

Accommodating Perceptual Conditioning in the Valuation of Expected Travel Time Savings for Cars and Public Transport

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Keywords: Travel time variability, travel time distribution, perceptual conditioning, non-linear probability weighting, willingness to pay, and value of expected travel time savings

Revised: 14 February 2012

Research in Transportation Economics (RETREC)

ABSTRACT

Travel time variability (i.e., random variations in travel time) leads to a travel time distribution for a repeated trip from a fixed origin to destination (e.g., from home to work). To represent travel time variability, a series of possible travel times per alternative (departure time, route or mode) are often used in stated choice experiments. In the traditional models, the probabilities associated with different travel scenarios (e.g., arriving early, on time and late) shown in the experiments are directly used as weights. However, evidence from psychology suggests that the shown probabilities may be transformed (underweighted or overweighted) by respondents. To account for this transformation of probabilities, this study incorporates perceptual conditioning through a non-linear probability weighting function into a utility maximisation framework, within which the empirical estimate of the value of expected travel time savings is estimated. The key advantage of this framework is that the estimated willingness to pay value can be directly linked to the source of utility (i.e., the probability distribution of travel time), while taking into account the perceptual transformation of probabilities.

1. Introduction

Travel time variability leads to multiple possible travel scenarios for a trip (e.g., arriving on time, earlier or later relative to the expected arrival time), and there are probabilities associated with these scenarios. This 'probabilistic' influence of travel time variability is reflected in many stated choice (SC) experiments for travel time variability, with two typical representations for an alternative associated with travel time variability per respondent' choice set: (1) as the extent and frequency of delay relative to normal travel time (e.g., one out of five chance of a 5-minute delay) and (2) a travel time distribution (e.g., a probability of 0.6 for arriving on time, 0.3 for arriving later by 10 minutes, and 0.1 for arriving earlier by 5 minutes, using three points as an example). The latter form is preferred (see Hamer *et al.* 2005), which is commonly embedded in the models based on the Maximum Expected Utility (MEU) theory, proposed by Noland and Small (1995). MEU has become the dominant behavioural paradigm within which to analyse and value travel time variability, under which the mean-variance model and the scheduling model are two state-of-practice modelling frameworks for valuing travel time variability.

However, most travel behaviour studies have a rather simple treatment of uncertainty, that is, as a purely statistical issue (see Bonsall 2004). For example, the standard deviation (or variance) of travel time is simply added in the utility function established on the mean-variance model as an extra attribute, along with other attributes such as the average travel time and travel cost. In these traditional modelling frameworks, the probabilities of occurrence are directly used to weight the corresponding travel outcomes. However, evidence from psychology and behavioural economics has shown that in many cases, the raw probabilities provided in the experiments were transformed by subjects, and the transformed probabilities were used as the probability or decision weights. This transformation is also referred to as ‘perceptual conditioning’, which has been overlooked in the traditional frameworks for travel time variability. Given this, the primary purpose of this paper is to develop a more behaviourally realistic model, within which perceptual conditioning is addressed through a non-linear probability weighting function incorporated into a utility maximisation framework. This modelling framework allows for the transformation of probabilities provided in the experiment and the estimation of the value of expected travel time savings (VETTS) which takes into account the travel time distribution due to travel time variability. The key innovation and advantage of this framework over the traditional models is that the willingness to pay (WTP) value can be directly linked to the source of utility (i.e., the probability distribution of travel time).

The remaining sections are organised as follows. The next section provides a brief literature review on two dominant approaches to travel time variability, identifies an important gap of these approaches, and introduces a method to address this gap. This is followed by an improved modelling framework used in this paper. Then a stated choice data, conducted in Australia in 2009 in the context of modal choice (public transport vs. car as well as public transport vs. public transport (e.g., bus vs. train)), is briefly described. This is followed by the model estimation and empirical estimates of value of expected travel time savings. We also provide an example of how to use these estimates and the associated policy implication, before summarising the conclusions.

