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**The Role of Source Preference and
Subjective Probability in Valuing
Expected Travel Time Savings**

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ABSTRACT: This paper proposes a fully subjective approach to capture the impact of travel time variability on travel decision making that accommodates subjective probabilities and source preference, the latter construct referring to respondent preferences to make judgments on matters that they have reasonable if only vague beliefs about than on matched chance events. The methods of eliciting subjective probabilities and source preference are discussed together with a suggested way forward to introduce, and hence capture parametrically, attitudes towards uncertainty. Using a 2014 survey of commuters in Sydney, we provide examples of modelling source preference and the implications for valuing expected travel time savings. The paper highlights the limitations of stated choice experiments when subjective attribute levels and their occurrence are relevant, suggesting a return to a revised focus on revealed preference data.

KEY WORDS: *travel time variability, risk, uncertainty, subjective probability, uncertainty aversion, source preference, value of expected travel time savings*

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1. Introduction

Travel time variability, a feature of transport systems, is gaining interest as congestion and system unreliability (both on the road and in public transport) become daily occurrences and a major concern for service providers and politicians. Gaver (1968) is one of the earliest studies that investigated individuals' behavioural responses to travel time variability, including it within a framework based on utility maximisation, and found that a traveller would plan an earlier departure time when facing travel time variability, compared with the circumstance with certain travel times. This typical behaviour is explained by the notion of a "safety margin" proposed by Knight (1974). Since the early 1990s, the focus of research has been on empirically estimating the value of willingness to pay (WTP) for improved travel time reliability (see e.g., Small *et al.*, 1999; Bates *et al.* 2001; Bhat and Sardesai 2006, Hensher *et al.*, 2011) assuming degrees of risk aversion; however the majority of the studies have assumed risk neutrality.

In recognising that travel times vary for a repeated trip activity (such as the commuting trip), Expected Utility Theory (EUT) has been drawn on as the representation of travel time variability, known as Maximum Expected Utility (MEU) (Noland and Small 1995), which 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 reliability studies (see e.g., Small *et al.* 1999; Bates *et al.* 2001; Hollander 2006; Asensio and Matas 2008). The research focus is to estimate the value of reliability (VOR) or variability, along with the value of travel time savings (VTTS); while some recent studies (see e.g., Hensher *et al.* 2011, 2013) have focused on the valuation of *expected* travel time (probability weighted time), arguing that the distinction between VTTS and VOR is not necessary when the full travel time distribution for a given trip on repeated occasions is recognised.

The most common approach to accommodating trip time variability in the valuation of travel time reliability is a stated choice experiment. This paper highlights a potential limitation of the traditional stated choice (SC) experiment which predefines the attribute levels (including attribute occurrence probabilities) under a specific statistical design rule such as D-optimality, in contrast to behavioural relevance. We question the merits of the traditional SC experiment in circumstances where statistical precision could be a high price for behavioural relevance. This means that an individual is advised of the variations in travel time for a repeated trip (such as the regular commute) and is told of the occurrence (or likelihood) of a specified travel time occurring. In reality, it is common to recognise that individuals form beliefs and opinions about the likely travel time, and this is known as the subjective probability associated with the occurrence of the perceived level of a specific attribute.

The challenge is to find a way to recognise and accommodate this feature of choice making in choice studies, be they linked to a stated choice experiment or some modification of the standard information sought under a revealed preference regime. There appears to be (at least) two ways to resolve this. One approach is to stay with the traditional stated choice experiment design pedagogy and to find a way of conditioning the objective probabilities associated with specific attribute outcomes so that a subjective assessment is invoked. A promising way is through an additional belief-based weighting which imposes some subjective perceptual conditioning on the role of the offered objective probability. The second approach involves abandoning some of the strict design features, that are essentially statistical and not necessarily behavioural, and adopting a method such as the one used in this paper which is a modified revealed preference approach¹. The latter approach introduces an

¹ This may also be a way to use the idea of a reference (or status quo) alternative to define the attribute levels in a choice experiment; however the probabilities associated with the incidence of specific attribute levels such as travel time will no longer be the subjective levels, although now we have a bounding guide based on the subjective levels.

additional behavioural perspective to the concept of travel time variability, by embedding subjective probabilities and sources of influence on uncertainty of occurrences (referred to as source preference) into the behavioural specification.

This paper is organised as follows. The next section provides a review of existing travel time variability studies using stated choice methods, and identifies a potential limitation associated with using an objective approach to represent travel time variability. We then discuss the differences between *risk* and *uncertainty*, and introduce the concept of subjective probability for decision making under uncertainty. This is followed by a comparison of different approaches to eliciting subjective probabilities using evidence from the psychological literature. A new revealed preference data set of commuter mode choice, collected in 2014, is used to demonstrate the role of source preference and its implications for valuation of expected travel time savings. The concluding section highlights avenues for future travel time variability research.

2. Existing Travel Time Variability Research: An Overview

The MEU framework is the generally accepted state-of-practice method to measuring and valuing travel time variability (see Li et al. 2010a for a review). The progression from traditional Random Utility Maximisation (RUM) to MEU not only changes the specification of a utility function that incorporates travel time reliability, it also leads to significant innovation in the way that stated choice experiments have to be designed to capture travel time variability. In recognition that travel time does vary, a series of arrival times (or travel times), rather than the extent and frequency of delay, have been considered in recent stated choice (SC) experiments (see, e.g., Small et al. 1999; Hollander 2006; Asensio and Matas 2008; Batley and Ibáñez 2009; Li et al. 2010a). However, in SC studies that do not incorporate a EUT probability weighting function, travel time variability is typically presented by the extent and frequency of delay relative to ‘normal’ travel time (see e.g., Jackson and Jucker 1982).

In terms of a modelling framework, the mean-variance model and the scheduling model are the two dominant approaches in the transport literature. While most stated preference experiments are similar to the approach developed by Small et al. (1999) (see Figure 1) with some slight changes (e.g., some used vertical bars to represent travel times (e.g., Batley and Ibáñez 2009), some provided 10 travel times instead of five (see e.g., Bates et al. 2001, and some show the departure time explicitly to the respondents (e.g., Holland 2006)). The behavioural paradigm widely used in the MEU model is a mix of RUM and EUT (i.e., a linear utility specification with linear probability weighting).

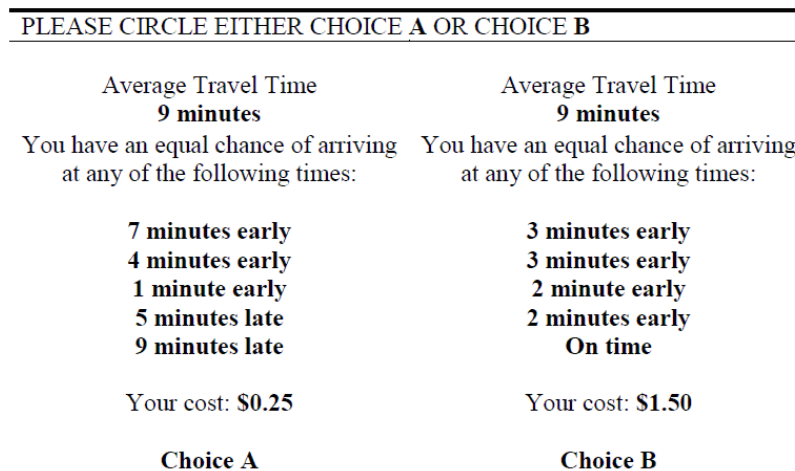


Figure 1: A choice example from Small et al. (1999)

In addition to RUM and MEU, a relatively small number of transportation studies have adopted alternative behavioural theories to analyse travellers' choices given the presence of travel time variability. For example, Prospect Theory (see Kahneman and Tversky 1979 for its original version and Tversky and Kahneman 1992 for its cumulative version) has become increasingly popular in traveller behaviour studies (see Li and Hensher 2011 for a review of Prospect Theoretic contributions in traveller behaviour research). In addition to Prospect Theory (PT), other alternative theories have been adopted by transport researchers, such as Expected Utility Theory (see e.g., Senna 1993; Polak et al. 2008; Li et al. 2010b), Extended EUT (see Hensher et al. 2013), and Rank-Dependent Utility Theory (RDUT) (see e.g., Michea and Polak 2006; Hensher and Li 2012), mainly using stated choice methods.

