JOURNAL OF ADVANCED TRANSPORTATION
J. Adv. Transp. 2013; **47**:206–224
Published online 14 January 2011 in Wiley Online Library (wileyonlinelibrary.com). **DOI**: 10.1002/atr.160

Accommodating risk in the valuation of expected travel time savings

David A. Hensher*, Zheng Li and John M. Rose

The University of Sydney, Faculty of Economics and Business, Institute of Transport and Logistics Studies, Newtown, NSW 2006, Australia

SUMMARY

Valuation of travel time savings is a critical measure in transport infrastructure appraisal, traffic modelling and network performance. It has been recognised for some time that the travel times associated with repeated trips are subject to variation, and hence there is risk embedded in the treatment of expected travel time. In the context of the expected utility framework, we use a nonlinear probability weighting function to accommodate choice made under risk. Although the empirical findings suggest small differences between the value of expected travel time savings (VETTS) in the presence and absence of risk, the mean estimate does make a noticeable difference to time benefits when applied to real projects. By incorporating nonlinear probability weighting, our model reveals that the probabilities associated with specific travel times that are shown to respondents in the choice experiment are transformed, resulting in overweighting of outcomes with low probabilities and underweighting of outcomes with high probabilities. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS: travel time variability; expected travel time; passenger transport; willingness to pay; choice under risk; expected utility theory; nonlinear probability weighting; extended expected utility model

1. INTRODUCTION

Time savings is generally recognised as the most important user benefit in transport appraisal, typically contributing over 60 per cent of user benefits [1]. In calculating the time benefits in monetary units, a value of travel time savings (VTTS) has to be obtained. de Jong *et al.* [2] amongst others have pointed out that an important user trip benefit that is often neglected in transport appraisal is the valuation of travel time variability. This is out of line with the growing number of studies which have investigated the significance of travel time variability in traveller behaviour (see e.g. [3,4,5] and [6] for a review)[1]. Some of these studies obtained higher values for reducing travel variability than for reducing scheduled journey time or for average travel time (see e.g. [7,8]).

Within a choice theoretic framework, that is commonly used to obtain empirical estimates of the values of travel time savings and time variability, the most popular specification assumes that an individual acts as if they are a utility maximiser, and that the inability of the analyst to observe and measure all influences on utility maximising behaviour engenders a theory of Random Utility Maximisation (RUM) [9]. However, RUM assumes that the individual's choice is made under certainty or risk neutrality [8], despite the inability of the analyst to observe and measure all influences on utility

*Correspondence to: David A. Hensher, The University of Sydney, Faculty of Economics and Business, Institute of Transport and Logistics Studies, Newtown, NSW 2006, Australia. E-mail: david.hensher@sydney.edu.au
[1]Similar to VTTS studies, travel time variability studies predominantly use stated choice data, although some studies employed RP data (see e.g. [45,46]).

(which engenders the randomness). In recognition that travel time variability introduces risk or uncertainty[2] *at the attribute level*, other theoretical platforms have been proposed and introduced as a way to accommodate travel time variability. Since the early 1990s, a number of studies have incorporated Expected Utility Theory (EUT) into the representation of travel time variability, as a way of recognising individual travel choice under risk (see e.g. [10,11]). This model, known as Maximum Expected Utility (MEU), involves a choice process in which the alternative with the highest value of expected utility is preferred. Since Noland and Small's seminal paper in 1995, this has become the standard approach in travel time variability studies (see e.g. [5,7,12,13]).

Such a willingness to pay estimate can be obtained from suitable revealed preference data, using a choice model that identifies the trading between time and other factors including monetary outlays.[3] However in recent years, stated choice methods have increasingly been used and are now the dominating data paradigm, largely due to the difficulties of identifying real market situations where analysts can observe and measure the trade-offs between the attributes required to establish measures of WTP (e.g. [1,9,14–18]).

The purpose of this paper is to estimate values of travel time savings using stated choice methods that account for the distribution of travel time for repeated travel, embedding risk into the treatment of expected travel time. We present an approach that (i) addresses respondents' risk attitude, (ii) accounts for nonlinearity in probability weighting and iii) integrates these constructs into the value of expected travel time savings (VETTS). The model form is nonlinear in the parameter set, specifically accommodating risk attitude in the levels of the attributes, and the perceptual processing of occurrence probabilities[4] for attributes displaying varying levels over repeated trip activity for a trip with a common purpose and origin and destination (e.g. the regular weekly commute).

This paper is organised as follows. The following section introduces pioneering travel time variability (often referred to as reliability) studies developed within a utility maximisation framework (e.g. [3,4]). This is followed by the contributions that focus on choosing a travel outcome with the highest expected utility (or the lowest expected disutility) (e.g. [5,12]). We introduce nonlinearity through the explicit allowance for attribute risk. Within an EU framework, we also apply a nonlinear probability weighting function (which we call extended EUT) to identify how induced probabilities in stated choice experiments are transformed. We integrate these additional behavioural constructs into a willingness to pay for expected total travel time savings experienced over repeated trip activity (mean and variability), referred to as the VETTS. Using a 2008 stated choice data set from Australia for commuters choosing amongst alternative trip attribute packages for car travel, we estimate a series of models based on the alternative behavioural paradigms and compare the findings. Conclusions are drawn along with recommendations.

2. TRAVEL TIME VARIABILITY AND RANDOM UTILITY MAXIMISATION

Early travel time variability studies, developed within a utility maximising framework such as Jackson and Jucker [3], proposed a mean-variance form in which utility, U, is defined as a function of the usual (or mean) travel time and the variance, assuming that travellers trade-off time against variability (variance). They postulate that variability directly leads to disutility, similar to the mean travel time, and hence time variability can be represented by the variance or standard deviation[5] of travel time (i.e. the mean-variance approach). The mean-variance model was also employed by Pells [19] and Black and Towriss [20]. The objective is to minimise the sum of these elements (Equation (1)).

$$U = \overline{T} + \lambda V(T) \tag{1}$$

[2]Risk is associated with a known probability distribution whereas uncertainty is associated with an unknown probability distribution.
[3]See e.g. Brownstone *et al.* [47] and Steimetz and Brownstone [48].
[4]Referred to in prospect theory as under- and over-weighting.
[5]Some SP studies also use the coefficient of variation (i.e. standard deviation divided by mean travel time) in the utility function (see e.g. Noland *et al.* [49]).

DOI: 10.1002/atr

where λ is a parameter measuring the influence of the variance in travel times; $\overline{T}$ is the usual or mean travel time; and $V(T)$ is the variance of travel time.

Unlike the mean-variance model, in which variability is the direct source of disutility, in the context of trip timing (or departure time choice), Small [4] introduced the concept of schedule delay, defined as the difference between actual arrival time and official start time, and he posited that utility would be decreased if arriving early (SDE) or arriving late (SDL) relative to a planned arrival time. Small proposed the scheduling model as an alternative way to understand travellers' departure time choices in order to satisfy on-time arrival, as given in Equation (2).

$$U = \eta T + \beta \mathrm{SDE} + \gamma \mathrm{SDL} + \theta D_L + \dots \tag{2}$$

T is travel time, SDE is schedule delay early, SDL is schedule delay late, D_L is a dummy variable equal to 1 when there is an SDL and 0 otherwise; and the estimated parameters (η, β, γ and θ) are assumed to be negative.

Fosgerau and Karlström [21] make an important recent contribution in unifying the schedule delay and variance models Using the scheduling utility of Small [4] and observed travel times at a congested radial road in Greater Copenhagen, Fosgerau and Karlström [21] showed that the maximal expected utility is linear in the mean and standard deviation of trip time, and use this evidence to provide a unification of the scheduling model and the mean-variance model. They also estimated a model which suggested that travel time variability accounts for 15 per cent of total time cost. They state that the validity of key assumptions used in their study should be addressed in future research, including the fixed travel time distribution which may not be known by the decision maker and the assumed linear utility specification.

The above studies did not consider the stochastic characteristic of travel time variability. That is, given travel time variability, it is assumed that it is not possible for travellers to anticipate their travel times, and consequently different travel times have an associated probability of occurrence as well as the element of risk attitude. Therefore, there should be a distribution of travel times rather than a fixed travel time, and hence travel choice is no longer made under certainty or risk neutrality.

