Integrating the Mean-Variance and Scheduling Approaches to allow for Schedule delay and Trip Time Variability under Uncertainty

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Abstract Uncertainty of travel times and the impact on travel choice behavior has been recognized as an increasingly important research direction in the past decade. This paper proposes an extension to the popular scheduling approach to modeling traveler's departure time choice behavior under uncertainty, with the main focus on a richer representation of uncertainty. This more general approach incorporates a separate term to reflect the risk aversion associated with uncertainty. Recognizing the correlation between expected schedule delay and travel time variability, the schedule delay components in the generalized approach are defined in terms of expected travel time, which differs from the scheduling approach. This approach is developed based on the analytical investigation of the relationship between the expected schedule delay and the mean and standard deviation of travel time. An analytical equivalence was found between the scheduling approach and the general approach given a departure time *t*. To investigate the empirical performance of the generalized approach, two state preference (SP) data sets are used; one from China with a symmetric travel time distribution and the other from Australia with an asymmetric distribution. Both studies show empirical evidence of an equivalence in respect of statistical fit between the generalized and the scheduling approaches, as found from analytical investigations. The Chinese study gives support in the generalized model to including both the mean-variance and the scheduling effects; whereas the Australian study finds only the mean-variance specification has statistical merit. Despite the different travel contexts, it is noteworthy in both empirical settings, that the parameter estimate for arriving earlier than the preferred arrival time (PAT) in the generalized model is positive. This suggests that commuters tend to prefer to arrive earlier in order to guarantee he/she will not be late. This paper contributes to a better understanding of performances of different reliability measures and their relationships. The practical value of the various unreliability measures is provided showing that these indicators are easy to obtain for inclusion in project appraisal.

Keywords: Uncertainty; Trip time variability; Departure time choice; Scheduling approach; Generalized approach, Mean-variance approach

1. INTRODUCTION

In transport networks, travel times and travel costs experienced by travelers within and between days are stochastic due to stochastic supply and fluctuating travel demand (Emam and Al-Deek 2005; Tu 2008; Tu *et al.* 2012). The uncertainty and heterogeneity in travelers' behavior (for instance driving behavior) also leads to variations and unpredictability in travel times, and in associated travel costs. Travel time uncertainty appears to have a significant impact on travelers' choice behavior; for instance route choice, departure time choice and mode choice. Bates *et al.* (2001) indicated that the reason why travel time variability is so important can be explained by at least the following sources: the anxiety or stress caused by uncertainty, additional cognitive burden associated with planning activities, and sensitivity to the consequences of the uncertainty, for instance late arrivals, etc. Modeling travel behavior under uncertainty has become an important research direction, gaining increasing attention from many researchers (Abdel-Aty *et al.* 1996; Bates *et al.* 2001; De Palma and Picard 2005; Batley 2007; Liu and Polak 2007; Hensher et al. 2015a). In the context of uncertainty, departure time adaptation appears to be one of the most important behavioral changes in attempting to arrive on time at work and to reduce the probability of arriving late (Li *et al.* 2009a; Siu and Lo 2013). Many studies (Abdel-Aty *et al.* 1996; Noland *et al.* 1998; Bogers and van Zuylen 2004; Van Amelsfort *et al.* 2008; Li *et al.* 2012) have analyzed the impacts of travel time variability on travelers' departure time/route choice behavior and suggested ways to model their choice behavior under uncertainty.

These exist a number of theories designed to describe and model human choice behavior under uncertainty, such as expected utility theory (Noland and Small 1995), prospect theory (Kahneman and Tversky 1979), cumulative prospect theory (Kahneman and Tversky 1979; Sumalee *et al.* 2009; Hensher and Li 2012), and extended prospect theory (Van de Kaa 2008), etc. The difference between expected utility theory and other theories is that it does not account for the cognitive tasks in traveler's decision making. However, in general expected utility theory is sufficiently widely accepted as useful to deal with choices made under uncertainty, and can be extended to incorporate elements of prospect theory such as perceptual conditioning (Hensher *et al.* 2011). In this paper we set out a model form to capture uncertainty which aligns with the framework of (expected) utility theory. For research on the choice behavior under uncertainty using prospect theory, we refer to, for example, Avineri and Prashker (2006), Van de Kaa (2008) and Hensher and Li (2012). For a review of different theories for modeling traveler's choice behavior under uncertainty, we refer to, for example (Fujii and Kitamura 2004).

Under the behavioral assumption of utility maximization, various behavioral models have been proposed in the literature to model traveler's choice behavior under uncertainty. In general, there are two common approaches, the mean-variance approach (Jackson and Jucker 1981) and the scheduling approach (Small 1982). The relationship and similarities between these two approaches have been investigated by several authors (Li *et al.* 2009b; Fosgerau 2010). It has been shown by Fosgerau that the maximal expected utility based on the scheduling approach (without the probability of being late) is linear in the mean and standard deviation of travel time distribution under the assumption that the travel time distribution is independent of departure times. Li *et al.* (2009b) also found that the scheduling approach could be transformed into a linear function of the mean and the standard deviation of travel times assuming independence of travel time distributions on departure time t. They conclude that the scheduling approach is more general than the mean-variance approach in terms of modeling departure time choice behavior. Motivated by this conditional equivalence and on a basis of deeper insights into the scheduling approach, this paper proposes a generalized approach for departure time choice modeling under uncertainty. The link between the scheduling approach and the generalized approach will be discussed and then two stated preference studies (in China and Australia) will be used to compare the performance of the generalized approach and the scheduling approach.

This paper will firstly present an overview of the widely used behavioral models for departure time choice behavior under uncertainty. Then the motivation for the generalized behavioral model is provided, with a discussion of the relationship between the scheduling approach and the generalized approach. Two surveys undertaken out in Shanghai and in Brisbane are described followed by the empirical estimates obtained from four behavioral models, and the evidence is contrasted. Finally some conclusions are drawn and future research is discussed.

2. ALTERNATIVE BEHAVIORAL MODELS

A number of behavioral models have been proposed in the literature as different hypotheses on choice behavior that account for uncertainty. de Jong and Bliemer (2015) provide an extensive literature review on different behavioral models accounting for the impact of unreliability on behavior, and give suggestions on how to include reliability in economic appraisal. The model forms differ in the mathematical expressions and indicators of uncertainty. For example, a hypothesis of a 'safety margin' being selected by travelers was specified by Gaver (1968) and Knight (1974), which assumed that travelers make their choice decisions by considering the expected travel time and adding some extra time budget, the so-called safety margin, to cope with uncertainties.