Michea and Polak (2006) and Polak et al. (2008) used SC data collected by Bates et al. (2001) shown in Figure 2, in which respondents were presented two train operators with different fares, timetables, and combinations of 10 equally possible arrivals (early or late) at the destination in terms of the clockface of cards for each alternative. Senna (1994) used an SC experiment, shown in Table 1, where one route has no travel time variability on five occasions, and the alternative route has different levels of mean travel times and variability, along with cost. The choice response is sought from a five-point semantic scale. Both designs are similar to the one shown in Figure 1 by Small et al. (1999).

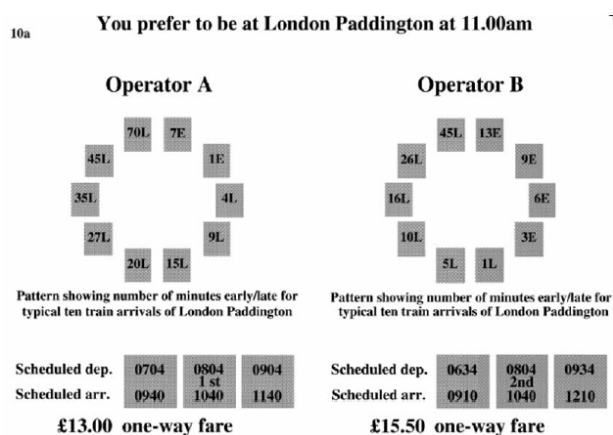


Figure 2: A choice example from Bates et al. (2001)

Table 1: A SP task from Senna (1994)

Option	Journeys (minutes)					Mean	Cost	Card 1	Choice
	1	2	3	4	5				
A	20	20	20	20	20	20	35.00	Definitely choose A Probably choose A Indifferent	
B	20	30	45	20	35	30	27.00	Probably choose B Definitely choose B	

A series of studies by Hensher, Rose and Li used an alternative design, given available data, (see Figure 3), which assumes a fixed level for arriving earlier or later (e.g., arriving 6 minutes earlier and 24 minutes later) within each choice scenario. This contrasts with Small *et al.* (1999) who presented five *equally likely* arrival times (see Figure 1) for a journey to respondents, along with the extent of arriving earlier (or later) than an average travel time, which can be varied within a choice set (e.g., for early arrival: 7 minutes, 4 minutes and 1 minutes; for late arrival: 5 minutes and 9 minutes). However, between choice scenarios, the design used by Hensher and Li varies the probability of early, on-time or late arrivals, and hence recognises the stochastic nature of a travel time distribution (e.g., the probability of arriving early can vary from 10 percent to 40 percent). In contrast, the probability associated with each possible travel outcome is fixed (i.e., if there are five travel times for an alternative, then each has a probability of 0.2) in designs such as Small *et al.* (1999) and Asensio and Matas (2008), or not mentioned (but assuming that travel times are equally distributed when estimating models) in experiments such as Bates *et al.* (2001) and Hollander (2006). Although this design offers some differences, the probabilities of different travel scenarios are *designed and exogenously presented* to respondents, as other travel time reliability studies have done.

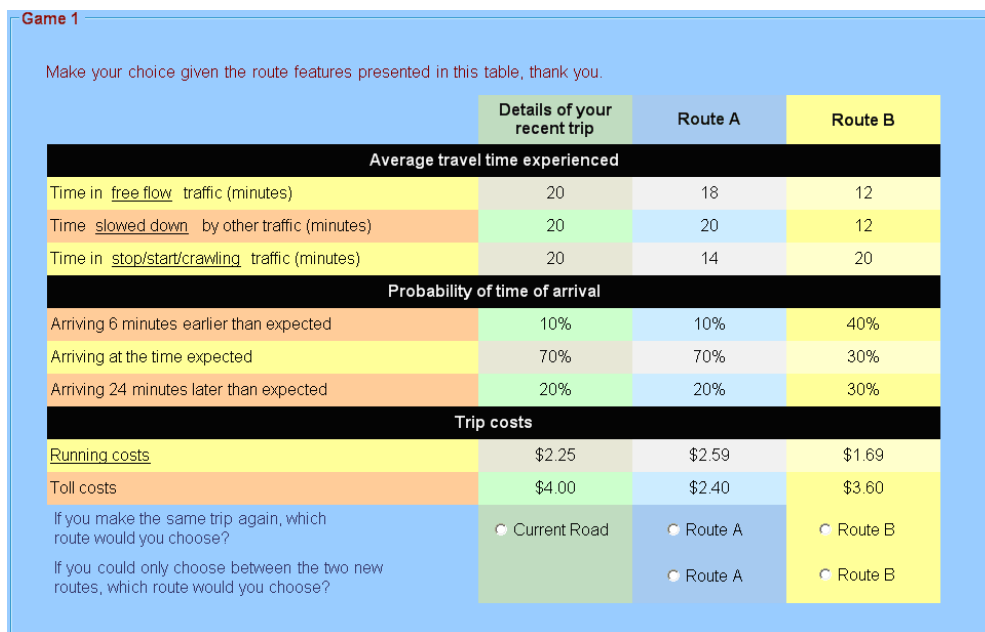


Figure 3: Illustrative stated choice screen of an alternative design

The common theme to all of the existing travel time variability studies cited above is that objective probabilities were used to describe a decision maker's perception of the travel time distribution, and hence the understanding of travel time variability is within the risk domain, given that risk relates to a given or known probability of occurrence distribution. We argue that subjective probability needs to be addressed in order to more meaningfully represent the perceptual nature of travel time variability. The reality is that the *perception* of unreliability in travel times may differ across respondents. This moves the approach into the realm of uncertainty.

3. The Distinction between Uncertainty and Risk

Knight (1921), in the first study that addressed the distinction between uncertainty and risk argued that the economic environment is characterised by unmeasurable uncertainty rather than measurable risk. If a choice is made under risk, objective probabilities are known, since decision makers have the full picture of all potential outcomes. For example, the objective probability of betting on the flip of a fair coin can be calculated (i.e., 0.5). However, such objective probabilistic information about the occurrence of events is not available in decision making under uncertainty (e.g., the likelihood of a road accident). Ellsberg's two-colour paradox (Ellsberg 1961) revealed that people prefer to bet on drawing a red or black ball from an urn which has 50 red and 50 black balls (under risk) than from another urn containing 100 red and black balls in unknown proportions (under uncertainty). When the choice is made under uncertainty, decision makers have to assess the probabilities of potential outcomes with some degree of vagueness associated with their beliefs (i.e., subjective probabilities).

As highlighted above, travel time variability is typically random and unsystematic. Noland and Polak (2002) emphasised that the difference between travel time variability and congestion is linked, in that travellers have difficulty in predicting the latter (e.g., congestion caused by unforeseen road accidents or service cancellations) from day to day, while they can, to some extent, predict the variation in travel time due to congestion (e.g., peak hours vs. off-peak hours). This concept of unsystematic and unpredictable travel time variability is reinforced in a series of studies (see Bates *et al.* 2001 and Li *et al.* 2010a among others). In reality, travellers need to assess the probability distribution of possible travel times for a future trip based on their experience, beliefs, etc. Hence, the decision-making process with travel time variability is better described under *uncertainty* rather than *risk*.

However, the distinction between uncertainty and risk has not been clearly addressed in the travel time reliability literature. Some studies use 'risk' to describe variability in travel time. For example, Senna (1994) used risk averse, neutral or loving to specify individuals' risk attitudes in the face of travel time variability; in a EUT framework. Batley and Ibáñez (2009) interpreted travel time variability as 'time risk'. The concept of travel time variability is strictly uncertainty rather than risk, with any ambiguity leading to a crucial problem in understanding the subjective nature of travel time reliability.

A real challenge for modellers, given the popularity of stated choice experiments, is how to accommodate the perceptual or subjective feature of perceptual conditioning into a choice experiment. Given that choice experiments 'impose' attribute levels, if we are to continue to use choice experiments we will need to find a mechanism to 'adjust' the objective levels of relevant attributes so as to represent the re-interpretation that is the basis of choice making. Alternatively, we may have to abandon the stated choice approach and rethink how revealed preference data can be used to obtain the relevant data on subjective levels.

There is an extensive literature in psychology that promotes the idea of a belief-based measure of outcome probability associated with a particular attribute (in our case it is travel time variability), which enables us to identify the likely levels that a subject actually processes (probability ambiguity), and what we call the equivalent subjective or belief adjusted attribute-specific outcome probability.

This is aligned with the idea of source preference (discussed in a later section). This is essentially a way of recognising and accommodating uncertainty, which may reduce the appeal of stated choice studies in favour of a revised revealed preference setting.