3. RECOGNISING EXPECTED UTILITY

EUT has been extensively applied in a number of fields such as experimental economics, environmental economics, health economics and in travel time variability studies after the 1990s. Unlike RUM models, which typically assume a linear-additive utility function for the observed or representative consumer component (i.e. $U = \sum_k (\beta_k x_k)$, where β_k are the estimated parameters and x_k are the attributes that underlie individual preferences), EUT models postulate a nonlinear functional form, for example, $U = x^\alpha$ where α is an estimated parameter which explains respondents' attitudes towards risk. A basic *EUT* model is given in Equation (3).

$$E(U) = \sum_m \left(p_m x_m^\alpha\right) \tag{3}$$

where $E(U)$ is the expected utility; m (=1,. . .,M) are the possible outcomes for an attribute and $m \geq 2$; p_m is the probability associated with the mth outcome; and x_m is the value for the mth outcome.

Noland and Small [11] extended Small's scheduling model to accommodate travel time variability through the incorporation of EUT, which is often referred to as MEU[6]. Travel time (T) is no longer deterministic but has a distribution dependent on departure time (t_h) [5]. Hence, the expected utility of the scheduling model is expressed as Equation (4), where the possible delay or early arrival with respect to the preferred arrival time are modelled separately, and their consequences are measured by separate parameters[7]. That is, expected utility ($U(t_h)$) is a function of the expected travel time ($E[T(t_h)]$), the expected schedule delay early ($E[\mathrm{SDE}(t_h)]$), the expected schedule delay late

[6]MEU adopts linear probability weighting of EUT, however still within a linear utility maximisation framework.

[7]The travel time destination needs to be assumed for estimating the values of parameters, which is often assumed to be equi-probable (see e.g. [12,5]).

DOI: 10.1002/atr

($E[\mathrm{SDL}(t_h)]$), and the probability of experiencing a late arrival ($P_{\mathrm{L}}(t_h)$).

$$E[U(t_h)] = \eta E[T(t_h)] + \beta E[\mathrm{SDE}(t_h)] + \gamma E[\mathrm{SDL}(t_h)] + \theta P_L(t_h) + \ldots \tag{4}$$

Small *et al.* [12] among others also used an MEU framework to analyse traveller responses to travel time variability, within the mean-variance framework developed by Jackson and Jucker (Equation (1)). A typical mean-variance specification is shown in Equation (5).

$$E(U) = \beta_T E(T) + \beta_{\mathrm{SD}} \mathrm{SD}(T) + \beta_C C \tag{5}$$

where $E(U)$ is expected utility, β_{T}, β_{SD} and β_{C} are the estimated parameters for the expected travel time ($E(T)$), the standard deviation of travel time ($\mathrm{SD}(T)$), and travel cost (C), respectively.

Despite the appeal of EUT, in most travel time variability studies which adopt *MEU*, a linear functional form was used (see References [5,7,8,12,13]) with equal occurrence probabilities for each described level of travel time. Polak [22] is one of the earliest studies that addressed travellers' decision making under risk, proposing a number of alternative model forms, for example, *a quadratic utility specification* (i.e. $U = \beta_1 x + \beta_2 x^2$), and an exponential utility function (i.e. $U = -e^{-\alpha x}$). Senna [10] used a nonlinear utility specification to investigate travel choice; however he imposed an assumption (rather than estimated the relevant parameter) on this nonlinearity (i.e. the value of risk attitude parameter): 0.5 (risk seeking) for commuters with fixed arrival time, 1.4 for commuters with flexible arrival time and 1.4 (risk averse) for non-commuters. Whether those assigned values are able to reflect respondents' true attitudes is unknown. Polak *et al.* [23] also applied EUT in investigating travel choice in the face of travel time variability, using Bates *et al.*'s data within an multinomial logit (MNL) framework with a constant *absolute* risk aversion (CARA), $U = (1-e^{-\alpha x})/\alpha$.

EUT not only changes the utility function for travel time variability, it also leads to significant challenges in the way that stated choice (SC) experiments have to be designed to capture travel time variability. In studies that do not incorporate an EUT probability weighting function, travel time variability is typically presented as the extent and frequency of delay relative to normal travel time (which we refer as a Type 1 experiment). For example Jackson and Jucker [3] ask respondents to make a choice between a journey that always takes 30 minutes and a journey which has a shorter time, but a possibility of 5-minute delay once a week (Table I).

In recognising that travel time does vary, a series of arrival times (normally five or 10 levels), rather than the extent and frequency of delay, have been considered in recent SC experiments (referred to as Type 2) (see, e.g. [7,8,10–13]). An example of the Type 2 design is given in Figure 1, which has five outcomes related to the travel time attribute, giving information to calculate the expected value.

The two types of models[8] (Equations (4) and (5)) above dominate the current transport literature on valuation of travel time variability. The key outputs include the value of reliability (VOR) that is defined as the travellers' WTP for a unit reduction in variability (shown as the standard deviation) in travel time (i.e. $\beta_{\mathrm{SD}}/\beta_{\mathrm{C}}$). An important output from these studies is the reliability ratio, defined as the marginal rate of substitution between average travel time and travel time variability (i.e. $\beta_{\mathrm{SD}}/\beta_{\mathrm{T}}$).

Our focus is different. The emphasis is on the treatment of $\beta_{\mathrm{T}}\, E(T)$ where we introduce nonlinear probability weighting to account for perceptual processing of occurrence probabilities and risk associated with the distribution of travel times. In a very real sense, travel time variability is being

Table I. Stated choice task from Jackson and Jucker [3], Type 1.

Card		Route 1	Route 2
1	Usual time:	30 minutes	20 minutes
	Possible delays:	None	5 minutes once a week

[8]A third type model is the mean lateness model, which is fast becoming the 'standard' approach for analysing variability (or reliability) for passenger rail transport in the UK [8], where travel unreliability is measured by the mean lateness at departure and/or arrival, while the mean earliness (i.e. negative lateness) is not considered.

DOI: 10.1002/atr

PLEASE CIRCLE EITHER CHOICE A OR CHOICE B	
Average Travel Time **9 minutes** You have an equal chance of arriving at any of the following times:	Average Travel Time **9 minutes** You have an equal chance of arriving at any of the following times:
7 minutes early **4 minutes early** **1 minute early** **5 minutes late** **9 minutes late**	**3 minutes early** **3 minutes early** **2 minute early** **2 minutes early** **On time**
Your cost: **\$0.25**	Your cost: **\$1.50**
Choice A	**Choice B**

Figure 1. Stated choice task from Small *et al.* [12], Type 2.

accommodated in the estimation of expected travel time, and hence in the valuation of (expected) travel time savings.

4. THE APPEAL OF NON-EXPECTED UTILITY MODELS

In EU models, the probabilities of different outcomes presented in a choice experiment are directly used to weight utility. EUT can be criticised for its failure to account for the way in which the probabilities offered in experiments are transformed by respondents in recognition of the perceptual processing of such probabilities, which entails elements of over and under-weighting, especially at the extremes of the occurrence distribution. Given this, nonlinear probability weighting was introduced into a number of non-EU models, either cumulatively (e.g. Rank-Dependent Utility Theory (RDUT) and Cumulative Prospect Theory (CPT)) or separably (e.g. Original Prospect Theory (OPT) as an instrument to explain the violation of the independence axiom[9] of EUT revealed by the Allais paradox [24], i.e. the induced probabilities in experiments can be over(under)weighted. A popular probability weighting function developed by Tversky and Kahneman [25] is given in Equation (6).

$$w(p_m) = \frac{p_m^{\gamma}}{[p_m^{\gamma} + (1-p_m)^{\gamma}]^{\frac{1}{\gamma}}} \tag{6}$$

$w(p_m)$ is the probability weight function; $p_m$is the probability associated with the mth outcome (e.g. travel time) for an alternative with multiple outcomes (over repeated occasions), and γ is the probability weighting parameter. If $\gamma = 1$, then $w(p) = p$, which implies EUT linear probability weighting. A common finding from Prospect Theoretical studies based on controlled laboratory experiments is that people tend to overweight outcomes with lower probabilities, and underweight outcomes with higher probabilities (see e.g. [25–27]). In the transportation literature, Schwanen and Ettema [28] and Michea and Polak [29] are two examples in which Prospect Theory was applied to investigate travel time variability (see [30] for a review on Prospect Theoretic contributions in traveller behaviour research).