2. Literature Review

Travel time variability (i.e., random variations in travel time due to demand fluctuations, accidents, traffic signals, road construction and weather changes) has become an important research focus in the transportation literature, in particular traveller behaviour research. Within a linear utility framework, the scheduling model and the mean-variance model, typically developed empirically within the stated choice theoretic framework, are two dominant approaches to empirical measurement of the value of time variability (Small *et al.* 1999; Bates *et al.* 2001; Arellana *et al.* 2012). The majority of recent travel time variability valuation studies (see Li *et al.* 2010 for a review) are established on Maximum Expected Utility (MEU), a theory proposed by Noland and Small (1995) where the attribute levels of travel time are weighted by the corresponding probabilities of occurrence, to address the fact that travel time variability leads to multiple possible travel times for a trip. Under MEU, a scheduling model is given in equation (1).

$$E(U) = \beta_{E(T)} E(T) + \beta_{ESDE} E(SDE) + \beta_{ESDL} E(SDL) + \beta_{Cost} Cost + \dots \quad (1)$$

The expected utility $E(U)$ is a linear function of the expected travel time ($E(T)$), the expected schedule delay early ($E(SDE)$) which is the amount of time arriving *earlier* than the preferred arrival time (PAT) weighted by its corresponding probability of occurrence, the

expected schedule delay late ($E(SDL)$) which is the amount of time arriving *later* than the preferred arrival time weighted by its corresponding probability of occurrence, and other attribute such as cost.

Under MEU, a mean variance model is defined in equation (2).

$$E(U) = \beta_{E(T)}E(T) + \beta_{SD}SD(T) + \beta_{Cost}Cost + \dots \quad (2)$$

where SD is the standard deviation of travel time.

In the stated choice experiment for travel time variability, a series of possible travel times for an alternative (departure time, route or mode) are used to represent travel time variability in many studies. For example, the experiment designed by Small *et al.* (1999) accommodates the measurement of travel time variability for cars by both the mean variance model and the scheduling model (see Figure 1).

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

Figure 1. SP task from Small et al. (1999)

The design attributes in this experiment are mean travel time, travel cost, departure time shift, and standard deviation of travel time; while each alternative in the experiment is represented by the mean travel time, travel cost, and five equi-probable arrival scenarios (early, late or on time) with respect to the PAT to illustrate the existence of travel time variability. For the mean-variance model, the standard deviation of travel time is calculated as equation (3).

$$SD(T) = \sqrt{0.2 \sum_{i=1}^5 [X_i - E(X)]^2} \quad (3)$$

where X_i is five schedule delay values (i.e., the difference between the preferred arrival time and the actual arrival time) for each alternative. The example values for alternative A in Figure 1 are -7, -4, -1, +5 and +9, and each has a probability of 0.2 (assuming equi-probable), where the negative sign indicates arriving earlier than the PAT (i.e., schedule delay early (SDE)) and the positive sign indicates a later arrival relative to the PAT (i.e., schedule delay late (SDL)), suggesting that the probability of arriving early is 0.6 and 0.4 for arriving later; and $E(X)$ is the expected value or average of schedule delay. For the scheduling model, the expected values for SDE and SDL are:

$$ESDE = \frac{(7+4+1+0+0)}{5} = 2.4 \quad (4a)$$

$$ESDL = \frac{(0+0+0+5+9)}{5} = 2.8 \quad (4b)$$

Equations (4a&4b) are originally provided in Small *et al* (1999) for calculating *ESDE* and *ESDL*. We transform equations (4a&4b) into equations (4c&4d) which directly illustrate the essence of *Maximum Expected Utility*, i.e., the probability weighted travel time as an attribute in the utility function.

ESDE= the probability of early arrival * the average minutes of arriving earlier than the preferred time = $0.6 * \frac{7+4+1}{3} = 2.4$; (4c)

ESDL= the probability of early arrival * the average minutes of arriving earlier than the preferred time = $0.4 * \frac{5+9}{2} = 2.8$ (4d)

The majority of travel time variability SC 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., Holland 2006), some provided 10 travel times instead of five (e.g., Bates *et al.* 2001), and some show the departure time explicitly to the respondents (e.g., Holland 2006)). For the probabilities of possible travel times for an alternative, either they were assumed equally distributed (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). The decision context covers departure time choice, route choice and modal choice. In addition to passenger cars (e.g., Small *et al.* 1999), public transport is also considered (e.g., Bates *et al.* 2001 for rail passengers; Holland 2006 for bus passengers; Tseng and Verhoef 2008 for a mix of passenger cars and public transport users¹).

These studies recognised travel time variability in their stated choice experiments in terms of a series of travel times for a trip (e.g., five or 10), and directly used the provided probabilities in the experiments to weight travel times. However, Allais (1953) in his paradox suggests that designed probabilities given in choice experiments are in reality transformed by respondents. To account for the perceptual translation of agents, non-linear probability weighting was introduced by a number of authors to transform the analyst-provided probabilities into chooser perceptions. Therefore, the transformed probability, rather than the original probability, should be used as the weight, if such perceptual conditioning exists. To address this issue empirically, we use the non-linear probability weighting function proposed by Tversky and Kahneman (1992), shown in equation (5), which has been widely used in psychology and behavioural economics.