The mean-variance approach was initially proposed by Jackson and Jucker (1981), in which the individual utility function is composed of expected travel time and travel time variance (or standard deviation of travel time). The variability of travel time is often measured by the standard deviation of travel time (Small *et al.* 1999). However, the safety margin based approach and the mean variance approach do not explicitly model the effect of travel time variability on scheduling decisions, which turns out to be very important in representing travelers' choice behavior under uncertainty (Small 1982), since travel time unreliability causes uncertainty in their arrival time, resulting in potential reprimands for commuters on fixed working hours in particular.

The scheduling approach based on expected utility theory (Polak 1987) as originally specified by Small (1982), hypothesizes that scheduling delay cost plays a very important role in the timing of departures under uncertainty, formulated as equation (1).

$$u_p^{od}(t) = \alpha \cdot E\left[\tilde{\tau}_p^{od}(t)\right] + \gamma_1 \cdot E\left[\left(PAT - \left(t + \tilde{\tau}_p^{od}(t)\right)\right)^+\right] + \gamma_2 \cdot E\left[\left(t + \tilde{\tau}_p^{od}(t) - PAT\right)^+\right] + \theta \cdot P_L(t), \quad \forall (o,d), p, t, \tag{1}$$

$u_p^{od}(t)$, $\tilde{\tau}_p^{od}(t)$ denote respectively the individual's (dis)utility and stochastic travel times on route *p* between OD pair (*o*, *d*) departing at time *t* under uncertainty. $E\left[\tilde{\tau}_p^{od}(t)\right]$ denotes the expectation of travelers' experienced travel times on route *p* between OD pair (*o*, *d*) departing at *t*. PAT is the preferred arrival time. The second and the third components are the expected schedule delay costs of being early and late respectively. Function $(x)^+$ is equivalent to $\max\{0, x\}$, since there is either early schedule delay or late schedule delay on a specific day. Travelers can never experience both delay costs at the same time. $P_L(t)$ is the probability of being late when departing at time *t*. α, γ_1, γ_2, and θ are parameters associated with travel time, early and late schedule delays and probability of being late, respectively.

In most studies, a simplified version is applied by assuming that the parameter of the probability of lateness equals zero. In this paper, we name it the simplified scheduling approach. It has been shown by Small *et al.* (1999) that scheduling costs explain the aversion to uncertain travel times. They conclude that in models with a fully specified set of scheduling costs, it is not necessary to add an additional disutility for unreliability of travel time. However it is found that scheduling delay costs cannot capture the travel time unreliability completely (Noland and Polak 2002; Van Amelsfort *et al.* 2008). Besides a scheduling effect, travel time unreliability appears to be a separate source of travel disutility. Fosgerau and Karlström (2010) and Li *et al.* (2009b) found that the scheduling cost (i.e., the second and the third components in expression (1)) can be transformed into a linear function of the mean and the standard deviation of travel times $\tilde{\tau}_p^{od}(t)$ when assuming independence of travel time distributions of departure time *t*. Li *et al.* (2009b), through their analytical derivations, derived the form in equation (2).

$$
\begin{aligned}
&E\left[\left(PAT-\left(t+\tilde{\tau}_p^{od}(t)\right)\right)^+\right]=\left(PAT-\left(t+E\left[\tilde{\tau}_p^{od}(t)\right]\right)\right)^+ +\xi_t\cdot Std\left[\tilde{\tau}_p^{od}(t)\right]\\
&E\left[\left(t+\tilde{\tau}_p^{od}(t)-PAT\right)^+\right]=\left(t+E\left[\tilde{\tau}_p^{od}(t)\right]-PAT\right)^+ +\xi_t\cdot Std\left[\tilde{\tau}_p^{od}(t)\right] \qquad (2)\\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad where\ \ 0\le\xi_t\le\frac{1}{2},
\end{aligned}
$$

This formulation holds for any distribution of travel times. It implies that the scheduling cost (i.e., expected scheduling delay early and late) has a large correlation with travel time variability. Motivated by the fact that the uncertainty in travel times is only reflected in part by the expected scheduling cost, and the linear transformation of the mean and the standard deviation (Eqn.(2)), a generalized approach is developed, given as expression (3).

$$
\begin{aligned}
u_p^{od}(t)=\alpha\cdot E\left[\tilde{\tau}_p^{od}(t)\right]+\gamma_1\cdot\left(PAT-\left(t+E\left[\tilde{\tau}_p^{od}(t)\right]\right)\right)^+ +\gamma_2\cdot\left(t+E\left[\tilde{\tau}_p^{od}(t)\right]-PAT\right)^+ \qquad (3)\\
+\beta\cdot Std\left[\tilde{\tau}_p^{od}(t)\right],\ \forall(o,d),p,t,
\end{aligned}
$$

For a given departure time *t*, the scheduling approach proposed by Noland and Small (1995) is equivalent to the generalized approach, according to Eqn.(2). This model (3) accounts for trip travel time on average, the scheduling effects and uncertainty. Th standard deviation is incorporated to fully account for uncertainty effects. Recognizing the potential correlation between the expected scheduling cost (see the second and the third components in Eqn.(1)) and the standard deviation, we define the scheduling effects in the proposed generalized model as seen in Eqn.(3) based on the expectation of travel times.

This generalized model differs from the scheduling model, not only in the additional standard deviation, but also in the treatment of schedule delay. It synthesizes the merits of the mean-variance approach and the scheduling approach. It is assumed that travelers, based on their experiences and expected travel time, estimate how early or late they will be at work.