In our empirical application, we incorporate the nonlinear probability weighting function in Equation (6) into the EU framework (see Equation (3)) separably, and refer to the EU model with

[9]That is, if two acts (alternatives) have the same consequence given a particular state, the preference between those two acts is independent of that state with the common consequence.

DOI: 10.1002/atr

nonlinear probability weighting as an Extended EU (EEU) model, given in Equation (7).[10]

$$EE(U) = \sum\nolimits_m [w(p_m) \times Um] \quad (7)$$

5. EMPIRICAL ASSESSMENT

The empirical focus is on estimating the nonlinear probability weighted travel time variability profiles, and deriving the willingness to pay for expected travel time savings. To illustrate the contribution of these ideas, we have used a data set that has sufficient elements to enable the empirical assessment of risk attitude and probability weighting for travel time variability[11]. The study was undertaken in Brisbane, Australia in the context of toll *vs* free roads, which utilised a stated choice (SC) experiment involving two SC alternatives (i.e. route A and route B) pivoted around the knowledge base of travellers (i.e. the current trip). The trip attributes associated with each route are summarised in Table II. To ensure that free flow, slowed down and stop/start/crawling/crawling time were understood, we provided explanations[12] and pictures through pull down screens which were equivalent in meaning to the standard Levels of Service A, C and E.

Each alternative has three travel scenarios—'a quicker travel time than average experienced trip time', 'a slower time than the average experienced trip time' and 'the average experienced trip time'. Respondents were advised that *departure time remains unchanged* and that each of the reported trip times is associated with a corresponding probability[13] of occurrence to indicate that travel time is not fixed but varies from time to time. We went to great lengths, with the interviewer present, to explain what this meant for each respondent. For example, the 30% associated with 9 minutes quicker for

Table II. Trip attributes in stated choice design.*

Routes A and B (for a given departure time) in context of commuting on repeated occasions
Average experienced time components for recent trip:
Free flow travel time
Slowed down travel time
Stop/start/crawling travel time
Total trip time associated with repeated occasions:
Time associated with a quicker trip
Time associated with a slower trip
Occurrence probabilities for each trip time:
Probability of trip being quicker
Probability of trip being slower
Probability of recent trip time
Average trip cost attributes:
Running cost
Toll cost

*The descriptive statistics for the time and probability variables are given in Appendix A.

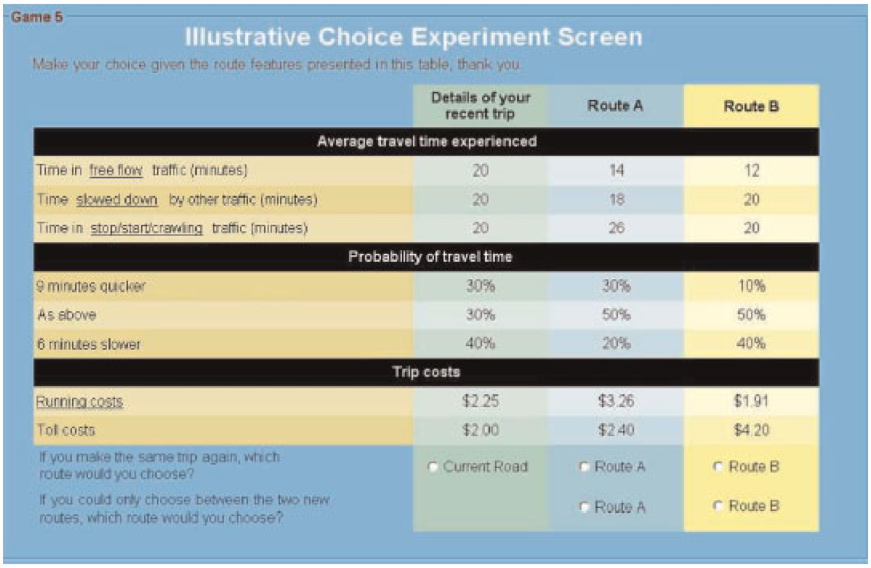
[10]We are not implementing any prospect theoretic model with referencing, but simply using a non-linear probability weighting function developed by Tversky and Kahneman [25], a well-known CPT paper, in an extended version of EUT. Some authors (e.g. [18] and [50]) have implemented the referencing feature of prospect theory but ignored the nonlinear probability weighting, and also assumed risk neutral attitudes.

[11]The data set, although not ideal (but one the better data sets collected to date), is being used herein to illustrate how one can build and estimate a nonlinear model that accommodates risk attitude and decisions weights. This is the real contribution and is a major step forward regardless of any limitations of the specific instrument used to illustrate the methods. The presence of mean times for three trip time components that were not separately presented as three levels with associated likelihood of realisation may have muddied the waters; however we do not believe this is a major concern despite our wish in future studies to also include the three realisations and associated probabilities of occurrence.

[12]Free flow as described as 'can change lanes without restriction and drive freely at the speed limit'. Slowed down time was described as 'changing lanes is noticeably restricted and your freedom to travel at the speed limit is periodically inhibited. Queues will form behind any lane blockage such as a broken down car'. Stop/start/crawling time is described as 'can only change lanes if others let you in. Consistently braking and accelerating in stop-start traffic.'

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

DOI: 10.1002/atr



Game 5

Illustrative Choice Experiment Screen

Make your choice given the route features presented in this table, thank you.

	Details of your recent trip	Route A	Route B
Average travel time experienced			
Time in free flow traffic (minutes)	20	14	12
Time slowed down by other traffic (minutes)	20	18	20
Time in stop/start/crawling traffic (minutes)	20	26	20
Probability of travel time			
9 minutes quicker	30%	30%	10%
As above	30%	50%	50%
6 minutes slower	40%	20%	40%
Trip costs			
Running costs	$2.25	$3.26	$1.91
Toll costs	$2.00	$2.40	$4.20
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

Figure 2. Illustrative stated choice screen.

Route A in Figure 2 was explained as 'for every 10 trips you might take, three out of the 10 trips the travel time will be 9 minutes less than the 58 minutes stated above as the average time experienced, or a trip time of 49 minutes'.

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 variations around the values for the most recent trip. Given the lack of exposure to tolls for many travellers, 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 III.

A survey was designed and implemented in 2008 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[14]. Sampling rules were imposed on three total time trip length segments: 10–30 minutes, 31–45

Table III. 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

[14]The survey has five major sections: The introduction to the survey task and background on the study; questions describing a current or recent trip in terms of travel times and cost (including tolls if paid); the SC experiment (16 screens); A series of attitudinal questions seeking views on the broader set of quality benefits of toll and freeway roads; and some socio-economic questions.

DOI: 10.1002/atr

Table IV. Quotas and final achievement numbers.

Total travel time	Quota			Achieved		
	Peak hours	Off peak hours	Total	Peak hours	Off peak hours	Total
10–30 minutes	60	40	100	61	50	111
31–45 minutes	60	40	100	71	32	103
46–120 minutes	60	40	100	51	15	66
Total	180	120	300	183	97	280

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[15] as trips beginning during the period 7–9 AM or 4.30–6.30 PM. All non-peak trips are treated as off peak in the internal quota counts.

There are three versions of the experimental design depending on the trip length, with each version having 32 choice situations (games) blocked into two subsets of 16 choice situations. In generating the designs, the free flow, slowed and stop/start times were set to 5 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. An example of a choice scenario is given in Figure 2[16]. The first alternative is described by attribute levels associated with a recent trip; with the levels of each attribute for Routes A and B pivoted around the corresponding level of actual trip alternative.

In total, 280 commuters were sampled for this study. The experimental design method of D-efficiency used herein is specifically structured to increase the statistical performance of the models with smaller samples than are required for other less-efficient (statistically) designs such as orthogonal designs (see Rose and Bliemer [31] and [32]).

