>17.0</td>
</tr>
<tr>
<td>Need to make extra stops on the trip but still need to arrive on schedule (ExtraStops)</td>
<td>9.0</td>
</tr>
</tbody>
</table>