4. The Implication of Decision under Uncertainty on Travel Time Reliability Experiments: Subjective Probability

The concept of subjective probability was originally proposed by Ramsay (1931) and further developed by Savage (1954). Subjective probabilities represent “degrees of belief in the truth of particular propositions”, which reflect individuals’ assessment based on their knowledge and opinions (Ayton and Wright 1994, p.164). Therefore, subjective probabilities actually represent the facts about a decision maker, not about the world, which arose as a response to the failure of frequency-based objective probability theory, when there is the occurrence of uncertain events (Pollock 2006). Anscombe and Aumann (1963) used the horse race as a descriptive example of subjective probability, where individuals made bets according to their subjective probabilities of each horse winning with uncertain consequences. However, risky gambles, such as a roulette wheel, have a finite set of terminal outcomes associated with objective probabilities. Ferrell (1994, p.413) concluded that “subjective probability can enter at any stage of the decision analysis process, implicitly and explicitly as a way of dealing with uncertainty ... as the means of quantifying the uncertainties in the models that relate the alternatives to possible consequences.” However, subjective probabilities are still constrained by the axioms of classical probability theory² (Ayton and Wright 1994). For example, the sum of a set of mutually exclusive and exhaustive set of events is one (see Hensher and Li 2014).

According to Vick (2002, p.3), the operational explanation of subjective probability is: “the probability of an uncertain event is the quantified measure of one’s belief or confidence in the outcome, according to their state of knowledge at the time it is assessed”. Besides emphasising personal belief and knowledge, this definition also mentioned the assessment time of subjective probability. The judgement of a future travel time distribution is determined by an individual’s belief (e.g., an optimistic decision maker would over-estimate the probability of arriving on time) and circumstance (e.g., departure time). As an example, Bates *et al.* (2001) defined total travel time ($T(t_h)$) to consist of free flow time (T_f), congestion time (T_x), and travel time variability (T_r), with the last two elements dependent on departure time (t_h), given in equation (1). All evidence suggests that travel time variability (i.e., a type of uncertainty) should be represented by subjective probability.

$$T(t_h) = T_f + T_x(t_h) + T_r(t_h) \quad (1)$$

It is clear that subjective probabilities should be used when respondents face travel time variability questions, i.e., decision making under uncertainty. Ramsey (1931) proposed two ways to identify subjective probability: (i) *introspective interpretation*, i.e., measuring subjective probabilities by asking respondents; and (ii) *behaviourist interpretation*, i.e., defining subjective probabilities as a

² Which begins with a set of hypothetical elements, consisting of individual elements (A, B, etc.) and their unions ($A \cup B$), intersects ($A \cap B$) and complements ($A-B$), and a number can be assigned to each of these elements. For an empty element, the assigned number is 0. The number assigned to a subset of elements is equal to the sum of the numbers assigned to each of its constituent elements (i.e., additively). The number assigned to the set of all elements is 1. The assigned numbers must be between 0 and 1, and the system is additive. See Beach and Connolly (2005) for more details.

theoretical entity inferred from a choice³. The behaviourist interpretation (i.e., subjective probabilities can be estimated from observed preference) was the dominant approach to the elicitation of subjective probabilities before the Ellsberg paradox (Ellsberg 1961). Based on the behaviourist interpretation, Savage (1954) also suggested that the decision rule under uncertainty is to maximise expected utility based on assigned probabilities (i.e., Subjective Expected Utility Theory (SEUT)). This normative theory has no distinctive difference between risk and uncertainty, which also suggested that uncertainty may be equivalent to risk for a rational man.

Given that subjective probabilities elicited from choice (i.e., the behaviourist interpretation) are always calculated based on the linear functional form, coherent probabilities cannot be assigned to an individual, unless their attitude toward uncertainty is neutral (Baron and Frisch 1994). Ellsberg (1961) also provided sufficient evidence about the violation of SEUT. Since the 1980s, there have been an increasing number of studies in the area of psychology, behavioural and experimental economics, which directly asked respondents for their probability judgements over certain outcomes (see e.g., Kahneman *et al.* 1982; Heath and Tversky 1991; Fox and Tversky 1998; Wu and Gonzalez 1999; Takahashi *et al.* 2007). For example, Heath and Tversky (1991) asked respondents to give probability assessments on football predictions and political predictions, and found that uncertainty has an impact on preference.

In Wu and Gonzalez (1999), respondents were asked to provide their personal probability assessments on a number of events (e.g., national election and the number of University of Washington football team victories), and their judged probabilities were mapped into decision weights through the non-linear probability weighting function, which they referred to as a two-stage modelling process. Beach and Connolly (2005) defined the elicitation of subjective probability as “asking people to give a number to represent their option about the probability of an event”. Fox and See (2003, p.307) summarised some characteristics of subjective probability as follows: (i) *subadditivity*: “the probability of an uncertain event is generally less than the sum of probabilities of constituent events” ($sp(A) \leq sp(a_1) + sp(a_2) + \dots + sp(a_m)$, where $sp(A)$ is the subjective probability for the whole event A , and $sp(a_m)$ is the subjective probability for the m^{th} constituent event), and (ii) *description dependent*: “as the description of the target event is unpacked into an explicit disjunction of constituent events, judged probability may increase”.⁴

With this clarification of uncertainty and subjective probability, we can revisit the two examples of stated choice experiments that were discussed in the previous section, as ways to incorporate travel time variability (Figures 1 and 3). The example in Figure 1 (the dominant design in the literature) explicitly tells respondents that they have an equal chance of five arriving times, i.e., 0.2 for each time and for all respondents, where the expected value is indeed the average. Although, the experiment in Figure 3 allows for variation in induced probabilities of early, on-time and late arrival, those probabilities were designed, and hence are objective, and which consequently may not necessarily reflect individuals' true circumstances: beliefs, knowledge and the time assessed. Both designs place travel time variability in the risk domain and fail to address each respondents' personal beliefs and assessments, and the consequence is that uncertainty (travel time variability) has been treated as risk.

Since travel time variability is best described under uncertainty rather than risk, respondents should be asked to provide their judged probabilities associated with different travel outcomes (i.e., subjective probabilities for uncertainty) in a choice study. Therefore, instead of designing the probabilities for arriving early, on time and late (see Figure 3) exogenously (i.e., objective probabilities for risk), respondents should assess these probabilities and provide their own subjective probabilities for early,

³ See von Winterfeldt and Edwards (1986, pp.116-117) on how subjective probabilities are estimated from observed choice.

⁴ We interchangeably use judged probability and subjective probability in this paper. Other studies, however, explicitly distinguish the role of judged versus subjective probabilities (see Fox and See 2003).

on-time and late arrival based on their experience, judgment and departure times. Besides asking respondents to provide their judged probabilities of possible travel scenarios, the numbers of minutes earlier than expected and later than expected are also endogenous and hence subjective. The variability in travel times has two dimensions (the extent and the likelihood), which both represent the facts about a traveller. This imposes a major limitation on choice experiments since the analyst cannot design them on behalf of each respondent through an SC experiment where the focus has been on statistical efficiency (recognising however to some degree, the desirable behavioural relationships between attributes, their levels and alternatives). This necessitates a major rethink as to the appropriateness of SC experiments and a possible return to a modified revealed preference approach (as implemented in section 7 below).

We do not believe that stated choice experiments can account for uncertainty; however before moving to a revealed preference setting, it is useful to comment briefly on reference (revealed preference) or status quo pivot-based designs that bring design levels of attributes ‘closer’ to the levels experienced in real markets. A pivot design entails constructing the SC alternatives by pivoting them off of a respondent’s real experience (revealed preference - RP) (see e.g., Hensher and Greene 2003; Hensher 2004, 2006, 2010; Rose *et al.* 2008). The key advantages of pivoting include: (i) more realism in the stated choice experiment since hypothetical alternatives are around the RP alternative (status quo)⁵, and (ii) better specificity in the context of the choice task (Train and Wilson 2008). Unfortunately such designs confound subjective and objective attribute levels in that the levels designed for the SC alternatives are not judged levels. Consequently this fails to recognise belief based systems that underpin judged or subjective attribute levels.

Given the discussion thus far, four levels of subjectivity and objectivity in the data on repeated occurrence of an attribute and its occurrence likelihood, can be constructed (see Table 2): (i) *Fully objective* (FO) where probabilities (e.g., early, on-time and late; or longest, shortest and most common) and attributes (e.g., three travel times) are objective (i.e., OPs and OAs); (ii) *Partially subjective* (PS(1)) where probabilities are objective (OPs) while attributes are subjective (SAs); (iii) *Partially subjective* (PS(2)) where probabilities are subjective (SPs) while attributes are objective (OAs); and (iv) *fully subjective* where probabilities and attributes are subjective (i.e., SPs and SAs).