The mean-variance approach and the scheduling approach have been widely applied to modeling traveler's choice behavior under uncertainty. The scheduling approach turns out to be more suitable for modeling departure time choices under uncertainty since the schedule cost is directly affected by the travel time variability, which is the major concern of travelers. Under certain conditions, the scheduling approach is a special case of the generalized approach. For instance, if a traveler always arrives earlier or always arrives later than the PAT, then expression (4) holds.

$$
\begin{aligned}
&E\left[\left(PAT-\left(t+\tilde{\tau}_p^{od}(t)\right)\right)^+\right]=\left(PAT-\left(t+E\left[\tilde{\tau}_p^{od}(t)\right]\right)\right)^+, \text{ if } PAT-\left(t+\tilde{\tau}_p^{od}(t)\right)\geq 0, \text{for all } \tilde{\tau}_p^{od}(t)\\
&E\left[\left(t+\tilde{\tau}_p^{od}(t)-PAT\right)^+\right]=\left(t+E\left[\tilde{\tau}_p^{od}(t)\right]-PAT\right)^+, \quad \text{ or } PAT-\left(t+\tilde{\tau}_p^{od}(t)\right)\leq 0, \text{for all } \tilde{\tau}_p^{od}(t)
\end{aligned}
\tag{4}
$$

This means that the expected schedule delay equals the schedule delay based on the expected travel time. Then besides the utility components in the scheduling approach, travel time variability measured by the standard deviation is included in the generalized approach. This approach is very plausible since it captures not only the average effects, but also the variability in travel times. An illustrative example is given below to demonstrate the mechanism of the two approaches under uncertain departure conditions as shown by Eqn.(4).

Table 1 presents two situations with different travel time ranges under which the traveler always arrives later than PAT. The departure times and arrival times are also given. Travel times at situation 2 are more reliable with less variability than that at situation 1. According to Eqn.(4), regardless of whether a symmetric or asymmetric travel time distribution is assumed or observed, the schedule delay early and late calculated by the scheduling approach (Eqn.(1)) is always equal to that calculated by the generalized approach respectively. When the travel time distribution is symmetric within the range, the two situations give the same average schedule delay late of 10 minutes; that is in both situations the traveler on average arrives at 9:10 in the morning. With the scheduling approach, the same disutility is derived for the two situations. The impact of the ranges of the travel time could not be identified by the scheduling approach (Eqn.(1)). It makes a difference for travelers encountering the two situations. Travelers might prefer situation 2 with a narrow travel time distribution. The evidence in this example and Eqn.(4) together imply that the scheduling cost in the scheduling approach capture, in part, the variability effect. Comparatively, as shown with this illustrative example, the generalized approach, in addition to the scheduling costs, incorporates the travel time variability separately in the utility function to reflect a more complete representation of travel time variability and its impact on the departure time choice behavior of individuals.

Table 1: Two uncertain departure situations with different travel time ranges

	Departure time	Travel time	Arrival time at work
Situation 1	8:30am	30 – 50min	9:00 – 9:20am
Situation 2	8:30am	35 – 45min	9:05 – 9:15am

Given the preceding reasoning and the analytical analyses (see Eqn.(2)), the proposed generalized behavioral model (3) is expected to perform similarly (due to the analytically derived equivalence for a given departure time *t*) to or better than the scheduling model. However, empirical evidence is required to demonstrate whether the generalized model could be an improved representation of behavior under uncertainty. The main aim is to conduct an empirical investigation of the performance of the alternative model forms above[1], with a focus on the generalized behavioral model. Comparisons among models will be undertaken to see how well the generalized behavioral model could represent real departure time/route choice behavior under uncertainty. We draw on a new stated preference (SP) survey undertaken in Shanghai, China in 2014 focusing on departure time choice, and an Australian SP study undertaken in 2008 on the choice of tolled vs. free route (Li *et al.* 2010). The data analyses based on the two surveys are presented in the following sections for a comparison among the different behavioral models.

3. STATED PREFERENCE SURVEY IN CHINA

3.1 Experimental Design

Stated preference (SP) surveys are increasingly used to investigate the willingness to pay for various attributes including travel time and travel time reliability (or variability). We have undertaken SP surveys in Shanghai to investigate the departure time choice behavior under uncertainty of travelers. The SP experiment aims to capture the effects of travel time, schedule delays and variability of travel times on travelers' departure time choice behavior. With regard to presenting reliability to respondents, Li *et al.* (2010) gives a comprehensive overview on different ways of presenting reliability and comparison among them. We conducted several pilot studies to test how reliability should be presented such that the respondents can understand the questions and provide reliable answers. Based on pilot studies, we found that the uncertainty in travel times directly determines the uncertainty in arrival times which travelers care most about. We chose to give a range of arrival times at work so as to provide respondents with a context associated with variability. Two alternative departure times with different travel times and variations are presented in each scenario as an unlabeled choice experiment. Table 2 presents an example of the scenarios for two unlabelled choices with predefined PAT=9:00AM.

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[1] There are other behavioral models based on different hypotheses on travelers' departure time/route choice behavior under uncertainty, which are not our main interest. For a comprehensive review, see Li et al. 2010.

Table 2: An example on the unlabelled choice scenarios

Scenario 1	**Option A**	**Option B**
Departure time	8:30	8:10
Average travel time	40min	50min
Arrival at work within	9:00 – 9:20	8:50 – 9:10
Your option:		

The attributes in the design are selected in order to identify the utility components in the scheduling and generalized models. Four attributes were selected for the experimental design, namely average travel time, a travel time range, and early and late arrival time based on the expected travel time (see Table 3). The attribute levels are selected as given in Table 3. Negative values of expected arrival time means arrival on average earlier than PAT, and vice versa. In the design, once it is expected that arrival time is earlier, then the arrival late will be zero, and vice versa. These two attributes are bounded within a constrained design. Although the attribute levels should be realistic, a wide range for an attribute is preferred to ensure that statistically significant parameters will be obtained.

Table 3: **Attribute levels for all attributes**

Average travel time	Expected arrival time	Travel time ranges
30 min	-20	10 min
40 min	-10	20 min
50 min	0	30 min
	10	
	20	

Ngene (ChoiceMetrics 2012) is used to generate the scenarios with a D-efficient design, designed to provide utility-balanced alternatives for each scenario and to avoid the dominating-alternative situations. This design increases the statistical performance of the models with smaller samples than are required for other less-(statistically) efficient designs, such as orthogonal designs (Rose *et al.* 2008). In total, 18 choice scenarios (which is larger than the number of parameters that need to be estimated in the models) are generated, blocked into three groups. Each respondent faces six choice situations. Since we are dealing with unlabelled choices, we switched the positions of the right and the left alternatives for each scenario and changed the order of scenarios appearing in each choice scenario in order to reduce biases stemming from the designs. Thus, six different questionnaires are designed and distributed.