¹ In Tseng and Verhoef (2008), a generic public transport is defined in their SC experiment, rather than a specific type(s) of public transport (e.g., bus, rail, metro) defined in this study.

$$w(p_o) = \frac{p_o^\gamma}{[p_o^\gamma + (1 - p_o)^\gamma]^\frac{1}{\gamma}} \quad (5)$$

$w(p_o)$ is a non-linear probability weighting function; p_o is the probability associated with the o^{th} outcome for an alternative with multiple outcomes (e.g., travel times over repeated trips for the same origin and destination and start time); and γ is the probability weighting parameter which needs to be estimated; if $\gamma \neq 1$, then $w(p) \neq p$, which implies the existence of non-linearity in probability weighting (i.e., the original probabilities shown in the experiment would be over-weighted ($w(p) > p$) or under-weighted ($w(p) < p$) by respondents).

3. An Alternative Modelling Framework

In reality, for a repeated trip, there is a distribution of travel time rather a single time for a trip, influenced by day-to-day fluctuations (i.e., travel time variability) on the demand side as well as the supply side of traffic, as shown in Figure 2 (van Lint *et al.* 2008). Hence, both the levels of times and probabilities of occurrence needed to be addressed simultaneously to measure the distribution due to travel time variability.

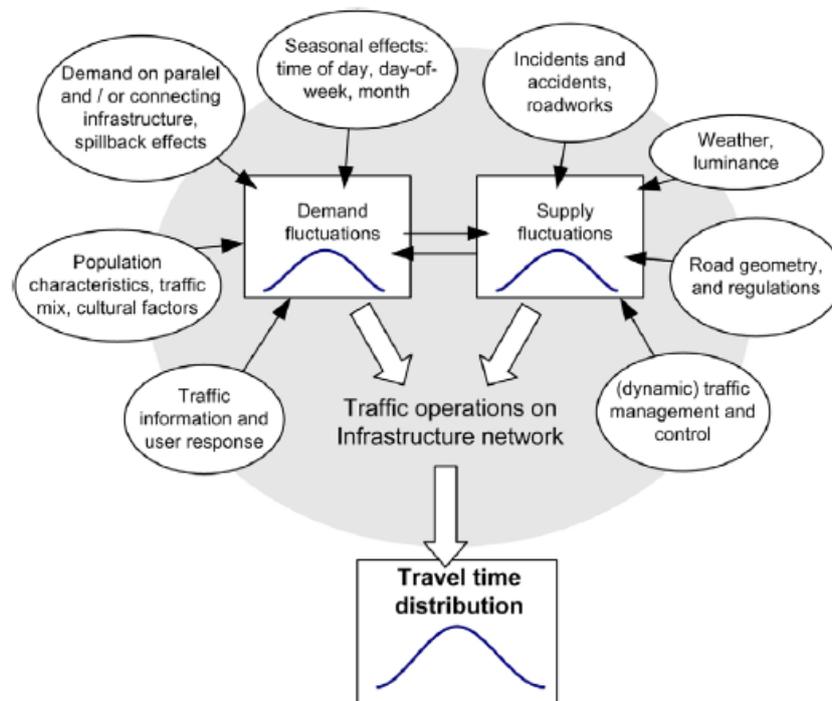


Figure 2. Factors impacting the distribution of travel time

In the previous section, we introduced two state-of-practice approaches to travel time variability valuation, where utility is represented by either a linear function of the average travel time, the expected schedule delay early (ESDE), the expected schedule delay late

(ESDL) and other attributes (e.g., travel cost) in the scheduling model, or a linear function of the expected travel time, the standard deviation of travel time (SD) and other attributes in a mean-variance model. In this section, an alternative modelling framework is introduced, which takes into account the full distribution of travel time (times and probabilities). This framework, namely the valuation of expected travel time savings (VETTS), developed by Hensher and Li, has been implemented in a number of travel time variability valuation studies for passenger cars (see e.g., Hensher and Li Forthcoming; Hensher *et al.* 2011a). Instead of treating mean travel time and variability separately, this VETTS framework integrates these two components of a travel time distribution, and a simplest form is shown in equation (6) with more than one possible travel scenario for a trip.

$$U = \beta_{E(T)}[\sum_o (P_o * T_o)] + \beta_{Cost} Cost + \dots \quad (6)$$

T_o is the o^{th} possible travel time for a trip with a probability of P_o . Given that the probabilities of occurrence in the experiment may be transformed by respondents, we embed a non-linear probability weighting function to account for perceptual conditioning which has been ignored in the mean-variance and scheduling models. The alternative model is shown in equation (7).