Commuters in the Brisbane Metropolitan area in Australia were sampled. A telephone call was used to establish eligible participants from households. During the telephone call, a time and location were agreed for a face-to-face Computer Aided Personal Interview (CAPI). A $20 incentive was offered for a complete survey. The face-to-face interview involves the interviewer entering information into a laptop computer program as the respondent answers a set of questions on each screen. Although a respondent could enter the data, the process works better if the interviewer undertakes this task as the questions are put to the respondent. The data is automatically stored in an MS-Access database. Upon completion of interviews, the data files were emailed by the survey firm to the study team. The effective interviews represent 6.5 per cent of all contacts, but in terms of eligible respondents, this is 8.4 per cent.

Table IV shows the initial quotas for six segments, and the number of interviews achieved. All segments, with the exception of long distance off-peak hour commuters were close to, or exceeded the specified quota. The discrepancy arose in the field as we learnt more about the incidence of specific trip lengths for each time of day. The socio-economic profile of the data is given in appendix A, together with a descriptive overview of choice experiments attributes.

6. MODEL ESTIMATION AND VALUATION OF EXPECTED TRAVEL TIME SAVINGS

Instead of treating mean travel time and variability separately, we develop models that integrate these two components of a travel time distribution, based on the theoretical frameworks set out in previous sections[17]. We present (i) an *EU* model in which risk neutral attitude is assumed together

[15]The way we handle trips that are partly in the peak: a trip is peak if 60 per cent or more of the trip falls within the peak period.
[16]We captured the time taken to complete each of the 16 choice screens, as graphed below. This depicts a steady reduction in time, in part due to greater confidence in how to process the information. It is known that respondents often spend more time on the first screen as they familiarise themselves with the process. This is not cognitive burden but an indication of a commitment to review the information seriously. As one gets familiar with the format of the screens and what is required, one can focus on the attribute levels. What we see here, we believe, is that over 70 per cent of time is spent assessing the attributes (after allowing up to 8 seconds in choice screen one of familiarisation with the task overall).
[17]Although there are only three points defined on the travel time distribution for each respondent, each with an occurrence probability, the levels vary across the sample, and given the interest in sample-level estimates we have good coverage of the full distribution.

DOI: 10.1002/atr

with a linear additive weighting of probability occurrences for the travel time attribute, (ii) a variation of (i) with risk attitude associated with travel time and (iii) an Extended *EU* model with nonlinearity in the utility function through accommodating risk attitude as well as nonlinear probability weights.[18]

To be able to develop and estimate these models using the available data described above, we have converted the times into actual trip times to give three travel times (including the time associated with the most recent trip), each associated with a probability of occurring[19]. We will refer to these times as Most Recent (MR_T) (or 'as above' in Figure 2), shorter (S_T) (or *x* minutes quicker as in Figure 2) and longer (L_T) (or *y* minutes slower as in Figure 2), even though they are used herein as three varying travel times regardless of whether they are shorter or longer relative to the recent travel time level. Ideally we would want to have many more points for the trip time variability distribution; however despite the potential limitations of the available data, we are able to illustrate the advantages of a range of nonlinear utility expressions to derive the willingness to pay to save time, accounting for the variability in such time over repeated trips. When we combine the time associated with a trip on a surveyed occasion with a probability distribution of time occurrence, we suggest that we no longer have the conventional measure of VTTS but a measure that incorporates the variability in VTTS which we call the value of expected travel time savings or VETTS.

6.1. *Risk neutral utility function with linear probability weighting (Model 1)*

A linear utility function with a linear probability weighting function is given in Equation (8).[20,21]

$$U = \beta_T(P_{\mathrm{MR}}\mathrm{MR_T} + P_{\mathrm{S}}S_{\mathrm{T}} + P_{\mathrm{L}}L_{\mathrm{T}}) + \beta_{\mathrm{Cost}}\mathrm{Cost} + \beta_{\mathrm{Cost\times Income}}(\mathrm{Cost} \times \mathrm{Income}) + \beta_{\mathrm{Tollasc}}\mathrm{Tollasc} + \beta_{\mathrm{Age}}\mathrm{Age} \tag{8}$$

P_{MR} is the probability of most recent trip time, shown to respondents; MR_T is the most recent travel time; P_S is the probability of a shorter time shown to respondents; S_T is the actual travel time for the shorter trip time scenario; P_L is the probability of the longer travel time shown to respondents; L_T is the actual travel time for the longer trip; Cost is the trip cost including the running cost and the toll cost; Cost $\times$ Income is Cost interacted with Income, where Income is personal income per annum; the average income of the sampled car commuters is \$53 300 in 2008 (Au\$2008); age is a person's age in years. Tollasc is the dummy variable to indicate whether a specific alternative is a tolled road. β_T, β_{cost}, $\beta_{\mathrm{Cost\times Income}}$, β_{age} and β_{tollasc} are parameters to be estimated. The MNL model results are given in Table V.[22,23,24]

All parameters are significant at the 99 per cent confidence interval. The estimated parameter for the *Reference* (status quo) specific constant is positive, which suggests, after accounting for the observed influences, that sampled respondents prefer their most recent trip experience relative to two stated choice alternatives, with this tendency stronger as the age of a respondent increases (0.0063). The

---

[18]Ongoing research is investigating extensions to incorporate preference and scale heterogeneity.

[19]The adding up assumption is in line with the evidence from supplementary questions. We asked whether attributes with a common metric were added up. For travel time, 82.8 per cent of respondents added all three time, and for cost, 81.2 per cent added the two cost components.

[20]In addition to the interaction of Cost with Income (i.e. (Cost × Income)), we investigated other interactions such as Cost with Age and Cost with Gender, but they were not statistically significant.

[21]Age as a stand alone variable is associated with the reference (status quo). This applies to all models in this paper.

[22]We investigated a number of socio-economic effects (e.g. income, gender) but did not find any statistically significant except age).

[23]We also estimated a model where the sum of three components of time explicitly shown to the respondents (i.e. free flow, slow down and stop/start/crawling) is used as the mean time, with a linear utility specification. This model (with the same number of parameters) delivers a marginally worse model fit and a similar mean WTP, compared with model 1 under risk neutrality given in Table V (Log-likelihood: −3434.75 *vs* −3427.58, *VETTS*: Au\$16.87 *vs* Au\$16.66 per person hour.

[24]To account for the panel nature of the data, we implemented a 'random parameter' specification that treated the *cost* parameter as a random parameter but with a constant that set the standard distribution of the beta distribution to zero. Another way to address this issue is as an error component model. We ran a series of error component models; however, the model performance of the reported model with a random parameter specification is far better, and hence this approach has been used for Models 1–3 as reported in Tables 5–7.

DOI: 10.1002/atr

Table V. Model 1: risk neutral utility function with linear probability weighting.

Variable	Parameter		*t*-ratio
Reference constant	0.4565		6.62
Expected time (minutes)	−0.0723		−32.66
Cost* ($)	−0.3258		−15.18
Cost interacted with income	0.0011		6.60
Tollasc	−0.2926		−2.98
Age (years)	0.0063		7.12
No. of observations		4480	
Information criterion AIC		6859.74	
Log-likelihood		−3423.87	

*Akaike information criterion: AIC = −2 × log-likelihood + 2 × K where K is the number of parameters. The smaller AIC indicates a better model fit.

parameter estimate for Cost × Income is 0.0011, which is positive and suggests that car commuters on higher incomes tend to be less price (or cost) sensitive compared to those on lower incomes. Tollasc is negative, which indicates that, on average after accounting for the time and cost of travel, other factors bundled into the idea of a ‘toll road quality bonus’ are less desirable for a tolled route than a non-tolled route, mainly due to the lack of exposure to tolls for our sampled respondents.

