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Impact of information on risk attitudes: Implications on valuation of reliability and information

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Risk attitudes are an important behavioural characteristic that influences people's valuation of information and reliability. In a transport context, information has become widely accessible to road users through ITS systems, GPS technology and the internet justifying the importance of understanding the valuation of information by travellers. There have been a number of studies that have looked at the value of information and the value of reliability for a road user. However, to date there has not been a study that explicitly evaluates the impact of having information within a choice set on an individual's risk attitudes, which ultimately affects their valuation for information and reliability. This study conducts a controlled laboratory experiment, using methods of experimental economics, to measure the risk attitudes of users with and without the presence of information in the choice set. A model derived from Expected Utility Theory is used to infer the risk attitudes of the participants. The results of the analysis indicate that the presence of information in the choice set reduces risk aversion, which causes a reduction in people's valuation of information and reliability. It is critical to systematically incorporate these differences into behaviour models, since neglecting this fundamental difference could result in erroneous policy decisions, with respect to overpricing information, or inappropriately allocating funds for information systems.

1. Introduction

The provision of online information about driving conditions has become increasingly prevalent throughout transport networks. Information was initially provided with signage for upcoming detours and road works; this was further reinforced with radio traffic reports and the utilisation of Variable Message Signs (VMSs). Within the last decade, information has become even more accessible through Advanced Traveller Information Systems (ATIS), GPS navigation technology and the internet. Congestion mitigation strategies utilising information has predominantly been used to influence route choice behaviour to distribute traffic in an efficient manner (Mahmassani et al., 1986). It is therefore critical for transportation agencies to understand the value travellers place on information.

Information is used to reduce risk or at best resolve it. Risk attitudes influence the value an individual places on information and reliability within a transport network. An individual who is risk averse would have a greater value of information and reliability as compared to a risk loving person and therefore an individual's risk attitude influences their

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choice regarding information acquisition. Furthermore, the presence of information within a user's choice set may impact their risk characteristics which can affect the value of an information source post implementation. Thus, if risk attitudes impact upon the valuation of information by a user, neglecting these impacts could result in disastrous pricing and investment strategies regarding infrastructure for information provision. This study attempts to address the critical question: Do risk attitudes remain the same when people are placed in a context where information acquisition is a choice? The answer to this question has wide ranging impacts on the valuation of information and reliability.

This study uses methods of experimental economics to design a controlled laboratory experiment to study risk attitudes and the choice of information acquisition in context of driving behaviour. The value of using laboratory experiments with methods from experimental economics is the ability for the researcher to induce utilities and study behavioural parameters, which is not possible with field data. Field data limits the control of variables and thus makes it difficult to isolate and study behavioural parameters and test theories. Vernon Smith won the Nobel Prize for Economics for his work on Induced Value Theory (Smith, 1976, 1982), which underpins the science of the methods within experimental economics.

The findings of this study indicate that the presence of information acquisition in the choice set results in a reduction in an individual's risk aversion. This implies that individuals actually value information and reliability much less compared to what would be estimated based on data where information acquisition was not in the choice set.

This paper is structured to first present the relevance of this study in the context of available literature. Section 3 provides details regarding the experimental design, which is followed by Section 4 that discusses the maximum likelihood procedure used to estimate the risk attitudes. Section 5 presents the results and the paper concludes with a discussion of the contribution and findings of the study.

2. Literature review

Information aims to mitigate the presence of risk and uncertainty, therefore the value individuals place on information and reliability is related to their risk attitudes. Jackson and Jucker (1982), suggest that travellers consider more than just expected travel time when selecting a route, but also the level of reliability. Since then, there have been numerous studies (Bates et al., 2001; Lam and Small, 2001; Brownstone and Small, 2005) over the years which have presented empirical evidence on the value travellers place on reliability while evaluating routes and transport modes.