In addition to the choice scenario screens, a respondent is required to fill in his/her personal information, and current travel information.

3.2 Empirical Analyses

The China data on commuter's choice of departure time was collected in 2014 in Shanghai. The respondents in general are high-level educated commuters working in research centers or transportation-related institutes. 400 surveys were distributed and 357 returned, with a usable sample of 309. With six choice scenarios, we have 1,854 observations for model estimation. Figure 1a summarises the gender of the respondents. In total, 117 female respondents and 192 male respondents completed the survey. Respondents were asked whether they can be late at work and how late they can tolerate. Three options were provided with "cannot be late", "can be late within 10min" and "can be late for 10-15min". Figure 1b presents the number of respondents with different degrees of tolerance of being late at work. It can be seen that most commuters have very strict work start time and are not willing to be late.

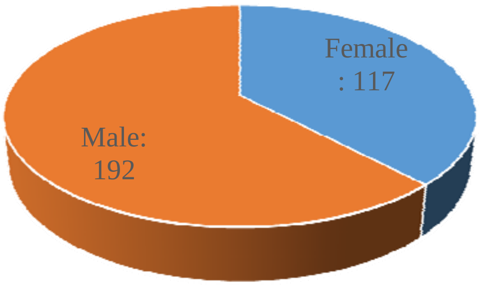

Figure 1a: Gender of respondents

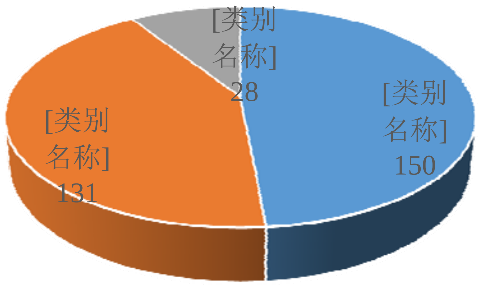

Figure 1b:Statistics of tolerance of late arrival

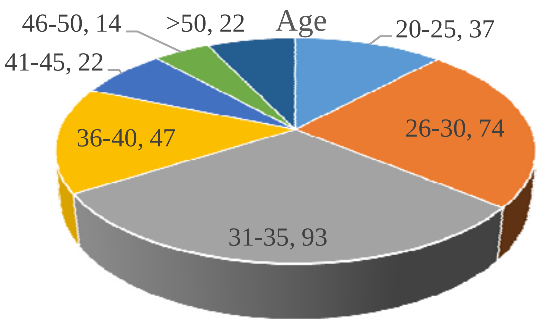

Figure 1c: Age profile

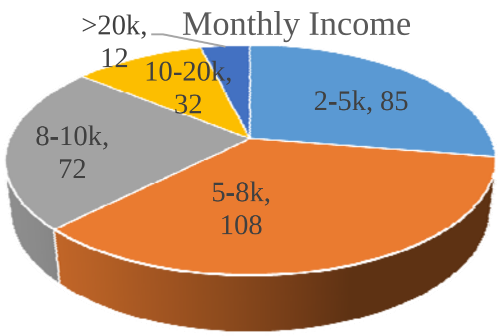

Figure 1d: Personal Income

Figure 1: Socioeconomic Profile

Figure 1c presents the number of respondents in each age group; for example, 74 respondents are between 26 to 30 years old. Most respondents are young commuters. Figure 1d summarizes the monthly salary; for example, 12 respondents have a monthly salary higher than 20,000￥ (approximately US$3,200).

Six questionnaires were designed, each representing a block in choice experiment design To obtain unbiased parameter estimates, an equal number of surveys from each block are required. Figure 2 summarizes the number of returned surveys associated with each block, which are reasonably well balanced.

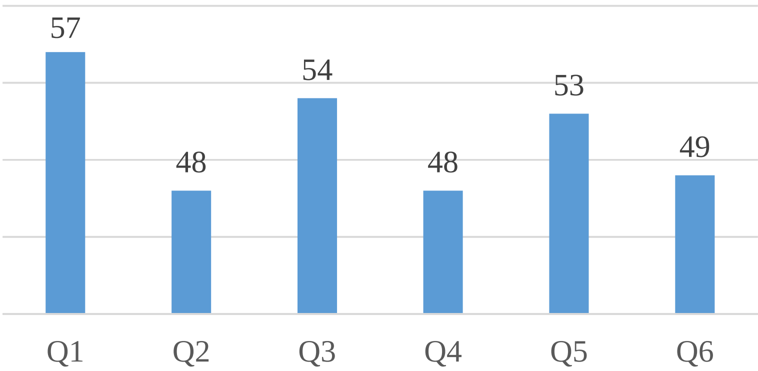

Figure 2: Numbers of respondents for each choice experiment block

Multinomial logit (MNL) and mixed logit (ML) models were estimated using Nlogit5, with the panel nature of the data taken into account in the mixed logit model estimation. Given the unlabeled nature of each choice set, parameters were estimated as generic across the alternatives. Table 4 and Table 5 present the estimation results for the MNL and ML models respectively. Only the parameter of travel time is estimated as random with a constrained triangular distribution when the ML model is estimated, to account for the panel nature of the data and to test preference heterogeneity in the sample.

The overall goodness of fit of all but the mean variance model is quite similar. The mean variance model is statistically inferior and the expected travel time has a positive sign which is intuitively implausible in the both MNL and ML models. Although unclear, this may be due to exclusion of other important attributes in the choice scenarios that have been excluded from the ‘pure’ mean variance specification. However, the expected travel time has a plausible sign in the other models, suggesting that there is no major error in the data set that might have led to a consistent implausibility across all model specifications.

The simplified scheduling approach (without probability of being late), the scheduling approach (Eqn.(1)) and generalized approach (Eqn.(3)) have quite similar statistical goodness of fits. The scheduling approach performs best when MNL is applied, while the generalized approach slightly outperforms the other two when mixed logit is used. The differences in the goodness of fit among the three models are insignificant. Both the MNL and ML models suggest that the generalized approach and the scheduling approach are more or less equivalent in representing departure time choice behavior under uncertainty. It is consistent with our previous finding through the analytical investigation on the relationship among these models.