Table 2: Four levels of subjectivity and objectivity in experiments

Level i	FO = OPs+OAs
Level ii	PS(1) = OPs+SAs
Level iii	PS(2) = SPs+OAs
Level iv	FS = SPs+SAs

⁵ Hensher (2010) concluded after an extensive review of the literature on hypothetical bias as follows: “A way forward within the context of choice experiments, when the interest is on estimating [marginal willingness to pay] MWTP under conditions of habit, which is common in many transport applications, is to recognise the real market information present in a reference alternative. What we find, empirically, is that when a pivoted design is used for constructing choice experiments, and the model is specified to have estimated parameters of time and cost that are different for the reference alternative than the hypothetical alternatives, the estimated value of travel time savings is higher for the reference alternative than for the hypothetical alternatives. This model specification is not the specification that researchers have generally used with data from pivoted experimental designs. Usually, time and cost are specified to have the same parameters for the reference and hypothetical alternatives. The proposal herein for reducing hypothetical bias (given the Brownstone-Small ‘benchmark’), is to use a pivoted design and allow different parameters for the reference and hypothetical alternatives.” This adds realism but not source preference.

Notes:

FO: fully objective, PS(1): Partially subjective

PS(2): Partially subjective, FS: fully subjective

SPs: Subjective probabilities, SAs: Subjective attributes

OPs : Objective probabilities, OAs: Objective attributes

The majority of previous travel time reliability studies are established on the FO level, where travel times and associated probabilities are objective and exogenous. An exception is the design shown in Figure 3 (used in Li *et al.* 2010 and Hensher and Li 2012) which included supplementary questions to elicit from respondents the experienced range of travel times for the referenced trip. This information helped identify the range of minutes arriving earlier or later than the expected (normal) time used in the design. However, the associated probabilities were objective. Hence it is a PS(1) design.⁶

The discussion herein suggests that the traditional SC paradigm may better be replaced with what might be best referred to as an extended revealed preference ‘experiment’, if subjective probabilities and subjective attribute levels are required for *all alternatives*. The repetition of information based on prior experience and future expectations conditioned on accumulated belief employed in the proposed approach may provide a better paradigm for understanding choice making under uncertainty.

5. The Implications on Choice Modelling of Decision Making under Uncertainty

5.1 Savage’s Subjective Expected Utility Theory and its Violation (Ellsberg’s Paradox) as the precursor to Source Preference

Savage’s Subjective Expected Utility Theory (SEUT) is one the earliest expositions of uncertainty. SEUT, based on Expected Utility Theory (EUT), assumes that the objective of a decision maker is to maximise expected utility defined over final outcomes. Savage’s Subjective Expected Utility (SEU) model is a classical normative model of decision under uncertainty, where utility of each potential consequence is weighted by subjective probability, as shown in equation (2):

$$SEU(x) = \sum_m [sprob_m \sqcup U(x_m)] \quad (2)$$

$U(x_m)$ is the utility of the m^{th} outcome and $sprob_m$ is the associated subjective probability. The decision maker chooses the act that maximises subjective expected utility (SEU). In Savage’s SEU model, subjective probability and utility can be inferred simultaneously from observed preferences. For example, if there is no difference in a subject choosing: (1) winning \$10 if tomorrow rains and nothing if not, and (2) a sure win of \$5 (winning \$10 for a head when tossing a fair coin (with an objective probability of 0.5)), then we can infer a subjective probability is 0.5. The number of sure wins can be varied so to identify individuals’ beliefs (subjective probabilities).

The most significant assumption of SEUT is the ‘sure-thing’ principle. That is, if two acts have the same outcome given a particular state, the preferences between acts are independent of that common outcome (Savage 1954). The sure-thing principle allows for the measure of subjective probabilities to be linear-additive. However, Ellsberg’s paradox (Ellsberg 1961) revealed evidence which violates this fundamental principle of SEUT. Ellsberg’s two-colour example suggests that people are more willing to bet in the situation with objective (or provided) probabilities than with subjective (or judged)

⁶ In addition to the absence of subjective probabilities, another limitation of this design is that there is no variation in the minutes of being earlier or later within a choice set (i.e., same minutes (x and y) apply to all three alternative routes within a choice). A revised design should address this variation.

probabilities. This typical behaviour is referred to as ‘uncertainty or ambiguity aversion’, which also highlights the important distinction between risk and uncertainty.

5.2 *Uncertainty Aversion and Source Preference*

In the real world, decision makers often need to judge the probabilities of potential consequences by themselves (e.g., the outcome of a football match), based on their beliefs, knowledge and even the time when they make the assessment. Hence they are uncertain about those judged probabilities, due to missing information. Uncertainty aversion (i.e., less ambiguous information is preferred) is shown by probability ambiguity (i.e., the range of subjective probabilities) in Ellsberg’s paradox:

“An individual . . . can always assign relative likelihoods to the states of nature. But how does he act in the presence of uncertainty? The answer to that may depend on another judgment, about the reliability, credibility, or adequacy of his information (including his relevant experience, advice and intuition) as a whole.” (Ellsberg, 1961, p. 659)

The violation of the sure-thing principle suggests that SEUT cannot accommodate this behaviour. Rank-Dependent Utility Theory and Prospect Theory are sufficient to explain decision under risk (known probabilities), but not enough for decision under uncertainty (unknown probabilities). Ellsberg’s paradox (two-colour balls) revealed uncertainty aversion. It would be more uncertain to correctly guess its colour when drawing a ball from the urn which has 100 red and black balls in unknown proportions than from another urn containing 50 red and 50 black balls, because their *sources of uncertainty* are different. Hence *source preference* must be addressed when a decision is made under uncertainty. In the current study we are focussing on a single but repeated event, namely the commuting trip, and suggest that an individual’s willingness to make a judgment on an uncertain event (i.e., a commuting trip travel time) depends not only on the degree of uncertainty but also on its source. Source preference is exhibited if someone prefers to make a judgment informed from one source rather than a judgment informed from another source. In this study the source preference is consistent with the competence hypothesis (Heath and Tversky 1999) which proposes that individuals often prefer ambiguous *ability*-based prospects to unambiguous chance-based prospects. According to the competence hypothesis (Heath & Tversky 1991), this pattern derives from favourable perceptions of one’s competence⁷. In studying the phenomenon of commuting travel time variability and its role in travel choice making, the source of preference revelation is expertise in commuting where beliefs associated with commuting travel time, even if vague (and possibly unobserved or measured), are brought to bear in preference to those on matched chance events, which may be the alternative preference response context for non-commuters.

Fox and Tversky (1998) suggested a belief-based approach to decision making under uncertainty which involves a further transformation (ϖ) on the basis of nonlinear probability weighting for risky events. The example of a belief-based approach in the current study is the respondents views on what they believe are likely (i.e., subjectively perceived) travel times under repeated commuter trip making behaviour (see empirical application in a later section). In the psychology literature this is referred to as probability judgements that are used (in the context of a belief-based account) to predict decisions under uncertainty. This approach accommodates source preference, while maintaining the segregation

⁷ There is no guarantee that this is always the preferred situation. Klein *et al.* (2010) found that participants preferred an unambiguous chance-based option to an ambiguous ability-based option when the ambiguity derived from chance rather than uncertainty about one’s own ability.

of belief (i.e., judged (subjective) probability) and preference. This transformation for capturing source preference is given in equation (3), proposed by Fox and Tversky (page 893):

$$\varpi = [w(sprob_m)]^\theta \quad (3)$$

where $sprob_m$ is the subjective probability for the occurrence of the m^{th} outcome, w is some probability weighting function⁸, $\theta \neq 1$ reveals the different source between risk (given probabilities) and uncertainty (judged probabilities). This difference is the basis of an adjustment required in model estimation when an individual is initially offered ‘given probabilities’ in a choice experiment. Source preference can be defined empirically by a number of candidate constructs; however the notion of belief offers an appealing interpretation of the perceptual conditioning mechanism and aligns well with Ellsberg’s contribution.

Our preferred interpretation of source preference is based on two points⁹: ‘A belief in the likelihood of the target event’ (language of Fox and Tversky) which is used to refer to the decision weight expression (linked to gamma), and the overall function w^θ which reflects an individual’s preference to ‘bet’ on that belief. We have assumed that commuters as a group are much more able to express a preference to bet on the belief in the occurrence of commuting travel times than non-commuters where the latter might be expected to be more prone to betting on matched chance events. The basketball sample used in Fox and Tversky to study betting on basketball is the equivalent to our commuters making probabilistic judgments on the occurrence of commuting travel times.