The willingness to pay for total expected time savings is related to three trip times, each exogenously probability weighted, which includes the most recent travel time and times that vary around the most recent experienced level. The VETTS equation for Model 1 is given in Equation (9), in which in addition to the estimated parameters, the VETTS is also influenced by the level of personal income. By applying the actual incomes of our sampled respondents, the derived VETTS value ranges from Au$13.31 to Au$22.81 per person hour, with a mean of Au$16.65 per person hour and a standard deviation of Au$2.47 per person hour, Multiplying by 60 converts the VETTS from $/min to $/hour.

$$\text{VETTS} = 60 * \frac{\beta_T}{\beta_{\text{Cost}} + B_{\text{Income}\times\text{Cost}}\text{Income}} \tag{9}$$

6.2. *Accommodating attribute risk and linear probability weighting (Model 2)*

Model 2 jointly estimates all the parameters in the utility function containing the attribute parameters and the risk attitude parameter. For this specification, we adopt the constant *relative* risk aversion (CRRA) model form. CRRA postulates a power specification (e.g. $U = x^{\alpha}$), which has been widely used in behavioural/experimental economics and psychology (see e.g. [25,33,34]) and often delivers ‘a better fit than alternative families’ ([35], p. 1329). We estimate the CRRA model form as a general power specification (i.e. $U = x^{1-\alpha}/(1-\alpha)$), more widely used than the simple x^{α} form ([33,36]), following the EUT specification shown in Equation (3) (i.e. the sum of probability weighted utilities of all possible outcomes). Our EUT model (Model 2) is given in Equation (10).

$$\begin{aligned} E(U) = {} & \beta_T\left[\left(P_{\text{MR}}\text{MR}_T^{1-\alpha} + P_S S_T^{1-\alpha} + P_L L_T^{1-\alpha}\right)/(1-\alpha)\right] + \beta_{\text{Cost}}\text{Cost} \\ & + \beta_{\text{Cost}\times\text{Income}}(\text{Cost} \times \text{Income}) + \beta_{\text{Tollasc}}\text{Tollasc} + \beta_{\text{Age}}\text{Age} \end{aligned} \tag{10}$$

Compared with Equation (8), one extra parameter (i.e. α) needs to be estimated and the value of $(1-\alpha)$ indicates the attitude towards risk, which is associated with the risky attribute only (i.e. travel time). If $(1-\alpha) = 1$, Equation (10) collapses to a linear utility function (i.e. Equation (8)). The model results are summarised in Table VI.

All estimated parameters are significant at the 99 per cent confidence interval. This model delivers similar behavioural responses to the previous linear model. Model 2 empirically addresses the attitude towards risk of the sampled car commuters. The risk attitude parameter is 0.7811 (= 1−0.2189). For decision making where risk is associated with travel time, a risk attitude parameter less than one

DOI: 10.1002/atr

Table VI. Model 2: EUT with risk attitude and linear probability weighting.

Variable	Coefficient	t-ratio
Reference constant	0.4412	6.35
Alpha (α)	0.2189	3.61
Expected time (minutes)	−0.1653	−4.57
Cost ($)	−0.3239	−15.07
Cost interacted with income	0.0011	6.63
Tollasc	−0.2906	−2.96
Age (years)	0.0066	7.38
No. of observations	4480	
Information criterion: AIC	6858.37	
Log-likelihood	−3422.18	

suggests risk-seeking attitudes; and a risk attitude parameter greater than one suggests risk-averse attitudes [10] [25]. Model 2 estimates a positive α and hence the calculated risk attitude parameter is less than unity (i.e. $(1-\alpha)=0.7811$) which suggests risk-seeking attitudes. As an example, commuters prefer an expected trip time (*E(T)*) which has a 50 per cent chance of being 10 minutes and a 50 per cent chance of being 30 minutes, in contrast to a 100 per cent (sure) chance of the expected trip time being 20 minutes. This risk-seeking finding is in line with Senna's assumption for his sampled commuters with a fixed arrival time.

The value of expected travel time savings under risk is given in Equation (11):

$$\text{VETTS} = 60 * \frac{\beta_T\left(P_{\text{MR}}\text{MR}_T^{-\alpha} + P_S S_T^{-\alpha} + P_L L_T^{-\alpha}\right)}{\beta_{\text{Cost}} + B_{\text{Income}\times\text{Cost}}\text{Income}} \tag{11}$$

VETTS under risk is dependent on the probabilities associated with the travel times and the travel times over the trip time distribution. The mean estimate of VETTS (weighted by raw probabilities of three travel times) is Au$17.39 per person hour and the standard deviation is Au$2.84 per person hour, based on the sample data. The distribution of VETTS is dependent on knowing the distribution of occurrence times, which may be limiting in applications, despite the added realism, as well as personal income of each sampled respondent. Analysts can always impose specific distributional assumptions given evidence from real travel time activity. The arguments are no different to those made by practitioners when asked to use full distributions of VTTS based on a random parameter specification, in which the response by the majority of practitioners is to use mean estimates for each one-third of the distribution, instead of taking repeated draws over the full distribution.

6.3. Extended EU model with non-linear probability weighting (Model 3)

Applying the nonlinear probability weighting function (Equation (6)) suggested by Tversky and Kahneman [25] in a separable manner, our extended EU (EEU) model is given in Equation (12).

$$\begin{aligned} EE(U) = \beta_{\text{T}}\left\{\left[W(P_{\text{MR}})\text{MR}_T^{1-\alpha} + W(P_S)S_T^{1-\alpha} + W(P_L)L_T^{1-\alpha}\right]/(1-\alpha)\right\} + \beta_{\text{Cost}}\text{Cost} \\ + \beta_{\text{Cost}\times\text{Income}}(\text{Cost}\times\text{Income}) + \beta_{\text{Tollasc}}\text{Tollasc} + \beta_{\text{Age}}\text{Age} \end{aligned} \tag{12}$$

$W(P)$ is a nonlinear probability weighting function which converts raw probabilities (P) as shown in a choice experiment (Figure 2), and γ is an estimated parameter. The value of γ determines the shape of the weighting function. If $\gamma = 1$, Equation (12) will be the same as Equation (10). The results are summarised in Table VII.

[25]Senna [10] assumed that commuters with fixed arrival time are risk-prone (-seeking), where the assumed risk attitude parameter is 0.5(<1), and explained this in the following way: 'commuters are frequently travelling in the same route and this situation provides them information about the distribution of travel time' (p. 220), and 70 per cent of his sampled commuters have no penalties for late arrival.

DOI: 10.1002/atr

Table VII. Model 3: Non-linear probability weighting function with risk attitude (EEU).

Variable	Coefficient	t-ratio
Reference constant	0.4465	6.43
Alpha (α)	0.3624	6.30
Gamma (γ)	0.7648	3.25
Expected time (minutes)	−0.2740	−4.89
Cost ($)	−0.3223	−14.68
Cost interacted with income	0.0011	6.11
Tollasc	−0.2757	−2.80
Age (years)	0.0068	7.59
No. of observations	4480	
Information criterion: AIC	6846.32	
Log-likelihood	−3415.16	

All estimated parameters are significant at the 99 per cent confidence interval. This model incorporates an estimate of the degree of curvature of the probability weighting function, γ which is 0.7648 and statistically significant from 1, with a *t*-ratio of 3.25. It has a significant impact on the shape of the weighting function (see Figure 3) in which outcomes with lower probabilities tend to be overweighted (e.g. $W(P=0.2)=0.247$), while outcomes with high probabilities tend to be underweighted (e.g. $W(P=0.8)=0.714$).

Similar to the previous EU model, the VETTS of the EEU model can be calculated in the same manner as Equation (11), with the difference being that transformed probabilities are used rather than the stated probabilities in the choice experiment (see Equation (13)). The VETTS (weighted by the transformed probabilities of nonlinear probability weighting) has a mean of Au$18.04 per person hour and a standard deviation of Au$3.63 per person hour, based on the sample data.

$$\text{VETTS} = 60 * \frac{\beta_T\left[W(P_{\text{MR}})\text{MR}_T^{-\alpha} + W(P_S)S_T^{-\alpha} + W(P_L)L_T^{-\alpha}\right]}{\beta_{\text{Cost}} + B_{\text{Income}\times\text{Cost}}\text{Income}} \tag{13}$$

6.4. Comparison of outcomes from Models 1–3

We summarise the key results of the three models in Table VIII: willingness to pay for expected travel time savings, the parameter estimates of all variables except travel time, and model fit. The mean VETTS values (Au$2008 per person hour) estimated from the three models are, respectively, $16.65, $17.39 and $18.04. The differences in mean estimates may appear to be small, but when converted to time benefits for projects, the differences can amount to sizeable sums. Compared with RUM, EU and EEU incorporate attribute risk, which we argue are pivotal to a behaviourally relevant representation of travel time variability.