All the parameters have the expected signs, although the sign of schedule delay early could be positive or negative. This suggests that commuters tend to prefer to arrive earlier in order to guarantee he/she will not be late, which is not an unreasonable finding, like the ‘safety margin’ idea. It is consistent with the survey data that most commuters have very strict work start times. Almost half of the commuters reported that they cannot be late. It is found that the schedule delay early is positive as expected; but marginally statistically insignificant. The mean travel time and late schedule delay in all three models are statistically significant at the 1% level, which implies that travel time and schedule delay late are the most crucial factors influencing travelers’ departure time choice decisions under uncertainty. The standard deviation in the generalized approach is also statistically significant at the 1% level, suggesting that variability is an important property considered by travelers. The probability of being late is not statistically significant in the scheduling model, primarily because it is correlated with the expected schedule delay.

The generalized approach captures uncertainty, schedule delay and mean travel time, all being statistically significant. The empirical equivalence to the popular scheduling approach suggests that it could be an alternative model for departure time choice behavior of individuals under uncertainty. Given that the mean and standard deviation of travel time are easier to be measure in real travel situations than the expected schedule delay under the scheduling approach, this has great appeal in project appraisal where there is an interest in integrating the wider set of reliability effects.

Table 4: MNL estimation results

	Mean-variance		Simplified Scheduling		Scheduling		Generalized	
	Coefficient	**t-ratio**	Coefficient	**t-ratio**	Coefficient	**t-ratio**	Coefficient	**t-ratio**
Expected travel time	0.02514 ***	6.88	-0.05124 ***	-9.83	-0.05472 ***	-9.65	-0.06221 ***	-7.46
Schedule delay early			0.01081	1.63	0	ns	0.02115 ***	2.99
Schedule delay late			-0.16266 ***	-15.66	-0.14973 ***	-11.46	-0.16137 ***	-11.81
Probability of being late					-0.41939	-1.54		
Standard deviation of	0.09747 ***	7.56					-0.04967 **	-2.04

travel time								
Final log-likelihood	-1243.79		-1046.40		-1045.20		-1048.76	
AIC	2491.6		2098.8		2098.4		2105.5	
No. of Observations	1845		1854		1854		1854	

*****, **, * denote Significance at 1%, 5%, 10% level**

The travel costs were not included in this survey; hence only the relative importance to travel time is calculated. The ratio β_{SDL} / β_{TT} is 2.2 indicating that travelers have very strict work schedules and are not willing to arrive late at work. In the generalized model approach, the reliability ratio of β_{SD} / β_{TT} is 0.75.

Table 5: Mixed Logit estimation

	Mean-variance		Simplified Scheduling		Scheduling		Generalized	
	Coefficient	**t-ratio**	Coefficient	**t-ratio**	Coefficient	**t-ratio**	Coefficient	**t-ratio**
Random parameter								
Expected travel time (mean)	0.13981 ***	4.47	-0.08613 ***	-5.13	-0.08734 ***	-5.67	-0.09534 ***	-7.21
Expected travel time (StDev)	0.13981 ***	4.47	0.08613	5.13	0.08734 ***	5.67	0.09534 ***	7.21
Nonrandom parameters								
Schedule delay early (SDE)			0.01148 *	1.82	-0.00020	-0.02	0.01928 **	2.48
Schedule delay late (SDL)			-0.19144 ***	-16.7	-0.17504 ***	-11.83	-0.20624 ***	-11.11
Probability of being late					-0.47282	-1.6		
Standard deviation (SD) of travel time	0.10215 ***	7.66					-0.07145 **	-2.32
Final log-likelihood	-1212.47		-998.647		-997.48		-996.44	
AIC	2432.9		2007.3		2007.0		2004.9	
No. of Observations	1854		1854		1854		1854	

*****, **, * denote Significance at 1%, 5%, 10% level**

Akaike information criterion: AIC = -2 × log-likelihood + 2 × K, where K is the number of parameters. The smaller AIC indicates a better model fit. Simulations are based on 100 Halton draws with a constrained triangular distribution.

4. THE STATED PREFERENCE SURVEY IN AUSTRALIA

4.1 Data Collection

A Stated Choice survey was conducted in 2008 in Australia, in the context of toll versus free roads. For each choice scenario, a revealed preference (RP) reference alternative is given together with two other stated preference (SP) alternatives that are pivoted around the RP alternative. Detailed information about this survey is provided in Li *et al.* (2012) and Hensher and Li (2012). In total, 280 Australia commuters were sampled for this study and each commuter has 16 choice scenarios. An illustrative choice scenario (cited from Li *et al.* (2012)) is given in Table 6.

Table 6: An illustrative stated choice scenario screen for the Australian study

Game 1	**Details of your recent trip**	**Route A**	**Route B**
Average travel time experienced			
Time in free flow traffic (min), t_f	25	14	12
Time slowed down by other traffic (min), t_s	20	18	20
Time in stop/start/crawling traffic (min), t_{ss}	35	26	20
Probability of time of arrival			
Arriving 6 min earlier than expected, $t_e=6$	30%, P_e	30%	10%
Arriving at the time expected, t_{on}	30%, P_{on}	50%	50%
Arriving 24 min later than expected, $t_l=24$	40%, P_l	20%	40%
Trip costs			
Running costs, C_r	$2.25	$2.59	$1.69
Toll costs, C_t	$4.00	$2.40	$3.60
If you make the same trip again, which route would you choose?	**Current Road**	**Route A**	**Route B**
If you could only choose between the two new routes, which route would you choose?		**Route A**	**Route B**

Each alternative has three travel scenarios - ‘a quicker travel time than recent trip time’, ‘a slower time than recent trip time’, and ‘the recent trip time’[2]. Respondents were advised that departure time remains unchanged. Each is associated with a corresponding probability[3] of occurrence to indicate that travel time is not fixed but varies from time to time. For all attributes except the toll cost, minutes for quicker and shorter trips, and the probabilities associated with the three trip times, the values for the SC alternatives are

[2] The data was not collected specifically to study trip time variability, and hence the limit of three travel times, in contrast to the five levels used by Small *et al.* (1999) and 10 levels used by Bates *et al.* (2001), where the latter studies focused specifically on travel time variability (or reliability).