$$U = \beta_{E(T)}\{\sum_o [W(P_o) * T_o]\} + \beta_{Cost} Cost + \dots \quad (7)$$

$W(P)$ is the non-linear probability weighting function. In this model, in addition to the taste parameters such as $\beta_{E(T)}$ (the expected travel time parameter) and β_{Cost} (the cost parameter), the parameter determining the probability weighting curvature (e.g., γ shown in equation 5) also needs to be estimated, which demonstrates how the original probabilities (P) are transformed into decision weights ($W(P)$). The detailed models for this study are defined in Section 5, along with the WTP formula which accommodates the impact of transformed probabilities on the value of VETTS.

4. Empirical Application

The empirical focus herein is on deriving the willingness to pay (WTP) pay for expected travel time savings while taking into account the transformation of the probabilities of the travel time distribution provided in the choice experiment. The data are drawn from a study undertaken in Sydney to identify the patronage potential of a proposed Metro rail system for Sydney. As part of this study, a stated choice (SC) study (modal choice) was undertaken to establish the role of attributes such as travel times, variability in time, costs and crowding.

The SC experiment is in the context of modal choice including car, bus, rail and proposed metro. Any one respondent however is limited to choosing amongst a maximum of two existing alternatives plus the proposed Metro. The survey itself was conducted using a computer aided programmed interview (CAPI) with respondents asked to provide information, either real or perceived, associated with relevant alternatives for a recent trip that they undertook. The SC experiment then ‘pivots’ the attribute levels of the various alternatives, where a pivot from the reference trips makes sense. The attributes to pivot are the travel times and costs.

Given that road modes (i.e., bus and car) are inevitably associated with delays and uncertainty in trip times due to traffic, breakdowns and accidents etc., travel time variability

applies to bus and car in the experiment, which is defined as three possible travel scenarios for a trip: quickest, normal and slowest, and each has a level of travel time and corresponding probability of occurrence. For car and bus modes, the probability for the quickest trip ranges from 0.1 to 0.3, 0.4-0.6 for the normal trip time, and 0.1-0.3 for the slowest trip time, and a car or bus alternative has a mix of three scenarios in the experiment. For rail modes, a single trip time is emphasised, on the reasonable assumption that the existing rail system and the proposed new Metro are not influenced by traffic levels². Each sampled respondent evaluated six (6) choice profiles, choosing amongst a maximum of two stated choice (SC) alternatives defined by existing alternatives plus the Metro. An example choice scenario screen is shown in Figure 3 for metropolitan wide trips. In addition to travel times, time variability and costs or fares, other important service quality attributes for public transport (PT) are also included in this choice experiment such as crowding represented as *the percentage of passengers seated* (25%-100% in the design) and *the number of standing passengers* (0-27 for bus/light rail, 0-120 for train and 0-125 for metro in the design), the number of transfers, and headway showing the frequency of service (e.g., every 6 minutes a service). For a full description of the design and characteristics of the SC experiment, see Hensher *et al.* (2011b).

Practice Scenario		Car	Metro	City Rail
Departure time	---	---	---	---
Desired arrival time	8:30 AM	8:30 AM	8:30 AM	8:30 AM
Getting to your main mode of transport				
Walk time	OR	19 mins	13 mins	13 mins
Public transport time (including time spent waiting)	OR	12 mins	9 mins	9 mins
Fare (one-way)	OR	\$1.50	\$2.25	\$2.25
Car travel time	OR	6 mins	10 mins	10 mins
Parking cost	OR	\$5.63	\$0.00	\$0.00
Main mode				
Fuel cost	OR	\$2.88	\$5.00	\$5.00
Toll cost	OR	\$3.75	0	2
Parking cost (per day)	OR	\$2.63	every 6 mins	every 40 mins
Quickest trip time	OR	47 mins (40%)	21 mins	35 mins
Travel time on average	OR	51 mins (40%)	21 mins	35 mins
Slowest travel time	OR	63 mins (20%)	21 mins	35 mins
Level of crowding	OR		25% of seats are occupied, 0 people are standing	100% of seats are occupied, 90 people are standing
Getting from the main mode to your destination				
Walk time	OR	11 mins	12 mins	7 mins
Public transport time (including time spent waiting)	OR	11 mins	10 mins	11 mins
Fare (one-way)	OR	\$2.25	\$2.00	\$2.00
Car pick up from stop at station / taxi time	OR / AND	4 mins	4 mins	4 mins
Taxi fare	OR / AND	\$6.75	\$5.25	\$5.25
Your choice of travel				
Given the above information, if I were to make the same trip that I described previously and these were the options available to me, I would choose to travel by	OR	<input type="radio"/> Car	<input type="radio"/> Metro	<input type="radio"/> City Rail