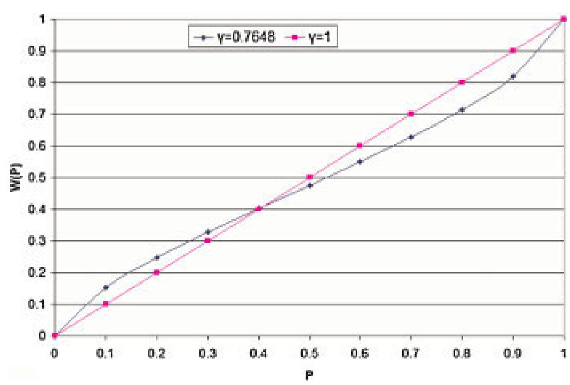


Figure 3. Nonlinear probability weighting function.

DOI: 10.1002/atr

Table VIII. Comparison of three models.*

	EU without attribute risk	EU with attribute risk	EEU
	Model 1	Model 2	Model 3
Willingness to Pay (Au$ per person hour)			
VETTS (Mean)	16.65	17.39	18.04
VETTS (Std. Dev.)	2.47	2.84	3.63
Parameters			
Reference constant	0.4565	0.4412	0.4465
Cost ($)	−0.3258	−0.3239	−0.3223
Cost interacted with income	0.0011	0.0011	0.0011
Tollasc	−0.2926	−0.2906	−0.2757
Age (years)	0.0063	0.0066	0.0068
Alpha (α)	—	0.2189	0.3624
Gamma (γ)	—	—	0.7648
Model fit			
AIC	6859.74	6858.37	6846.32
Log-likelihood	−3423.87	−3423.18	−3415.16

Note: All parameter estimates are significant at the 99 per cent confidence interval.
*Estimates of VTTS based on Equations (1) and (2) are presented in Li *et al.* [6]. The mean estimates are higher, close to $22 per person hour, although these relate to the average travel time.

We also compared the parameter estimates other than expected time[26] and found no significant differences in Reference, Cost, Cost × Income, Tollasc and Age, which suggest that including attribute risk and nonlinear probability weighting has a marginal impact on those parameters. The EU and EEU models have produced a similar mean estimate of risk attitude parameters. The three models have similar model fits, although the behaviourally more appealing models (EU and EEU) have very marginally better performance on the overall log-likelihood, with a one/two degree(s) of freedom difference between the EU/EEU models and the linear utility (risk neutral) model. What this suggests, in the context of a single data set, is that the more parsimonious linear utility model is a very good linear approximation.

Willingness to pay measures were also computed (see Table IX) using the Krinsky and Robb (KR) procedure [37] which utilises, in addition, the information in the variance–covariance matrix relevant to the specific attributes used in the WTP calculations. The method for computing WTP is given in Haab and McConnell [38]. Whilst other methods are available for constructing WTP measures, the KR procedure has the advantage of being more accurate, with the resulting asymmetric distributions, with

Table IX. Comparison Models 1–3 after allowing for the variance–covariance effects.

EU without attribute risk	Total
Average	$17.01
Median	$17.01
Std dev.	$0.96
Lower 95%	$15.16
Upper 95%	$18.90
EU with attribute risk	Total
Average	$15.75
Median	$15.53
Std. dev.	$2.31
Lower 95%	$12.19
Upper 95%	$21.41
EEU	Total
Average	$15.70
Median	$15.13
Std. dev.	$2.32
Lower 95%	$11.69
Upper 95%	$20.85

[26]Nonlinearity (function form or probability weighting) is only assigned to time related variables.

DOI: 10.1002/atr

asymmetric confidence intervals, appropriately dealt with, in contrast to other methods that produce confidence intervals based on symmetric asymptotic normal distributions (see [39] or [40]).

The finding in Table IX for Model 1 (i.e. a mean of \$17.01) is relatively similar in Table VIII (i.e. \$16.65), suggesting that the elements of the variance–covariance matrix have a small influence; however this is not the case for the EU and EEU models 2 and 3, respectively. The mean estimates decline noticeably (i.e. from \$17.39 and \$18.04 to \$15.75 and \$15.70, respectively, for EU and EEU), although the standard deviations are very similar. In particular the adjusted mean estimates are lower than for the simple models after accounting for the variance–covariance elements.

Despite these changes, which are of interest in themselves, for this one data set we do not find statistically significant differences between the WTP estimates for EU and EEU, and also between each of these behaviourally appealing models and the linear utility model with risk neutral attitudes. While this is encouraging support for a linear approximation, the jury must still be out as additional data sets are used. In particular the very similar attribute risk parameter is a key reason why the EU and EEU models produce similar results. In ongoing research, we are investigating other functional forms, including random parameters and accounting for scale heterogeneity, which may alter the relativity of the evidence. Nevertheless we have been able to introduce a fuller nonlinear specification in the utility function and probability weighting function in the literature on valuing expected travel time savings, as well as presenting an appealing representation of VETTS.

6.5. *Mixed multinomial Logit model with nonlinear utility functions*

We extend the MNL model to allow for preference heterogeneity in risk attitudes, taste and probability weighting parameters simultaneously, and to take into account the presence of 16 correlated observations per respondent, using a mixed MMNL model (see e.g. [41–44]) where unconstrained triangular distributions are used to represent *Alpha* and *Gamma* and a constrained triangular distribution is applied to the *Expected Time* parameter to ensure all individual time parameters are negative[27] within an Extended Expected Utility framework. As far as we are aware, only heterogeneity in risk attitudes has been tested in previous studies (see e.g. Anderson *et al.*, [36]). The modelling results of an EEU MMNL model, the preferred model, are given in Table X.[28]

This MMNL model has the same utility function and probability weighting function as Model 3 in Table VII, except that three random parameters are applied to *Alpha*, *Gamma* and *Expected Time.* Compared with Model 3 under MNL, the MMNL model delivers significant improvement in model fit (AIC: 5582.44 *vs* 6846.32, Log-likelihood: -2782.22 *vs* -3415.16). Four nonrandom parameters (Reference constant, Tollasc, Cost and Age) have the same sign but different values relative to the MNL estimates.

The distributions of the three random parameters (*Alpha*, *Gamma* and *Expected Time*) suggest that the calculated risk attitude parameter ($1-\alpha$) ranges from 0.8539 to 1.2521, suggesting that part of the sampled respondents have risk-seeking attitudes ($1-\alpha<1$) while others tend to be risk averse ($1-\alpha>1$). This is a very interesting finding relative to a generic risk-seeking attitude from the MNL models (e.g. MNL Model 3: $1-\alpha=0.7532<1$). Senna [10] assumed that his sampled commuters with flexible arrival times are risk averse when making risky time-related decisions, where the assumed risk attitude parameter is 1.4 (>1). The mix of risk-seeking and risk-averse attitudes revealed by the MMNL model may be attributed to commuters with a fixed arrival time and commuters with flexible arrival times, both sampled in our study.

---

[27]Let c be the centre and s the spread. The density starts at $c-s$, rises linearly to c, and then drops linearly to $c+s$. It is zero below c-s and above $c+s$. The mean and mode are c. The standard deviation is the spread divided by $\sqrt{6}$; hence the spread is the standard deviation times $\sqrt{6}$. The height of the tent at c is 1/s (such that each side of the tent has area $s\times(1/s)\times(1/2)=1/2$, and both sides have area $1/2+1/2=1$, as required for a density). The slope is $1/s^2$. For a constrained distribution, the mean parameter is constrained to equal its spread (i.e. $\beta_{jk}=\beta_k+|\beta_k|\,T_j$, and T_j is a triangular distribution ranging between -1 and $+1$), and the density of the distribution rises linearly to the mean from zero before declining to zero again at twice the mean. Therefore, the distribution must lie between zero and some estimated value (i.e. the β_{jk}). The mean and standard deviation is the same under a constrained triangular distribution.