[3] The probabilities are designed and hence exogenously induced to respondents, similar to other travel time variability studies.

variations around the values for the most recent trip. Given the lack of exposure to tolls for many travelers in the study catchment area, the toll levels are fixed over a range, varying from no toll to \$4.20, with the upper limit determined by the trip length of the sampled trip. The variations used for each attribute are given in Table 7, based on a range that we have shown in earlier studies (see Li *et al.* 2010) to be meaningful to respondents, while still delivering sufficient variability to identify attribute preference.

Table 7: Profile of the Attribute range in the SC design

Attribute	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Level 5**	**Level 6**	**Level 7**	**Level 8**
Free Flow time	-40%	-30%	-20%	-10%	0%	10%	20%	30%
Slowed down time	-40%	-30%	-20%	-10%	0%	10%	20%	30%
Stop/Start time	-40%	-30%	-20%	-10%	0%	10%	20%	30%
Quicker trip time	-5%	-10%	-15%	-20%	-	-	-	-
Slower trip time	10%	20%	30%	40%	-	-	-	-
Prob. of quicker time	10%	20%	30%	40%	-	-	-	-
Prob. of most recent trip time	20%	30%	40%	50%	60%	70%	80%	-
Prob. of slower trip time	10%	20%	30%	40%	-	-	-	-
Running costs	-25%	-15%	-5%	5%	15%	25%	35%	45%
Toll costs	\$0.00	\$0.60	\$1.20	\$1.80	\$2.40	\$3.00	\$3.60	\$4.20

A survey was designed to capture a large number of travel circumstances, to determine how each individual trades-off different levels of travel times and trip time variability with various levels of proposed tolls and vehicle running costs, in the context of tolled and non-tolled roads. Sampling rules were imposed on three trip length segments: 10 to 30 minutes, 31 to 45 minutes, and more than 45 minutes (capped at 120 minutes). Sampling by the time of day that a trip commences was also included, defining the peak[4] as trips beginning during the period 7-9 am or 4.30-6.30pm. All non-peak trips are treated as off peak in the internal quota counts.

There are three version of the experimental design depending on the trip length, with each version having 32 choice situations (or scenarios) blocked into two subsets of 16 choice situations each. In generating the designs, the free flow, slowed and stop/start times were set to five minutes if the respondent entered zero for their current trip. It is important to understand that the distinction between free flow, slowed down and stop/start/crawling time is solely to promote the differences in the quality of travel time between various routes – especially a tolled route and a non-tolled route, and is separate to the influence of total time.

[4] The way we handle trips that are partly in the peak: a trip is peak if 60 percent or more of the trip falls within the peak period.

The experimental design method of D-efficiency is used herein as done in the Chinese survey. The socioeconomic profile of the data is given in Table 8, and the descriptive overview of choice experiment attributes is given in Table 9.

Table 8: Descriptive socioeconomic statistics

Purpose	Statistic	Gender (1=female)	Income	Age
Commuter	Mean	0.575	$67,145	42.52
	Std. Deviation	0.495	$36,493	14.25

Table 9: Descriptive statistics for costs and times by segment

	All times of day		Peak		Off-Peak	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Running costs	$3.15	$2.56	$3.58	$3.01	$2.92	$2.26
Toll costs	$1.41	$1.50	$1.40	$1.50	$1.41	$1.51
Total time	39.29	16.58	36.93	16.25	40.54	16.61

The descriptive statistics for the time and probability variables are given in Table 10.

Table 10: Travel Times and Probabilities of Occurrence (for commuters only)

Variable	Mean	Std. Dev.	Minimum	Maximum
P_S	0.25	0.11	0.1	0.4
P_L	0.25	0.11	0.1	0.4
P_{MR}	0.50	0.15	0.2	0.8
X(quicker)	4.80	3.14	0	18
Y(slower)	9.60	6.28	1	36
MR_T	39.29	16.58	10	119
S_T	34.48	14.98	7	115
L_T	48.89	21.09	11	150
PT_S	8.61	5.61	0.8	40.8
PT_L	12.12	7.68	1.1	56.4
PT_{MR}	19.69	10.57	2	95.2

Notes: P_S, P_L and P_{MR} are probabilities for quicker, slower, and recent trip time, MR_T is the most recent travel time (the sum of three components: free flow, slowed down and stop/start times), X(quicker) and Y(slower) are the amounts of quicker and slower times compared with most recent time, which are designed and presented in the experiment. S_T is the actual quicker (or shorter) travel time (=MR_T -X(quicker)); L_T is the actual slower (or longer) travel time (=MR_T +Y(slower)); PTE (=P_S * E_T), PT_L (=P_L * L_T) and PT_{MR} (=P_{MR} * MR_T) are probability weighted values for quicker, slower and most recent time respectively.

Our design assumes a fixed level for a shorter or longer trip within each choice scenario. However, across the choice scenarios, we vary the probability of a shorter, a longer and a recent trip time, and hence recognize the stochastic nature of the travel time distribution (see Table 7 where, for example, the probability of travel time occurrence varies from 10% to 40% in the choice experiment). This contrasts with Bates *et al.* (2001) and Hollander (2006) who did not mention occurrence probabilities, implicitly assuming that travel times are equally distributed when estimating models. Further details about this survey is provided in Li *et al.* (2012) and Hensher and Li (2012). Given the panel nature of the data we used an estimation method that recognized the correlated structure of observations drawn from the same individual (see Hensher *et al.* (2015) for details).