We are now going to ask you to do 6 similar scenarios. Please make sure that you understand what you are being asked to do, as the interviewer is not allowed to help you after you go to the next screen. Also, recall that we want you to take this task seriously, as the results may help shape policy outcomes in the future. Thus, by not telling us what you would likely do in real life if you were really presented with these options, money may be spent on infrastructure improvements in a manner that you do not want.

Figure 3. Example Metro-wide Choice Scenario Screen

5. Empirical Analysis: a VETTS Framework

Given that in the choice experiment a bus or car alternative has three possible travel times (quickest, normal and slowest) within each choice set, the form of the general model (equation 7) is estimated herein for bus and car modes, shown in equation (8) and (9), where a number of service attribute are included in the utility function for bus. For rail and metro modes, there is a single travel time for a trip (no travel time variability in the design). Therefore, the travel time is directly used as an attribute in the utility functions for rail and metro (i.e., $\beta_{Time} Time$); along with the service quality attributes as in the bus mode.

² Although in reliability, rail is 100% reliable in terms of travel time.

$$U_{Bus} = \beta_{E(T)_{Bus}} [W(P_Q)T_Q + W(P_N)T_N + W(P_S)T_S] + \beta_{Fare} Fare + \beta_{Crowding} Crowding + \beta_{Headway} Headway + \beta_{Transfer} Transfer \quad (8)$$

$$U_{Car} = \beta_{E(T)^*_{Car}} [W(P_Q)T_Q + W(P_N)T_N + W(P_S)T_S] + \beta_{Cost} Cost \quad (9)$$

where P_Q is the original probability shown in the experiment associated with the quickest trip time (T_Q); P_N is the original probability associated with the normal trip time (T_N); P_S is the original probability associated with the slowest trip time (T_S); $W(P)$ is the probability weighting function defined in equation (6) where the probability weighting parameter (γ) needs to be estimated; $Fare$ is the one-way ticket fare for public transport; $Cost$ is the total cost of using a car (fuel, toll and parking) for a commuting trip; the $Crowding$ attribute in the utility functions for bus, rail and metro has two forms: *the percentage of passengers seated interacted with the travel time*, and *the number of standing passengers interacted with the travel time*³; $Headway$ shows the frequency of service; and $Transfer$ is the number of transfers during the trip when using public transport; $\beta_{E(T)}$ is the *expected travel time* parameter, which applies to bus and car with three possible travel times for a trip. For rail and metro with a single trip time per choice set, the utility functions for rail and metro have the same attributes ($Fare$, $crowding$, $Headway$ and $Transfer$) as in equation (8) for bus, with the only difference being that the *travel time* parameter (β_{Time}) is estimated (i.e., $\beta_{Time} Time$).

We focus on the commuter sample which consists of 3,144 observations from 524 respondents (although non-commuting and employer-business trips were also surveyed). The final choice model reported in Table 1 is of the error component logit (ECL) form (see Greene and Hensher 2007 for the specification of ECL).⁴

Table 1. Commuter model: Public Transport (PT) and car travel⁵

Variable	Modes	Parameter	(t-ratio)
<i>Public Transport Mode</i>			
Mode-specific constant	Bus only	-11.0889	(-55.53)
Mode-specific constant	Train only	-11.6342	(-66.17)
Mode-specific constant	Metro only	-11.1612	(-83.70)
Fare (\$)	Bus only	-0.5569	(-16.78)
Fare (\$)	Train and Metro	-0.4817	(-20.35)
Travel time (T: mins)	Train and Metro	-0.03145	(-6.17)

³ For bus, the normal travel time is interacted in the crowding attribute.

⁴ The *Headway* parameter and the other *Crowding* parameter are non-significant, which are not reported in the table.

⁵ A referee suggests that we should compare the reported model with the constants only (market shares) model. To statistically compare these two models, a likelihood ratio test (see Ben-Akiva and Lerman 1985) is used with two degree of freedom. Given that the log-likelihood for the estimated constants only model is -2278.24 and the log-likelihood for the reported model in Table 1 is -2156.35, the calculated test statistic (i.e., two multiplies the difference between the log-likelihood values of two models) is 243.78. Given the critical value (chi-square), with 11 degree of freedom, of 19.68 at the 95 percent confidence level, the model report in Table 1 delivers a statistically better fit than the constants only model (not reported). We also estimated a model same as the one reported in Table 1 but without 'perceptual conditioning' (i.e., the original probabilities are directly used as weights); however the model without perceptual conditioning delivered some insignificant parameter estimates such as the expected travel time parameters for bus and the travel time parameter for train and metro. Given this, the model with perceptual conditioning is behavioural superior to the one without perceptual conditioning.