[28]The MMNL model without the interaction of Income and Cost delivers a much better model fit than the MMNL model with this interaction (Log-likelihood: -2782.22 *vs* -3049.38; AIC: 5582.44 *vs* 6118.75). The model with cost interacted with income had a statistically insignificant parameter estimate for stand-alone age. The model without this interaction is reported in the paper. We might speculate that the heterogeneity associated with alpha (i.e. risky attitude) may be correlated with income and other socio-economic characteristics, and hence is the reason for the improved model fit.

DOI: 10.1002/atr

Table X. Mixed multinominal logit (MMNL) model within an EEU framework (Model 4) (Estimated using Nlogit5).

Variable	Coefficient	t-ratio
Non-random parameters:		
Reference constant	0.4793	3.29
Cost ($)	−0.3328	−10.86
Tollasc	−0.3067	−2.11
Age (years)	0.0278	9.13
Means for random parameters:		
Alpha (α)	−0.0538	−0.85
Gamma (γ)	0.2108	22.61
Expected Time (minutes)	−0.3435	−6.50
Standard deviations for random parameters:		
Alpha (α)	0.2009	4.57
Gamma (γ)	0.0376	2.24
Expected time (minutes)	0.3435	6.50
No. of observations	4480	
Information criterion: AIC	5582.44	
Log-likelihood	−2782.22	
VETTS	14.61 (0.75)*	

Notes: Simulation based on 50 Halton draws.
*The standard deviation of VETTS is given in parenthesis.

The mean VETTS under mixed logit is Au$14.61 per person hour compared to Au$18.04 under MNL, which is a significant difference, allowing for the small standard deviation of Au$0.75 per person hour for the mixed logit model and Au$3.63 per person hour for the MNL model.

7. CONCLUSIONS

Substantial effort has been invested in studies focussed on deriving estimates of the VTTS. To date, the popular approach has been embedded in a theory of MEU, wherein an individual is assumed to choose the option with the highest expected utility (see e.g. [5,7,12,13]). The approach adopts the probability weighting function of EUT, but within an attribute risk neutral setting specification. In this paper, within the current MEU approach we incorporate attribute risk with a linear probability weighting function; and then introduce attribute risk together with a nonlinear probability weighting function.

The empirical models take the observed distribution of travel time variability, which is commonly observed in reality over repeated travel experiences, especially in trip situations such as the weekly habitual commute between a fixed origin and destination, and use it to derive a single estimate of the value of expected travel time savings. This recognises that the valuation of time savings that applies to an individual travel activity and response is inherently linked to the degree of variability of the travel time, which is ever present every time a commuter commences a car trip.

For the single data set used herein, the mean VETTS estimates from our EU and EEU models are not statistically significantly different from the value obtained from the model with attribute risk neutrality and linear probability weighting. Our empirical evidence suggests, however, that EU and EEU models address individual choice under risk; however in this study, the EU and EEU models estimate similar attitudes towards risk. By incorporating nonlinear probability weighting, our EEU model reveals that the probabilities shown to respondents in the choice experiment have been transformed resulting in overweighting of outcomes with low probabilities and underweighting of outcomes with high probabilities.

8. LIST OF SYMBOLS AND ABBREVIATIONS

8.1. Symbols

α (Alpha) Risk attitude parameter
β (Beta) Taste parameter (e.g., expected travel time, cost)
γ (Gamma) Probability weighting parameter

DOI: 10.1002/atr

8.2. Abbreviations

AIC	Akaike's information criterion
CARA	Constant absolute risk aversion
CAPI	Computer Aided Personal Interview
CRRA	Constant relative risk aversion
EEU	Extended Expected Utility
EUT	Expected Utility Theory
MEU	Maximum Expected Utility
MMNL	Mixed multinomial logit
MNL	Multinomial logit
RUM	Random Utility Maximisation
SC	Stated choice
SDE	Schedule delay early
SDL	Schedule delay late
VETTS	Value of expected travel time savings
VOR	Value of reliability
VTTS	Value of travel time savings
WTP	Willingness to pay

ACKNOWLEDGEMENTS

We thank three referees for their comments which have improved this paper significantly.

REFERENCES

1. Hensher DA. Measurement of the valuation of travel time savings. *Journal of Transport Economics and Policy* 2001a; **35**(1):71–98.
2. de Jong G, Kouwenhoven M, Kroes E, Rietveld P, Warffemius P. Preliminary monetary values for the reliability of travel times in freight transport. *European Journal of Transport and Infrastructure Research* 2009; **9**(2):83–99.
3. Jackson WB, Jucker JV. An empirical study of travel time variability and travel choice behavior. *Transportation Science* 1982; **16**(6):460–475.
4. Small KA. The scheduling of consumer activities: work trips. *American Economic Review* 1982; **72**:467–479.
5. Bates J, Polak J, Jones P, Cook A. The valuation of reliability for personal travel. *Transport Research Part E* 2001; **37**:191–229.
6. Li Z, Hensher DA, Rose JM. Willingness to pay for travel time reliability for passenger transport: a review and some new empirical evidence. *Transportation Research Part E* 2010; **46**(3):384–403.
7. Asensio J, Matas A. Commuters' valuation of travel time variability. *Transportation Research Part E* 2008; **44**:1074–1085.
8. Batley R, Ibáñez N. Randomness in preferences, outcomes and tastes, an application to journey time risk, *International Choice Modelling Conference*, Yorkshire, UK. 2009.
9. Amador FJ, González RM, Ortúzar JD. Preference heterogeneity and willingness to pay for travel time savings. *Transportation* 2005; **32**:627–647.
10. Senna Lads. The influence of travel time variability on the value of time. *Transportation* 1994; **21**:203–228.
11. Noland RB, Small KA. Travel-time uncertainty, departure time choice, and the cost of morning commutes. *Transportation Research Record* 1995; **1493**:150–158.
12. Small KA, Noland RB, Chu X, Lewis D. *Valuation of travel-time savings and predictability in congested conditions for highway user-cost estimation, NCHRP Report 431*, Transportation Research Board, National Research Council. 1999.
13. Hollander Y. Direct *versus* indirect models for the effects of unreliability. *Transportation Research Part A* 2006; **40**(9):699–711.
14. Calfee J, Winston C. The value of automobile travel time: implications for congestion policy. *Journal of Public Economics* 1998; **69**:83–102.
15. Hensher DA. The valuation of commuter travel time savings for car drivers: evaluating alternative model specification. *Transportation* 2001b; **28**:101–118.
16. Hensher DA. How do respondents process stated choice experiments? – Attribute consideration under varying information load. *Journal of Applied Econometrics* 2006; **21**:861–878.
17. Jara-Diaz, SR, Guevara, CA. Behind the subjective value of travel time savings: the perception of work, leisure, and travel from a joint mode choice activity model. *Journal of Transport Economics and Policy* 2003; **37**(1):29–47.