4.2 Empirical Analysis

The same four model specifications applied to the Chinese data are also estimated using the Australian data. The Australian data is more detailed than the Chinese data with the mapping of the attributes into the four model forms summarized below (the symbols are defined in Table 6):

$E\left[\tilde{\tau}_p^{od}(t)\right] = t_f + t_s + t_{ss}$	expectation of travel time
$E\left[\left(PAT - \left(t + \tilde{\tau}_p^{od}(t)\right)\right)^+\right] = P_e \cdot t_e$	the second item in the scheduling approach
$E\left[\left(t + \tilde{\tau}_p^{od}(t) - PAT\right)^+\right] = P_l \cdot t_l$	the third item in the scheduling approach
$\left(PAT - \left(t + E\left[\tilde{\tau}_p^{od}(t)\right]\right)\right)^+ = \left\lvert\left(-t_e \cdot P_e + t_l \cdot P_l\right)^-\right\rvert$	the second item in the generalized approach, where $(x)^- = \min(x,0)$, $\lvert x\rvert$ is the absolute value of x
$\left(t + E\left[\tilde{\tau}_p^{od}(t)\right] - PAT\right)^+ = \left(-t_e \cdot P_e + t_l \cdot P_l\right)^+$	the third item in the generalized approach
$Std\left[\tilde{\tau}_p^{od}(t)\right] = \sqrt{P_e \cdot t_e^2 + P_l \cdot t_l^2 - \left(-t_e \cdot P_e + t_l \cdot P_l\right)^2}$	standard deviation of travel time
$C = C_r + C_t$	travel cost

MNL and mixed logit models were estimated and the panel effects were accounted for by using mixed logit model with random parameters. A reference constant was included for the current route alternative. Except for the parameter of travel cost and the RP reference specific constant, all other parameters are estimated as random variables with a constrained triangular distribution.

From Table 11 and Table 12, it can be seen that a positive constant is obtained for the current route alternative, which implies that, after accounting for the role of the set of observed attributes, that there is a bias on average in favor of the experienced alternative. The overall goodness of fit of the four models is quite similar. The mean variance approach performs much better in this case in contrast to the Shanghai study. The reason, as aforementioned, is that the Australian study is designed in a context of route choice modeling with tolling routes. Again, with this comprehensive survey, evidence suggests that the generalized approach is empirically equivalent to the scheduling approach in performance, as found in the analytical derivation.

This survey includes the travel cost in the trade off with travel times and their occurrence. Travel cost and expected travel time are statistically significant at the 1% level in all four models. The schedule delay late attribute in the three models has a negative sign as expected, while most of them are statistically insignificant except in the simplified scheduling model as it captures uncertainty. In general, the schedule delay early attribute is only marginally significant in the simplified scheduling model with MNL estimation, while it is statistically insignificant in all three models with ML estimation The schedule delay early, based on mean travel time in the generalized approach, has a positive sign as also found in the China study, while being statistically insignificant in this Australian case study. The probability of being late in the scheduling model is statistically significant and of the correct sign, suggesting that this is a stronger influence on choice of route than the scheduling influence (late or early). The standard deviation in the generalized model is statistically significant at the 1% level. It can be concluded for the Australia study that travel cost, average travel time and travel time variability are clearly important factors influencing route choices under uncertainty. The scheduling effects appear to be not important when modeling route choice behavior under uncertainty. The standard deviation, expected schedule delay and the probability of being late are all indicators of travel time variability. Only one of these influences however is significant in each model. If we were to remove the statistically non-significant parameter estimates in the generalized model, it collapses to the mean-variance model.

The product of late schedule delay (SDL) and probability of being late (PL) was included in the scheduling model to explore the relationship between SDL and PL. Table 12 shows the model estimation results for the scheduling approach with an interaction term (SDL*PL). It can be seen that the parameter of the interaction term is -0.47 and is significant at the 10% level. The mean of the SDL parameter is $\beta_{SDL}\left(mean\left|PL\right.\right)=\beta_{SDL}(mean)-0.47\times\mathrm{PL}$ which implies that the degree of a traveler's aversion to SDL increases with the increasing probability of being late. SDL and PL are positively correlated resulting in the stand alone SDL being not statistically significant in the scheduling approach while PL preserves its very strong statistical significance.

Table 11: MNL estimation results

	Mean-variance		Simplified Scheduling		Scheduling		Generalized	
	Coefficient	**t-ratio**	Coefficient	**t-ratio**	Coefficient	**t-ratio**	Coefficient	**t-ratio**
Expected travel time	-0.07164 ***	-17.00	-0.07241 ***	-17.08	-0.07209 ***	-16.99	-0.07182 ***	-16.87
Schedule delay early			-0.08050 *	-1.76	-0.06928	-1.51	0.10443	1.33

Schedule delay late			-0.13308 ***	-5.49	-0.01396	-0.34	-0.01711	-0.55
Probability of being late					-1.77170 ***	-3.53		
Standard deviation of travel time	-0.15387 ***	-5.45					-0.13436 ***	-3.91
Cost	-0.29844 ***	-15.32	-0.30074 ***	-15.35	-0.29855 ***	-15.23	-0.30163 ***	-15.4
Reference constant	0.88613 ***	17.87	0.87967 ***	17.60	0.89003 ***	17.74	0.87998 ***	17.61
Final log-likelihood	-3427.498		-3425.023		-3418.83		-3426.24	
AIC	6863.0		6860.0		6849.7		6864.5	
No. of Observations	4480		4480		4480		4480	

*****, **, * denote Significance at 1%, 5%, 10% level**

Table 12: Mixed logit estimation results

	Mean-variance		Simplified Scheduling		Scheduling		Scheduling + interaction term		Generalized	
	Coefficient	**t-ratio**	Coefficient	**t-ratio**	Coefficient	**t-ratio**	Coefficient	**t-ratio**	Coefficient	**t-ratio**
	Nonrandom parameters									
Reference constant	0.88109***	17.07	0.8705 ***	16.74	0.88319 ***	16.88	0.88487 ***	16.88	0.87016***	16.74
Cost	-0.33021 ***	-16.09	-0.33463 ***	-16.18	-0.33071 ***	-16.01	-0.33146 ***	-16.01	-0.33448 ***	-16.22
SDL*PL							-0.46697*	-1.74		
	Means of Random parameters									
Expected travel time	-0.11815 ***	-16.41	-0.1195 ***	-16.52	-0.11887 ***	-16.44	-0.11874 ***	-16.40	-0.11889 ***	-16.45
Schedule delay early （SDE）			-0.06537	-1.34	-0.05247	-1.07	-0.06061	-1.22	0.08801	1.10
Schedule delay late (SDL)			-0.16494 ***	-6.08	-0.03319	-0.71	0.20951	1.56	-0.04472	-1.32
Probability of being late (PL)					-1.83439 ***	-3.27	-1.87607 ***	-3.51		
Standard deviation of travel time	-0.1804 ***	-5.76							-0.14113 ***	-3.71
	Standard deviations of random parameters									
Expected travel time	0.11815***	16.41	0.1195 ***	16.52	0.11887 ***	16.44	0.11874 ***	16.40	-0.11889 ***	16.45
Schedule delay early （SDE）			0.06537	1.34	0.05247	1.07	0.06061	1.22	0.08801	1.10
Schedule delay late (SDL)			0.16494 ***	6.08	0.03319	0.71	0.20951	1.56	0.04472	1.32
Probability of being late					1.83439 ***	3.27	1.87607 ***	3.51		
Standard deviation (SD) of travel time	0.1804	5.76							0.14113 ***	3.71
Final log-likelihood	-3347.12		-3343.25		-3338.06		-3337.305		-3345.38	
Rho-square	0.3199		0.3207		0.3218		0.3219		0.3203	
AIC	6702.2		6696.5		6688.1		6688.6		6702.8	
No. of Observations	4480		4480		4480		4480		4480	