Expected Travel Time ($E(T)$: mins)	Bus only	-0.0604	(-5.66)
Crowding (#standing x travel time)	All PT	-0.00027	(-11.39)
Number of Transfers	All PT	-0.1663	(-3.71)
<i>Car Mode</i>			
Cost (\$)	Car only	-0.4430	(-77.63)
Expected Travel Time ($E(T)$: mins)	Car only	-0.3919	(-26.73)
<i>Perceptual Conditioning</i>			
Probability weighting (γ)	Bus, Car	2.0219	(43.48)
<i>Error Components</i>			
Bus, Train, Metro		-3.1252	(-2.22)
<i>Model Fits</i>			
Log-likelihood (β)		-2156.35	
Log-likelihood (0)		-4358.50	
Rho ² (relative to zero parameters)		0.5053	
Number of respondents		524	
Number of observations		3144	

The mode-specific constants for all public transport modes are negative (relative to the car-specific constant set to 0) and statistically significant. What this suggests is that, after accounting for the differential and correlated variances associated with the unobserved influences for each alternative, as well as the rich specification of factors that really do matter to travellers who are in-scope, that there remain significant unobserved influencing effects, on average. All parameter estimates are of the expected sign, for example the parameters for crowding and the number of transfer are negative, as well as cost (fare) and time. The curvature of the non-linear probability weighting function, with the estimate of γ of 2.0219, is given in Figure 4, suggesting that the original probabilities are underweighted ($W(P) < P$). The non-linear probability weighting parameter is statistically different from 1 with an impressive t -ratio of 21.98 ($= (2.0219-1)/0.0465$, where 0.0465 is the standard error of γ), showing the existence of perceptual conditioning; that is, the probabilities associated with possible travel times shown in the experiment are transformed into decision weights. This transformation would also impact the valuation of expected travel time savings for car and bus shown in the VETTS formulae 10 and 11.

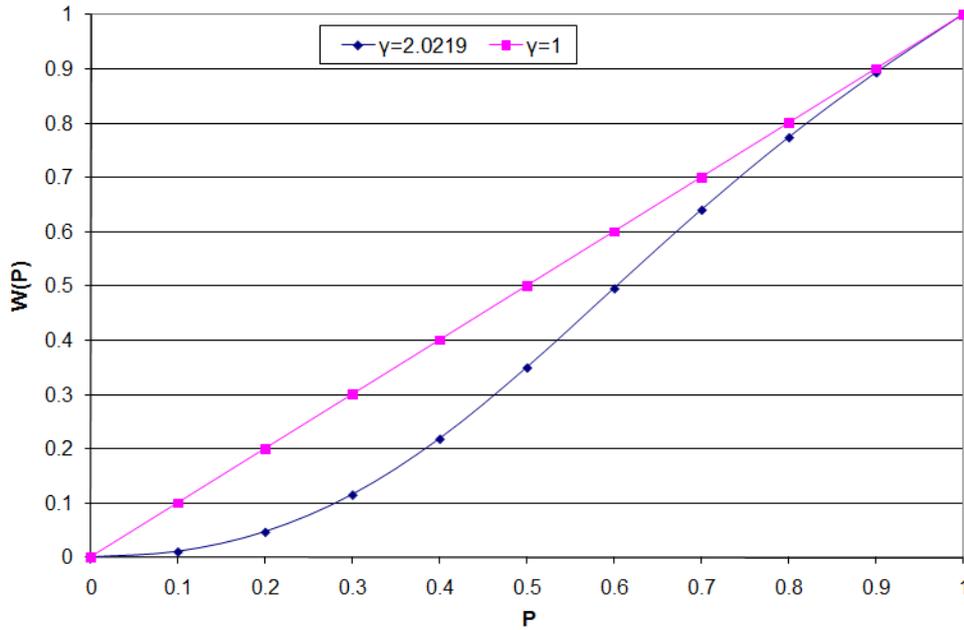


Figure 4. Identified probability weighting curvature

$$VETTS_Bus = \frac{\beta_{E(T)-Bus} [W(P_Q) + W(P_N) + W(P_S)]}{\beta_{Fare}} \quad (10)$$

$$VETTS_Car = \frac{\beta_{E(T)-Car} [W(P_Q) + W(P_N) + W(P_S)]}{\beta_{Cost}} \quad (11)$$