Hensher *et al.* (2013a) used belief weights in another study but not in the context of travel time variability. Belief weights can be constructed on a (subjective) probability scale. Hensher *et al.* (2013) focused on the voting (in a referendum) implications associated with recognising degrees of belief when assessing *buy in* via a voting choice model to alternative road pricing schemes. Degrees of belief underlie decision weights that provide perceptual conditioning of subjective probability judgments associated with the extent to which each proposed road pricing scheme is perceived by a respondent as making them better or worse off. This evidence, derived directly as a numerical probability judgment, plays an important role in conditioning the marginal (dis)utility attached to the elements of a road pricing scheme. Such conditioning is aimed at increasing, *ex ante*, the external validity of voting preferences in a referendum context. Hensher *et al.* (2013a) obtain a numerical subjective probability belief judgment through direct questioning of individuals. For example, in terms of a proposed road pricing scheme:

*Suppose that the government were to introduce a distance-based car use charge of X c/km at congested (peak) periods and Y c/km at un-congested (off-peak) periods throughout Sydney (or in the Sydney Central Business District) together with a reduction in fuel excise of Tc/litre and a reduction in annual car registration charge of \$W per annum.
To what extent do you think that each of these schemes will make you better (or worse) off? (0=not at all, 100=definitely).*

This measure was used to obtain probabilistic belief weights, denoted by $P(Z)$, where Z is a subjective belief response scale (0-100) associated with the road pricing scheme attributes in the utility expression for each alternative. It is well recognised in the psychology literature (see Tversky and Kahneman 1992) that degrees of belief are implicit in most decisions whose outcomes depend on uncertain events. In quantitative theories of decision making such as subjective expected utility theory or prospect theory, degrees of belief are related to decision weights and are typically identified by either prescribed levels as part of alternatives in a choice experiment or in a more direct manner using

⁸ Which could be linear or non-linear.

⁹ Fox and Tversky in a footnote (18) offer the prospect for accommodating source preference by varying the parameter of the risky weighting function, which is the gamma in our model.

a linguistic device such as judgments of numerical probability. Such estimates are often viewed as an approximation to the degrees of belief implicit in decisions or preference revelation (see Fox 1999).

It is well recognised that numerical probability judgments are often based on heuristics that produce biases. One of the methods proposed to accommodate some aspects of such potential bias was the idea of a decision weight (Kahneman and Tversky 1979) which accounts for the presence of perceptual conditioning in the way that information reported by decision makers or information offered to decision makers is heuristically processed. Specifically, the value of an outcome is weighted not by its probability but instead by a decision (or belief) weight, $w(\cdot)$, that represents the impact of the relevant probability on the valuation of the prospect. $w(\cdot)$ need not be interpreted as a measure of subjective belief – a person may believe that the probability of a road pricing scheme making them better off is, for example 0.5, but afford this event a weight of more or less than 0.5 in the evaluation of a prospect. Hence the notion of source preference is a way of capturing the essence of subjective probability. Various functional forms have been proposed to capture the role of such decision weights (see Hensher *et al.* 2011 for some examples and one form we use in the empirical study below).

6. Source Preference and Travel Time Uncertainty

To investigate the way in which source preferences can be built into an empirical choice model, and to contrast the evidence on the value of expected travel time savings under uncertainty with the ‘standard’ derivation of the value of expected travel time savings, we had to collect new data. We were surprised to find that there does not appear to have been any previous study that has focussed on subjective attribute levels and associated subjective probabilities for travel times (i.e., level iv).

For the probability weighting process under uncertainty, the first step is to ask respondents to provide their judged (subjective) probabilities ($sprob_m$) of target events, and the second step is to weight those judged probabilities by using a nonlinear probability weighting function for risk (i.e., risky weighting function). The distinction between decision under risk and uncertainty is captured in the further transformation of decision weights, which indicates individuals’ source preference through the source preference parameter (θ).

Given the new data from a real market, we can use a modelling framework which is capable of accommodating all important aspects of decision making under uncertainty including the attitude towards uncertainty, subjective probabilities, probability weighting and source preference, which is given in Figure 4 as suggested by Fox and See (2003).

The modelling process shown in Figure 4 integrates two essential components of research in behavioural decision theory: (i) the analysis of decision under risk (e.g., decisions weight in Prospect Theory and Rank-Dependent Utility Theory) and (ii) the study of judgment under uncertainty (e.g., subjective probability). It also extends Prospect Theory by teasing apart the role of personal belief and source preference in the weighting process.

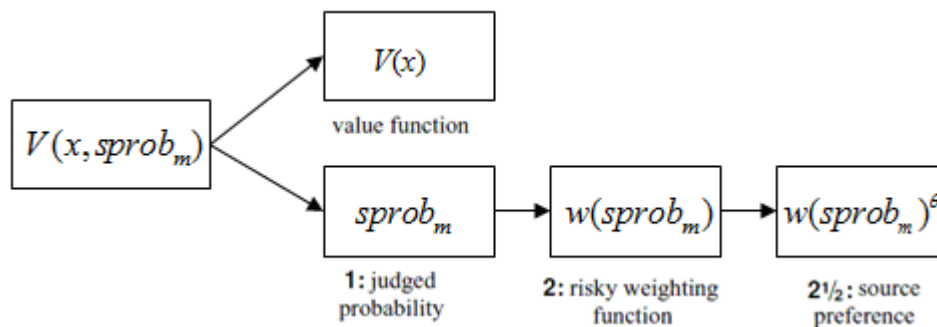


Figure 4: The process for modelling decision under uncertainty

Source: Fox and See (2003)

7. The Empirical Study

7.1. Data and models

An online survey was undertaken in March 2014 using a sample of car and public transport commuters in the Sydney metropolitan area. The data focussed on commuters who are regular users of car as a driver or public transport (single modal or multimodal of bus, train and ferry). To be eligible for the survey, at least one public transport (PT) option must be available to car commuters for commuting if they wanted to use it and vice versa for PT commuters. A target sample of 1,000 commuters (500 PT and 500 car commuters) was sought with the help of SSI, an online survey company. Respondents were recruited via email directing them to a customised online survey. In total, 4,046 invitation emails were sent and a sample of 994 qualified respondents (474 PT commuters and 520 car commuters) was obtained (a response rate of 25%). Compared to the 2011 journey to work census data, the sample on average has a higher income (\$76,930 vs. \$57,660 per annum), works shorter hours (29 vs. 34 hours per week), and includes more women (57% vs. 44%) and older workers (40.36 years vs. 39.08 years).

Commuters were asked to report three perceived commuting times and the likelihood of experiencing each travel time. The survey also included questions relating to travel cost, fuel consumption of the car used for commuting, number of times using car and public transport for commuting in the last two months, as well as socio-economic characteristics such as age, income, occupation and household car ownership. A process of cleaning and validating the data reduced the sample to 627 usable observations. Inconsistencies between reported household size and household structure and between public transport fares and toll costs of different travel outcomes are the main reasons for removing observations from the final dataset. Other reasons for dropping out observations include average speed being too slow or too fast and time variability across three possible travel outcomes being too much (more than 4 times) or too little (no time variability). Summary statistics of the sample are provided in Table 3 with the practical implementation being shown in a screen shot of the survey instrument in Figure 5.

Table 3: Summary statistics of the sample

Variable	Mean	Std. Dev.
Age (years)	39.08	14.11
Female	0.57	0.50
Weekly working hours	29.04	8.17

Personal income before tax ('000\$)	76.93	43.83
Number of household cars	1.67	0.88
Number of household adults	2.22	0.82
Number of household children	0.74	0.96
Number of times commuting by PT in last 2 months ^a	6.94	7.08
Number of times commuting by car in last 2 months ^a	7.46	5.83
Shortest commuting time (minute)	27.46	16.18
Most likely commuting time (minute)	36.13	18.18
Longest commuting time (minute)	45.98	22.74
Likelihood of having shortest time (%)	36.25	24.78
Likelihood of having most likely time (%)	41.25	24.18
Likelihood of having longest time (%)	22.28	16.62
Travel cost weighted by probability (\$)	6.55	7.53

^a The sample includes car commuters and PT commuters, with the number of times commuting by a specific mode over 16 provided in the questionnaire as 16+ and recoded as 16 for analysis.