*****, **, * denote Significance at 1%, 5%, 10% level**
Simulations are based on 100 Halton draws with a constrained triangular distribution.

The willingness to pay (WTP) estimates are presented in Table 13 for both the MNL and ML models. All four models produce values of travel time savings (VTTS) with similar means and standard deviations within each of MNL and ML models. As different utility components are included in the four models, values of schedule delay early (SDE) and late (SDL) are different. For the simplified scheduling approach, the estimated value of SDE is greater than VTTS with MNL, while the opposite is found with ML. . With ML estimation, conditional willingness to pay is calculated, instead of unconditional estimates. For example, the mean of VTTS with ML is calculated as $E\left(\beta_{TT} / \beta_{\cos t}\right)$, instead of $E\left(\beta_{TT}\right) / E\left(\beta_{\cos t}\right)$, which are not equal to each other. The mean of the reliability ratio VOR/VTTS is computed as $E\left(VOR / VTTS\right) = E\left(\beta_{SD} / \beta_{TT}\right)$, instead of $E\left(VOR\right) / E\left(VTTS\right)$. The ratio of SDL/VTTS is about 1.8, indicating a higher relative value for late schedule delay compared to VTTS. The value of the standard deviation or the value of reliability (VOR) is significantly greater in the generalized model than VTTS, with a reliability ratio of about 2 for the mean variance approach and about 1.5 for the generalized approach. These differences are large and the selection of a reliability ratio and the associated VTTS and VOR will have a noticeable influence of the benefits obtained by projects in an economic appraisal.

Table 13: Values of travel time savings, reliability, and scheduling cost ($Aud2008 per person hour)

	Mean-variance		Simplified Scheduling		Scheduling		Generalized	
	MNL	**ML**	**MNL**	**ML**	**MNL**	**ML**	**MNL**	**ML**
VTTS (mean)	14.40	19.67	14.45	19.63	14.49	19.75	14.29	19.53
VTTS (StDev)		7.08		7.09		7.12		7.05
VOR(mean)	30.93	32.62					26.73	25.29
VOR(StDev)		2.26						1.38
VOR/VTTS (mean)	2.15	1.97					1.87	1.55
VOR/VTTS (StDev)		1.05						0.84
SDE(mean)			16.06	11.67	13.92	9.49	20.77	-15.75
SDE(StDev)				0.24		0.18		0.28
SDL(mean)			26.55	29.42	2.81	5.99	3.40	7.99
SDL(StDev)				2.09		0.13		0.19
SDE/VTTS (mean)			1.11	0.71	0.96	0.57	1.45	-0.96
SDE/VTTS (StDev)				0.38		0.31		0.516
SDL/VTTS (mean)			1.84	1.79	0.19	0.36	0.24	0.49
SDL/VTTS (StDev)				0.96		0.19		0.26

Note: VOR is measured by the standard deviation of travel time.

5. Conclusions

Using a number of behavioral perspectives on the theoretical relationship between the variability of travel time and expected schedule delay, this paper has proposed a more general model to recognize influences on trip time variability associated with trip scheduling and uncertainty of travel time. This more general model accounts for the scheduling effects and explicitly incorporates a variability measure (standard deviation of travel times) to reflect a more complete representation of travelers' risk averse attitudes towards unreliability. Recognizing the potential correlation between the expected scheduling delay and standard deviation, the scheduling effects in the generalized approach are defined in terms of expected travel time. This generalized model differs from the scheduling model, not only through the additional standard deviation of travel time term, but also in the representation of schedule delay. This paper shows that the expected scheduling delay can only capture, in part, the uncertainty in travel times.

A conditional equivalence of the generalized approach and the scheduling approach was found in a previous study with an analytical approach. However, there was no empirical evidence. This paper focuses on an empirical investigation of the performance of the generalized approach in comparison to the popular scheduling approach using data sets from China and Australia.

The two distinct surveys (the China survey was designed by assuming a symmetric travel time distribution, while the Australia study with an asymmetric distribution) both produced empirical evidence of the equivalence in terms of overall goodness of fit of the generalized approach and the scheduling approach, as suggested in the theoretical formulations, suggesting that the extended generalized model is an eligible alternative specification in future choice modeling. This is an important finding that adds behavioral insights into the potential role of additional sources of travel time variability, suggesting that future empirical studies should contemplate testing the models presented in this paper in order to add support or otherwise for our findings.

This generalized approach brings benefits from two perspectives: 1) it has a mathematical formulation that has appeal for analytical analyses and offers a way forward with other data sources to undertake further inquiry into the growing role of travel time variability in influencing travel behavior; 2) it shows the practical (and feasible) value of the various measures of travel time uncertainty that are relatively easy to measure, that can and should be incorporated in project appraisal. Standard deviation and mean travel time are easier to derive in practice than the expected schedule delay as defined in the scheduling model. In the context of project appraisal, de Jong and Bliemer (2015) suggest beginning with incorporating the standard deviation as a reliability measure in project appraisal, recognizing the complexity of directly incorporating expected scheduling delay. This paper promotes incorporation of the standard deviation and scheduling effects into a generalized approach, for which standard deviation and expected travel time are straightforward to derive.

Further studies are recommended to test the generalized model with other data sets before offering a definite position on the relative advantages of each approach. The Chinese study gives support in the generalized model to including both the mean-variance and the scheduling effects; whereas the Australian study finds only the mean-variance specification has statistical merit.

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