In addition to the estimated expected time parameter and the cost (or fare) parameter, the VETTS value is also influenced by the transformed probabilities ($W(P)$). Based on the original probabilities in the design and the estimated probability weight parameter, the VETTS distributions for bus commuting and car commuting are given in Figures 5a and 5b, where the mean VETTS for bus travel is Au\$3.51 per hour with a standard deviation of Au\$0.42 per hour, and the mean VETTS for car travel is Au\$28.59 per hour with a standard deviation of Au\$3.39 per hour. By accounting for perceptual conditioning through a non-linear probability weighting function (see Figure 4), the VETTS framework is capable of capturing the impact of the transformed probability distribution of travel time due to travel time variability on WTP measures (see Figure 5a and 5b), where the standard deviations are caused by different levels of transformed probabilities.

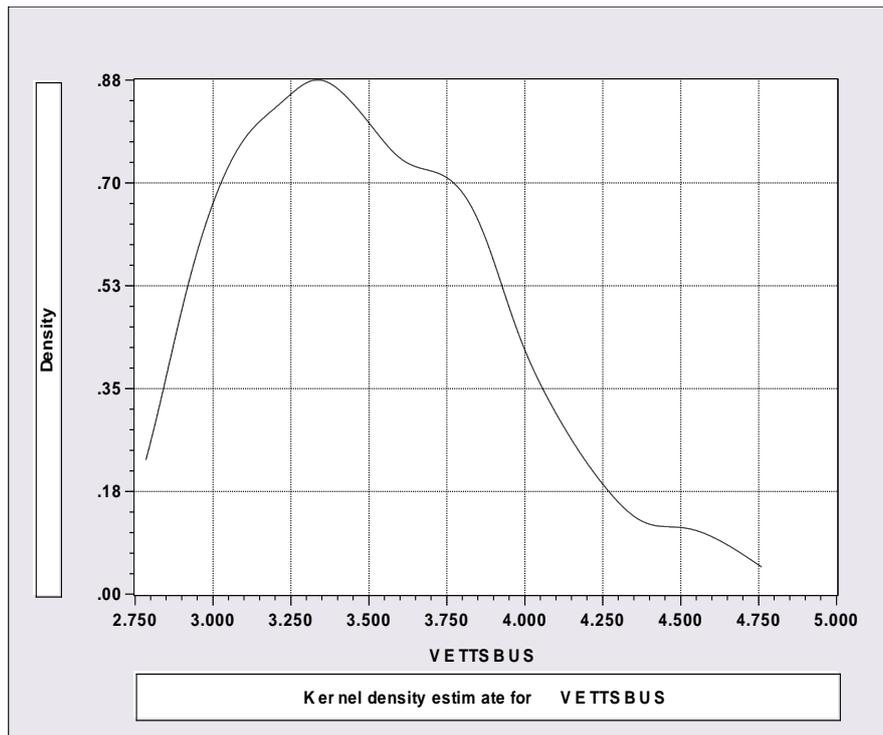


Figure 5a. VETTS distribution for bus

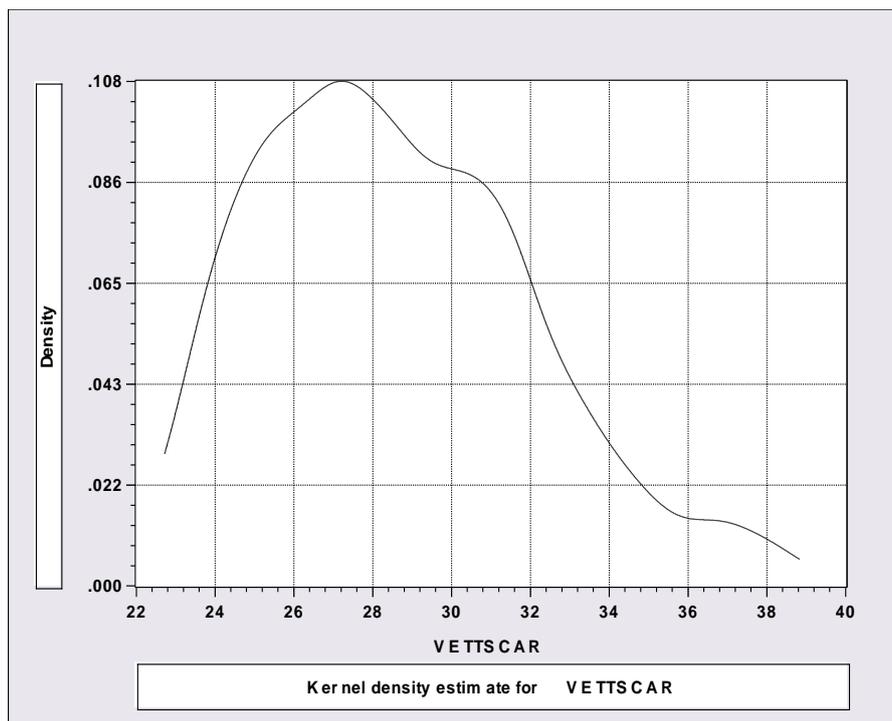


Figure 5b: VETTS distribution for car

6. Policy Implication

The approach presented in this paper takes into account both the possible levels of travel times and their probabilities of occurrences (i.e., the travel time distribution). To directly

illustrate the policy value of the approach, we construct relevant probability distributions within the range of the designed probabilities use these to calculate corresponding VETTS values for bus and car commuting, shown in Table 2⁶.

This policy scenario assessment suggests shows that the VETTS values vary across the assumed probability distributions defined over three typical possible travel times for a repeated trip (normal, slowest and quickest travel times), under the estimated probability weighting function. For car commuters, the VETTS estimates range from Au\$23.83 per person hour to \$32.97 per person hour, and for bus commuters the range is Au\$2.92 - 4.04 per person hour.. By asking a respondent to provide their observed probabilities for normal, slowest and quickest travel times over the repeated commuting experience from home to work during the previous weeks, policy analysts can derive the corresponding WTP values at the individual level. Suppose a sampled car commuter has a probability distribution with 50 percent chance of the normal trip time, 30 percent chance of the slowest trip time and 20 percent chance of the quickest trip time (i.e., ProbComb3), the corresponding VETTS is Au\$27.16 per person hour.

Table 2. VETTS values for bus and car commuting under assumed probability distributions (VETTS: 2009Au\$ per person hour)

	Normal	Slowest	Quickest	VETTS_Bus	VETTS_Car
ProbComb1	0.40	0.30	0.30	2.92	23.83