THE UNIVERSITY OF SYDNEY

Travel Time Uncertainty Survey

Car Commuter

You are qualified for this survey.

You said that you commute by **car as driver** and we know that your travel times will vary each time you travel to work for many reasons such as congestion, accidents, breakdowns, and road works.

Could you please share with us **3 possible travel outcomes** that you believe could occur on your **car trip to work**? (these could be based on your recent experience on your regular commuter trip, or your perceptions of what it is likely to be.)

The 3 possible travel outcomes must include: **one with the longest travel time, one with the shortest travel time and one with the most likely travel times.**

The likelihood of the most likely travel time must be highest amongst 3 possible outcomes and the likelihoods across 3 possible outcomes must add up to 100.

	Outcome 1	Outcome 2	Outcome 3
Door-to-door travel time (minutes)	<input type="text"/>	<input type="text"/>	<input type="text"/>
Travel distance by car (km)	<input type="text"/>	<input type="text"/>	<input type="text"/>
Toll paid (\$)	<input type="text"/>	<input type="text"/>	<input type="text"/>
The likelihood of this outcome actually occurring (%)	<input type="text"/>	<input type="text"/>	<input type="text"/>
Rank possible travel outcomes from 1 (most preferred) to 3 (least preferred)	<input type="text"/>	<input type="text"/>	<input type="text"/>
What is the average fuel consumption of the car that you would use for commuting?	<input type="text"/>		litres/100km
How many times in the last 2 months did you drive to work?	<input type="text"/>		

You said that you could use **public transport** to commute if you wanted to.

What would be the **3 possible outcomes** of your commuting trip by **public transport**? (use the same principles provided above for car commuting trip to provide your answers)

	Outcome 1	Outcome 2	Outcome 3
Door-to-door travel time (minutes)	<input type="text"/>	<input type="text"/>	<input type="text"/>
Fare (\$)	<input type="text"/>	<input type="text"/>	<input type="text"/>
The likelihood of this outcome actually occurring (%)	<input type="text"/>	<input type="text"/>	<input type="text"/>
Rank possible travel outcomes from 1 (most preferred) to 3 (least preferred)	<input type="text"/>	<input type="text"/>	<input type="text"/>
How many times in the last 2 months did you ride public transport to work?	<input type="text"/>		

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Figure 5: A screen shot of questions asked in the online survey

As shown in Figure 5, all respondents were asked to provide the likelihood of three possible outcomes of an alternative mode even if they never used it to commute. Instructions were provided to help commuters judge the likelihood of the three possible outcomes based on their recent experience (for those who have used alternative mode to commute) or perceptions of what it is likely to be. This is in line with the underlying theory of our binary model which predicts a lower probability for non-chosen alternatives, reflecting that people prefer alternative with known proportion of occurrence (i.e., subjective probability) to the alternative with unknown proportion (non-chosen alternative with less certain or unknown likelihood of occurrence, also see discussion in section 3).

A non-linear decision weight form is constructed to capture source preference in a binary model framework with the choice variable being commuting mode (car vs. PT). Tversky and Kahneman (1992) provided parametric formulae for the value functions under a constant relative risk aversion (CRRA) assumption, as well as a one-parameter probability weighting function. The probability weighting function suggested by Tversky and Kahneman (1992) is chosen and is given in equation (4)¹⁰. γ is the probability weighting parameter to be estimated, which measures the degree of curvature (or source sensitivity) of the weighting function. Equation (4) when scaled by the source preference parameter, θ , is the expression for ϖ in equation (3).

$$w(p_m) = \frac{p_m^\gamma}{[p_m^\gamma + (1 - p_m)^\gamma]^\frac{1}{\gamma}} \quad (4)$$

The utility expression associated with each alternative that accounts for source preference and risk attitude for travel time is given in equation (5). The equation is based on Hensher *et al.* (2011)'s Extended EUT (EEUT) model form which allows for perceptual conditioning (or decisions weights) associated with prospect theory, but which is not a fully specific prospect theoretic model because it does not account for asymmetry in gains and losses.

$$U = EEUT(U) + \sum_{z=1}^Z \beta_z S_z \quad (5)$$

$$\text{where } EEUT(U) = \beta_x [w(p_1)^\theta x_1^{1-\alpha} + w(p_2)^\theta x_2^{1-\alpha} + \dots + w(p_R)^\theta x_R^{1-\alpha}] / (1-\alpha) \quad (6)$$

$W(P)$ is a non-linear subjective probability weighting function which converts raw subjective probabilities (P) associated with perceived attribute levels x_1, x_2, \dots, x_R with R levels over R occurrences; and α, γ, θ and β have to be estimated; $(1-\alpha)$ indicates the attitude towards risk, θ is the source preference parameter that identifies deviations of uncertainty from risk, and β is the marginal (dis)utility parameter associated with travel time variability and perceptual conditioning.

A specific comment is required on how we interpret risk attitude in the current study, given that the data is a single cross-section, albeit with a data twist. The justification for including risk attitude (more commonly used in repeated experiments) is reflected in the repeat nature of travel time which engenders a meaning in terms of how the commuter treats travel time each time they undertake a trip. This is different to how they perceive the levels of travel time (i.e. the perceptual conditioning and believability arguments) associated with each commuting trip. Thus, some commuters who are risk taking are more prepared, *ceteris paribus*, to accept large variability in travel time; in contrast a risk averse person likes greater 'certainty' of travel times.

¹⁰ There are a number of alternative weighting functions, e.g., a two-parameter weighing function proposed by Goldstein and Einhorn (1987) and another version of a one-parameter weighting function derived by Prelec (1998). See Hensher *et al.* (2011) where all functional forms are implemented.

There are also a number of other variables (S) in the utility expression that are not specified this way, such as travel cost¹¹ and age of respondent, and are added in as linear in parameters. The presence of α , γ and θ in equations (5) and (6) results in an embedded attribute-specific treatment in the overall utility expression associated with each alternative, that is non-linear in a number of parameters. Only if $(1-\alpha) = 1$, $\theta=1$, and $\gamma=1$ does equation (6) collapse to a linear utility function. Estimation of this model requires a non-linear logit form.

Constant absolute risk aversion (CARA) and constant relative risk aversion (CRRA) are two main options for analysing the attitude towards risk, where the CARA model form postulates an exponential specification for the utility function, and the CRRA form is a power specification (e.g., $U = x^\alpha$). For the non-linear utility specification, the CRRA form rather than CARA is used in this study, given that CARA is usually a less plausible description of the attitude towards risk than CRRA (see Blanchard and Fischer 1989). Blanchard and Fischer (1989, p.44) further explained that “the CARA specification is, however, sometimes analytically more convenient than the CRRA specification, and thus also belongs to the standard tool kit”. CRRA has been widely used in behavioural economics and psychology (see e.g., Tversky and Kahneman 1992; Holt and Laury 2002; Harrison and Rutström 2009) and often delivers “a better fit than alternative families” (Wakker 2008, p.1329). We estimate the constant *relative* risk aversion (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 (Andersen *et al.* 2009; Holt and Laury 2002).

7.2 Findings

We investigated both multinomial logit (MNL) and mixed multinomial logit (MMNL) where the latter model allows for random parameters. We were unable to establish any statistically significant standard deviation parameters for the parameters tested (i.e., α , γ , θ and β associated with travel time). The MNL model is nonlinear in many parameters, and as a binary choice model we have no concern about the IIA assumption; furthermore there is only one (revealed preference) choice set per respondent and so correlated choice sets under typical stated choice experiments is not an issue.

The final results are summarised in Table 4. We present three models: a simple linear model in which travel time is probability weighted by the occurrence of each of the three subjective travel times (model 1, and Figure 6); two non-linear models in which we account for perceptual conditioning and risk attitude in the presence ($\theta \neq 1$) (model 3) or absence of source preference ($\theta=1$) (model 2, i.e., the decision-making context is treated as under risk). The overall goodness of fit of Model 3 is just statistically better than model 2 on a chi-square test. The pseudo- R^2 for all models is in the often supported ‘acceptable range’ between 0.2 and 0.4 for non-linear choice models.