DOI: 10.1002/atr

18. Hess S, Rose JM, Hensher DA. Asymmetrical preference formation in willingness to pay estimates in discrete choice models. *Transportation Research E* 2008; **44**(5):847–863.
19. Pells S. The evaluation of reductions in the variability of travel times to work, *PTRC Summer Annual Meeting*, Proceedings of Transportation Planning Methods Seminar, 1987; 313–325.
20. Black IG, Towriss JG. *Demand Effects of Travel Time Reliability.* Centre for Logistics and Transportation, Cranfield Institute of Technology: UK, 1993.
21. Fosgerau M, Karlström A. The value of reliability. *Transportation Research Part B* 2010; **44**(1):38–49.
22. Polak J. A more general model of individual departure time choice transportation planning methods, *Proceedings of Seminar C held at the PTRC Summer Annual Meeting*, P290, 1987; 247–258.
23. Polak J, Hess S, Liu X. Characterising heterogeneity in attitudes to risk in expected utility models of mode and departure time choice, *The Transportation Research Board (TRB) 87th Annual Meeting*, Washington, D.C., United States. 2008.
24. Allais M. Le comportement de l'homme rationnel devant le risque. *Econometrica* 1953; **21**:503–546.
25. Tversky A, Kahneman D. Advances in prospect theory: cumulative representations of uncertainty. *Journal of Risk and Uncertainty* 1992; **5**:297–323.
26. Camerer C, Ho T. Violations of the betweenness axiom and nonlinearity in probability. *Journal of Risk and Uncertainty* 1994; **8**:167–196.
27. Tversky A, Fox CR. Weighing risk and uncertainty. *Psychological Reviews* 1995; **102**:269–283.
28. Schwanen T, Ettema D. Coping with unreliable transportation when collecting children: examining parents' behavior with cumulative prospect theory. *Transportation Research Part A* 2009; **43**(5):511–525.
29. Michea A, Polak J. Modelling risky choice behaviour: evaluating alternatives to expected utility theory, Paper presented at *the 11th International Conference on Travel Behaviour Research*, Kyoto. 2006.
30. Li Z, Hensher DA. 2010 (Forthcoming). Prospect theoretic contributions in understanding traveller behaviour: a review and some comments. *Transport Reviews. First published on: 18 November 2010 (iFirst, http://dx.doi.org/10.1080/01441647.2010.498589).*
31. Rose JM, Bleimer MCJ. Stated preference experimental design strategies. In *Handbook of Transport Modelling*, Chapter 8, DA Hensher, KJ Button (eds). Elsevier: Oxford, 2008; 151–180.
32. Rose JM, Bliemer MC, Hensher Collins AT. Designing efficient stated choice experiments in the presence of reference alternatives. *Transportation Research Part B* 2008; **42**(4):395–406.
33. Holt CA, Laury SK. Risk aversion and incentive effects. *American Economic Review* 2002; **92**(5):1644–1655.
34. Harrison GW, Rutström EE. Expected utility theory and prospect theory: one wedding and a decent funeral. *Journal of Experimental Economics* 2009; **12**(2):133–158.
35. Wakker PP. Explaining the characteristics of the power (CRRA) utility family. *Health Economics* 2008; **17**:1329–1344.
36. Andersen S, Harrison GW, Hole AR, Rutström EE. Nonlinear mixed logit and the characterization of individual heterogeneity, *Working Paper 09-02*, Department of Economics, College of Business Administration, University of Central Florida. 2009.
37. Krinsky I, Robb AL. On approximating the statistical properties of elasticities. *Review of Economics and Statistics* 1986; **68**, 715–719.
38. Haab TC, McConnell KE. *Valuing Environmental and Natural Resources: The Econometrics of Non-Market Valuation*. Edward Elgar: Cheltenham, UK, 2002.
39. Armstrong P, Garrido R, Ortuzar JdeD. Confidence intervals to bound the value of time. *Transportation Research Part E* 2001; **37**(2–3):143–161.
40. Hole AR. A comparison of approaches to estimating confidence intervals for willingness to pay measures. *Health Economics* 2007; **16**(8):827–840.
41. Train K. Mixed logit models for recreation demand. In *Valuing the Environment Using Recreation Demand Models*, C Kling, J Herriges (eds). Elgar Press: New York. 1997.
42. Brownstone D, Train K. Forecasting new product penetration with flexible substitution patterns. *Journal of Econometrics* 1999; **89**:109–129.
43. McFadden D, Train K. Mixed MNL models for discrete response. *Journal of Applied Econometrics* 2000; **15**:447–470.
44. Hensher DA, Greene WH. The mixed logit model: the state of practice. *Transportation* 2003; **30**(2):133–176.
45. Small KA, Winston C, Yan J. Uncovering the distribution of motorists' preferences for travel time and reliability: implications for road pricing. *Econometrica* 2005; **73**(4):1367–1382.
46. Lam TC, Small KA. The value of time and reliability: measurement from a value pricing experiment. *Transportation Research Part E* 2001; **37**(2–3):231–251.
47. Brownstone D, Ghosh A, Golob T, Kazimi C, van Amelsfort D. Drivers' willingness-to-pay to reduce travel time: evidence from the San Diego I-15 congestion pricing project. *Transportation Research Part A* 2003; **37**:373–387.
48. Steimetz SSC, Brownstone D. Estimating commuters' 'value of time' with noisy data: a multiple imputation approach. *Transportation Research Part B* 2005; **39**:865–889.
49. Noland RB, Small KA, Koskenojia P, Chu X. Simulating travel reliability. *Regional Science and Urban Economics* 1998; **28**:535–564.
50. Jou RC, Kitamura R, WEng M, Chen C. Dynamic commuter departure time choice under uncertainty. *Transportation Research Part A* 2009; **42**(5):774–784.

DOI: 10.1002/atr

APPENDIX A: DESCRIPTIVE STATISTICS

Tables A1 and A2 summarise the mean and standard deviations by trip purpose for the personal income, gender and age variables captured within the data.[29]

Table A3 summaries the average and standard deviations of the costs as exposed to the sampled population during the course of the SC experiment.

Descriptive statistics for the travel time components of the experiment are shown in Table A4. Over all trip segments, the average free flow time was 13.42 minutes compared with 11.77 minutes for slowed down time and 14.1 minutes in stop/start/crawl time. The average times spent in the different traffic conditions varied markedly across each of the segments. Surprisingly, travelling in off-peak conditions reported higher average times in stop/start/crawl conditions than those travelling in peak time periods.

Table A5 shows the ratio of each time component to total time travelled. From the data, the commuter trip reported spending the greatest proportion of time in stop/start traffic conditions and the

Table A1. Travel times and probabilities of occurrences.

Variable	Mean	Std. Dev.	Minimum	Maximum	Cases
P_S	0.25	0.11	0.1	0.4	13440
P_L	0.25	0.11	0.1	0.4	13440
P_{MR}	0.50	0.15	0.2	0.8	13440
X(quicker)	4.80	3.14	0	18	13440
Y(slower)	9.60	6.28	1	36	13440
MR_T	39.29	16.58	10	119	13440
S_T	34.48	14.98	7	115	13440
L_T	48.89	21.09	11	150	13440
PT_S	8.61	5.61	0.8	40.8	13440
PT_L	12.12	7.68	1.1	56.4	13440
$\mathrm{PT}_{\mathrm{MR}}$	19.69	10.57	2	95.2	13440

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 ($=\mathrm{MR}_T$–X(quicker)); L_T is the actual slower (or longer) travel time ($=\mathrm{MR}_T+Y$(slower)); PTE ($=P_{\mathrm{S}}{}^* E_{\mathrm{T}}$), PT_L ($=P_L{}^* L_T$) and $\mathrm{PT}_{\mathrm{MR}}$ ($=P_{\mathrm{MR}}{}^* \mathrm{MR}_T$) are probability weighted values for quicker, slower and most recent time, respectively.

Table A2. 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 A3. Descriptive statistics for costs 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

[29]The socio-economic profile is based on the 2008 survey data. There is no current data in the study area to check the representativeness of this profile, given that the census is five years old and the travel survey data is even older and did not include personal income.

DOI: 10.1002/atr

Table A4. Descriptive statistics for free-flow, slowed down, stop start time by segment (minutes).

	Free flow		Slowed down		Stop start		Total time	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Commuter	13.419	10.990	11.766	9.340	14.102	13.844	39.286	16.575
Peak	18.063	13.360	9.687	8.855	9.175	11.088	36.925	16.251
Off-peak	10.957	8.527	12.868	9.404	16.713	14.437	40.537	16.610

Table A5. Ratio of free-flow, slowed down, stop start to total travel time by segment.

	Free flow		Slowed down		Stop start	
	Proportion	Std. Dev.	Proportion	Std. Dev.	Proportion	Std. Dev.
Car commuter	0.366	0.257	0.303	0.196	0.331	0.244
Peak	0.292	0.208	0.326	0.192	0.382	0.238
Non-peak	0.508	0.280	0.258	0.196	0.234	0.226

least in free flow traffic conditions. Smaller proportions of the total travel time are spent in free flow conditions for those travelling in the peak period compared to those travelling during the off-peak periods. For those travelling in non-peak period times, nearly 50 per cent of their total trip is spent in free flow conditions, with around 25–35 per cent spent in slowed down time.

DOI: 10.1002/atr