ProbComb2	0.45	0.30	0.25	3.08	25.12
ProbComb3	0.50	0.30	0.20	3.33	27.16
ProbComb4	0.55	0.30	0.15	3.66	29.83
ProbComb5	0.60	0.30	0.10	4.04	32.97
ProbComb6	0.45	0.25	0.30	3.08	25.12
ProbComb7	0.50	0.25	0.25	3.27	26.71
ProbComb8	0.55	0.25	0.20	3.55	28.95
ProbComb9	0.60	0.25	0.15	3.89	31.69

7. Conclusions

The empirical model in this study takes into account the travel time distribution due to the presence 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. A non-linear probability weighting function is used to account for perceptual conditioning to illustrate how the probabilities of travel scenarios (i.e., quickest, normal and slowest times in this choice experiment) provided in the experiment are transformed into probability weights. Within this framework, we can derive a single estimate of the value of expected travel time savings (VETTS) as an alternative to separate estimates of values of time savings and travel time reliability.

In addition to the empirical framework, the stated choice experiment used in this study offers some improvements over previous travel time variability valuation studies. The majority of

⁶ Table 2 tells the same story as shown in Figures 5a and 5b, but in a more direct way to illustrating the impact of the travel time probability mix on the VETTS.

previous experiments for travel time variability valuation have one travel mode only (see e.g., Small *et al.* 1999 with car only; Bates *et al.* 2001 with rail only; Hollander 2006 with bus only), and hence the choice is between different routes or departure times. As far as we are aware of, only Tseng and Verhoef (2008) provided both car and public transport alternatives within each choice question. Compared with previous studies, the design of this study offers both car and specific types of public transport (including the proposed metro and other existing PT) if a respondent has used a car recently; while only PT modes are shown to the respondent if they do not have a car available for the recent trip.⁷ This adds realism to the choice experiment, and more importantly it addresses the competition (choice) between car and PT, as well as the competition within PT (e.g., bus vs. rail), which provides a fuller picture of travel modal choice.

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⁷ The number and types of alternatives to be shown vary from respondent to respondent. This variation is determined by the responses given by respondents early in the survey in terms of the availability of the various alternatives for the recent trip being examined. For example, if the respondent reports not having a car available for the recent trip, then the car alternative will not be present in the SC experiment.

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