The three parameters of most interest are α , γ , and θ . In model 3, Given the null=1 for γ and θ , the t-statistic for the hypothesis that $\gamma=1$ is $(1.308-1)/0.6708=0.459$, and for $\theta=1$ it is $(0.857-1)/0.416 = 0.344$. These estimates have to be converted into p-values. For γ , the two-tailed test P value =0.6463, which is not statistically significant by conventional criteria; for θ the two-tailed test P value =0.7311, also not statistically significant. The null hypothesis for α is 0 (noting the form of the model in equation 6), and it is statistically significant from zero. In model 2, the t-statistic for the hypothesis that $\gamma=1$ is $(0.986-1)/0.109=-0.128$, and the two-tailed test P value =0.353, also not statistically

¹¹ We investigated a similar treatment of cost as given to time but the linear form was the best statistically significant effect.

significant by conventional criteria. For this one data set we can conclude that the perceptual conditioning and the source preference to allow for uncertainty are not statistically significant influences and that a behaviourally simple model form (essentially model 1 possibly with the addition of α) is an appropriate representation of the role of travel time variability. Despite this empirical finding, it is informative to illustrate that role that the additional terms might play, had they been statistically significant, given the null, offering a guide to other researchers on the approach they might implement with other data sets.

The estimated source preference parameter of 0.857, if statistically significant, would suggest the presence of uncertainty aversion given that $\theta > 0$ is inversely related to the attractiveness of uncertainty source. $\theta \neq 1$ reveals the different source between risk (given probabilities) and uncertainty (subjective probabilities). Although we are unable to identify a systematic source preference effect given our data, instead relying on theoretical and behavioural arguments offered in psychology (in particular the contribution of Fox and Tversky (1998)) we are able to recognise that if $\theta = 1$ then the source is of no consequence.

Table 4: Summary of Models

	Probability weighted time (Model 1)	Without source preference (Model 2)	With source preference (Model 3)
Car constant	-1.538 (-4.87)	-1.699 (-5.15)	-1.717 (-5.19)
Travel time (β)	-0.046 (-6.48)	-1.629 (1.93)	-2.305 (-1.99)
Travel cost	-0.329 (-9.27)	-0.321 (12.6)	-0.319 (-12.4)
Gamma (γ)	-	0.986 (9.04)	1.308 (1.95)
Alpha (α)	-	0.979 (6.25)	1.083 (6.57)
Source preference (θ)	-	1.0 (fixed)	0.857 (2.06)
Age (years) - car	0.014 (1.92)	0.015 (1.76)	0.015 (1.77)
<i>Log-likelihood:</i>			
At zero	-434.6	-434.6	-434.6
At convergence	-279.4	-269.8	-267.8
Pseudo R ²	0.357	0.379	0.384
AIC	0.904	0.880	0.877

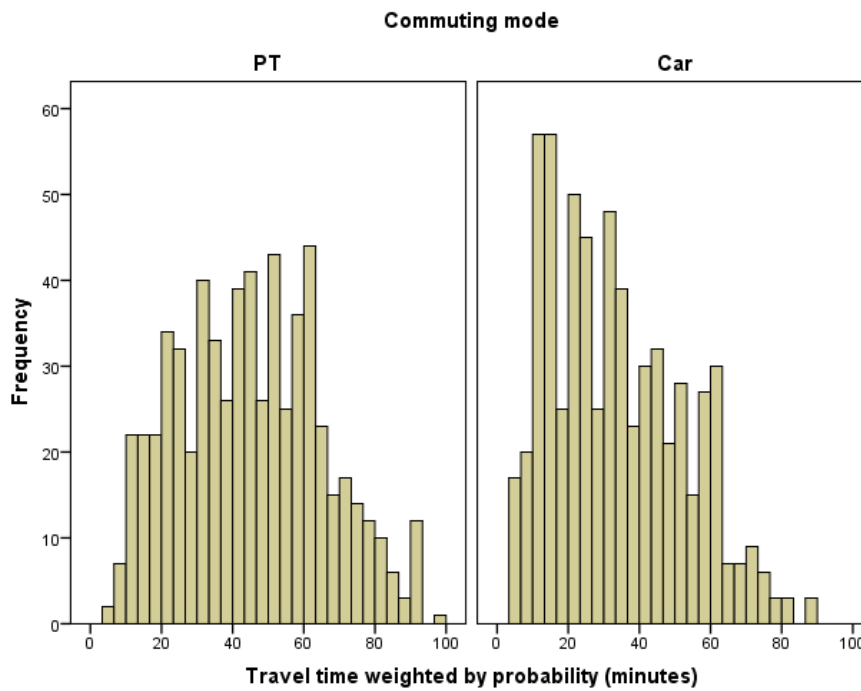


Figure 6: Travel time profile of sample

The empirical perceptual conditioning weighting expression (pwp_m) under source preference for model 3 is:

$$pwp_m = \frac{(p_m^{1.30813})}{(p_m^{1.30813} + (1 - p_m)^{1.30813})^{(1/1.30813)}}^{0.85717}; m=1,2,3$$

The distribution of pwp_m , $m=1,2,3$ is given in Figure 7 for the sample. The three possible travel outcomes are the longest travel time, the shortest travel time and the most likely travel time. The respective mean occurrences are 0.434, 0.285 and 0.288.

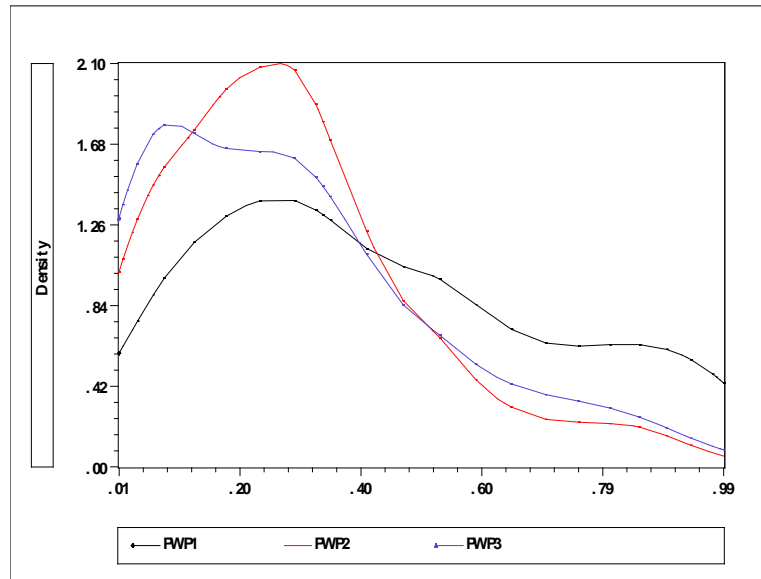


Figure 7: Perceptual conditioning with source preference profile of sample

In Figure 8, we have plotted the shape of the perceptual conditioning function for a given gamma as the probability varies. The line defined by $\gamma=1$ and $\theta=1$ is a 45 degree line, which is a perfect mapping of the decision weights and subjective probabilities.

The estimated values of γ and θ impact (direct and indirect) on the shape of the weighting function. Specifically, in standard prospect-theoretic form gamma is the determining estimate and it drives the shape; however in the model herein the relevant function is also influenced by the presence (model 3) and absence (model 2) of the additional term which is more like a shift parameter than a shape parameter. The presence of source preference results in an adjusted influence of the role of gamma and hence the differences in the graph. Figure 8 shows that when source preference is accounted for (model 3), outcomes with lower probabilities tend to be under-weighted (e.g., $w(p = 0.2) = 0.135$), while outcomes with high probabilities tend to be over-weighted (e.g., $w(p = 0.8) = 0.84$)¹². When source preference is not accounted for (model 2), we see the opposite effect; namely outcomes with lower probabilities tend to be over-weighted (e.g., $w(p = 0.2) = 0.23$), while outcomes with high probabilities tend to be under-weighted (e.g., $w(p = 0.8) = 0.756$). The evidence under source preference is consistent with a view that at low probabilities there is a tendency for the perceptual conditioning to be reduced down; in contrast at high probabilities there is a tendency for perceptual conditioning to be increased.

¹² As shown and discussed in Hensher et al. (2011), the direction of over and under-weighting is not behaviourally fixed. There is evidence of gamma being less than and greater than 1.0 and hence there are no fixed rules despite some behavioural expectations. Furthermore, much of the prospect theoretic evidence is based on financial gambles, which we would argue is different to perceptions of travel times, and trips times that occur less often can be overweighted if they were extremely bad experiences (e.g., very bad congestion).

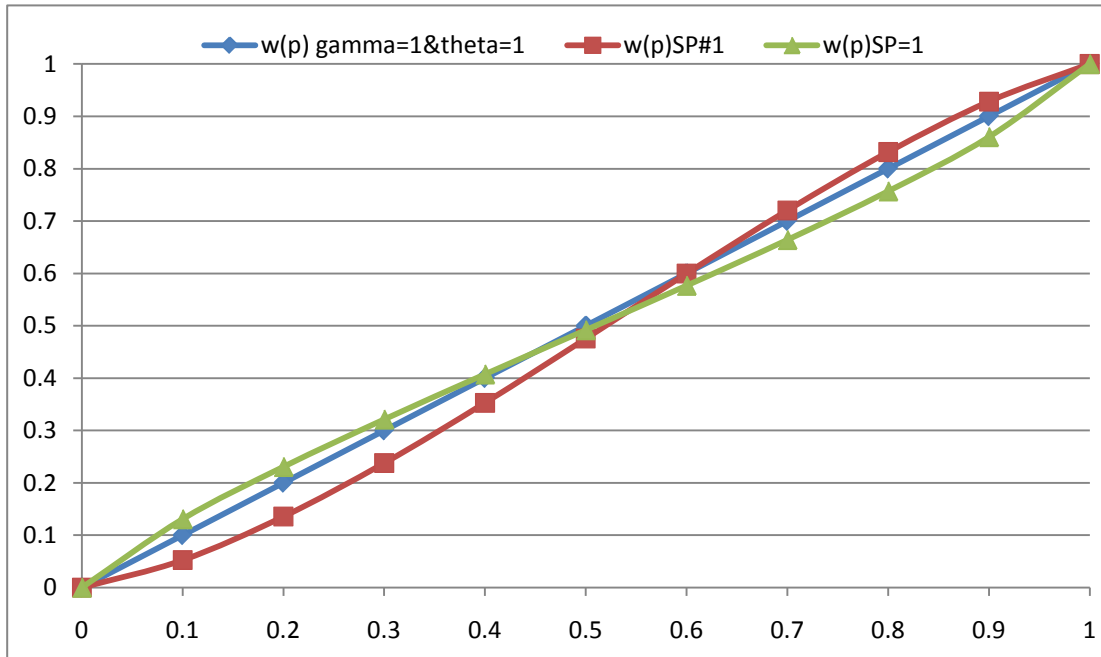


Figure 8: Relationship between Non-linear probability weighting functions model 2 and 3

The marginal (dis)utility of the travel time expression for model 3 is:¹³

$$MU_{\text{time}} = -2.30508 * (pwp_1 * (\text{time}_1^{-1.08344}) + pwp_2 * (\text{time}_2^{-1.08344}) + pwp_3 * (\text{time}_3^{-1.08344}))$$

The risk attitude parameter α is statistically significant in both models 2 and 3, respectively 0.979 (t-value=6.25) and 1.083 (t-value=6.57). For decision making where risk is associated with travel time, a risk attitude parameter less than one (as shown under the absence of source preference) suggests risk-taking attitudes; and a risk attitude parameter greater than one (in the presence of source preference) suggests risk-averse attitudes (Senna 1994).

Given the marginal (dis)utility of cost, we can derive the value of expected travel time savings (VETTS). VETTS (see Hensher *et al.* 2011) takes into account the levels of travel time on repeated occasions for the commuting trip and hence also allow for travel time variability. The mean VETTS for each of the three models 1-3 are respectively, \$8.37, \$12.80, and \$13.49 per person hour. The standard deviation VETTS for models 2 and 3, respectively, are \$10.04 and \$12.12 per person hour.

The model allowing for source preference (model 3) has a higher mean VETTS (5.39 percent greater) compared to model 2 which assumes source preference neutrality; however given the standard deviations, we cannot conclude statistically (for this one data set) that source preference matters, even though use of the mean estimate, common in project appraisal, makes a significant difference in time benefits.

We have graphed VETTS from model 3 in Figure 9, which shows that the majority of values are between \$5 and \$30 per person hour. There are clearly some commuters who place a very high value on reducing expected travel time (i.e. reducing trip time variability). For example, if we take a high value of, say, \$60 per person hour, given the sample of commuters whose gross personal income varies from \$10,000 to \$260,000 per annum, then given average income earning hours of 2,000 per

¹³ See Table 4 for equivalent parameters for model 2.

annum, some individuals earn up to \$130 per hour. Also, in Sydney, it is not uncommon on the toll road network to pay \$12-\$15 for a one-way commuting trip in order to save 20 mins, equivalent on average to \$36-\$45 per hour. The distribution of VETTS is more than the distribution of the value of travel time savings, allowing for the value of trip time variability reduction, and is arguably within a plausible behavioural range.

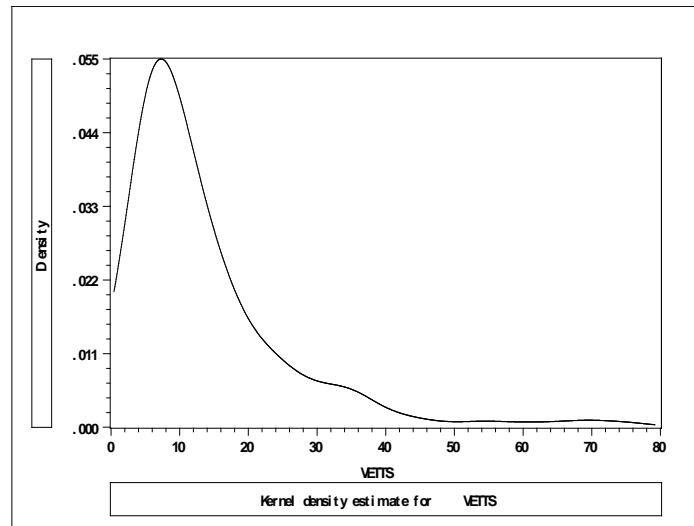


Figure 9: VETTS distribution for Model 3

8. Conclusions

Maximum Expected Utility theory proposed by Noland and Small (1995) is the foundation of many contemporary travel time reliability studies. However, some limitations are present that need addressing. First, travel time variability has been treated as risk in a number of stated choice experiments, in which the probabilities of different travel scenarios were clearly defined and exogenously induced to respondents (objective probabilities). According to psychological theories, decision making in the presence of travel time variability is made under uncertainty rather than under risk; consequently this raises questions about the usefulness of choice experiments given that they predefine attribute levels and the likelihood of occurrence. In this paper we suggest a return to a revealed preference setting in order to identify subjective (or judged) levels of attributes including their occurrence probability when a specific attribute's level is subject to uncertainty under a repeated activity situation as is commuting.

To account for the variability in attribute levels associated with a specific choice such as the car for the commuting trip, a number of transportation studies have used alternative behavioural paradigms (e.g., expected utility theory, rank dependent utility theory, and prospect theory) in which decision weights are measures of perceptual conditioning in respect to the occurrence of varying attribute levels. Although these models are capable of analysing decision making under risk, they cannot fully explain decision making under uncertainty. The Ellsberg paradox indicates that source preference must be addressed for uncertain events, which requires a further transformation over risky probability weighting. In this paper we have reviewed the contributions in psychology on source preference, and presented a parametric way forward to addressing attitude towards uncertainty (constant relative uncertainty aversion), and the identification of source preference.

Using a newly collected data set on commuting travel that provided data on subjective travel times and associated subjective occurrence probabilities, we estimated the source preference parameter, and

although it is not statistically significant on our single data set, the approach is sufficiently informative to illustrate the role that source preference might play on model performance (especially estimates of mean values of expected travel time savings) relative to a model assuming neutral source preference.

The process of subjective judgment of probabilities of occurrence incurs additional disutility captured as uncertainty aversion ($\theta > 0$). Deviations of the source preference parameter (θ), from 1.0 is a measure of the uncertainty-risk gap in decision making. Although in this single data set study, the deviation between the value of expected travel time savings distribution under source preference vs. risk is small, and statistically non-significant, this does not detract from the value of recognising the potential influence of sources of influence on uncertainty that are related to subjective measures of occurrence that cannot be accommodated in stated choice experiments. This suggests a more serious rethink about the role of revealed preference data which, if properly constructed as in this paper, can produce the necessary variability in attribute levels to circumvent the possible need for a choice experiment.

Bonsall (2004) argued that most travel behaviour studies have a rather simple treatment of uncertainty (i.e., as a purely statistical issue), and highlighted the importance of accommodating psychological aspects of response to uncertainty in travel behaviour research “since it is uncertainty in the mind of the traveller, rather than variability in the system, which directly influences behaviour, [and hence] we need to understand people’s perception of [uncertainty] and attitudes to uncertainty if we are to predict their responses to it” (p.45). This paper echoes Bonsall’s position, supporting further research on the influence of uncertainty in travel decision making from both behavioural and psychological perspectives.

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