Users make decisions based on *a priori* and online information. This particular study considers the behavioural implications with regard to online information which is received whilst a traveller is traversing a road network. Thus, from this perspective, the departure time of users is a foregone decision and will not affect their risk attitudes towards the information provided en-route. Accordingly, this study differs from the work of Ettema and Timmermans (2006), Arnott et al. (1991) and Jou (2001) which focussed on the impact of information in the context of departure time. Further to these works, De Palma et al. (2012) developed a theoretical model with heterogeneous risk attitudes, and found that risk neutral and moderately risk averse drivers benefited from information, while risk averse drivers would pay for information that would not necessarily benefit them. However an important assumption in all these studies were that people's risk attitudes do not change based on the access to information. If risk attitudes of road users are affected by the presence of information, evaluation processes carried out to determine the feasibility of ATIS infrastructure will also be affected. The costs and benefits of these systems will offer a different utility to the user at different stages of the implementation. For an example, prior to the implementation of an information system users may be risk averse and value the reduction in uncertainty the system offers. However, post implementation if the risk attitudes of users change, the value of the information system will also change. Accordingly, an awareness of changes in risk attitude will have a significant impact within infrastructure planning and decision making related to ATIS systems. This study attempts to fill this gap in knowledge by understanding the impact of the presence of information on users' risk attitudes in a controlled laboratory setting.

Recently, a few revealed preference studies have been conducted to evaluate the impact of pricing on the demand for information. Jou and Chen, 2013, surveyed Taiwanese drivers to understand the demand for real-time information under varied pricing and traffic conditions. They found that the presence of non-recurring conditions resulted in the greatest demand for information. In a similar study conducted by Tseng et al. (2013), it was found that drivers tend to react more strongly to variations in travel time when information is provided. As with the previous works, these studies provide insight into the value of information without taking into consideration the implication of risk attitudes towards the presence of information in the choice set.

The concept of reliability and its measures, such as travel time variability, have been extensively studied in recent times. The importance of reliability has been described in detail from a user perspective as well as a transport planning and operations level (Batley et al., 2009; Li et al., 2010; Robuste and Soriguera, 2010). In fact, travel time reliability has been valued more highly than travel time itself according to the study conducted by Batley et al. (2009). Risk attitudes have been incorporated in the measurement of travel time variability and the valuation of travel time savings (Hensher et al., 2011, 2013; Li et al., 2012; Hensher and Li, 2012). Hensher et al. (2011), Li et al. (2012) and Hensher et al. (2013) present a series generalised non-linear logit models which incorporates probably weighting of users and their risk attitudes within the utility function,. The models apply an extension of conventional Expected Utility Theory (EUT), "Extended Expected Utility Theory (EEUT)" by incorporating the underlying probabilities of outcomes for an attribute as a probability weighting function. By embedding these behavioural characteristics, the model has the ability to account for travel time variability in a holistic manner. The study presents a number of novel empirical findings with the presentation of a new willingness to pay metric, "value of time variability-embedded travel time savings" (VETTS). Hensher et al. (2013) suggests that the users transform probabilities presented within stated choice surveys resulting in overweighting of outcomes with low probabilities and underweighting of outcomes with high probabilities. In addition to the use of EUT, Prospect Theory (PT) and Regret Theory (RT) have been used to model and understand behaviour under risk and uncertainty in a route choice context. However as described by Li and Hensher (2011) there are a number of limitations involved with these approaches related to the necessity of a reference point when analysing a choice. This study contrasts to previous literature by attempting to understand the impact of exogenous provision of online information on the risk attitudes of the user and developing a simple measure to value reliability using data from a controlled laboratory experiment.

Li et al. (2010) provides a review of the different modelling approaches in the valuation of reliability which include the mean-dispersion model (Jackson and Jucker, 1982), the scheduling model (Bates et al., 2001; Small, 1982) and the mean lateness model (Batley and Ibáñez, 2012). In general, most applications of these models and other empirical valuations of reliability have focussed on the standard deviation of travel time (Bates et al., 2001; Lam and Small, 2001; Brownstone and Small, 2005). An alternative way to measure value of reliability is to evaluate the risk premium (Batley, 2007; Beaud et al., 2012). A risk premium is the amount of money an individual would forgo to resolve uncertainty and has been used extensively in Finance and Economics (Pratt, 1964). The paper by Beaud et al. (2012) compares individuals value of travel time savings under different risky scenarios to measure the value of reliability. Thus, by comparing a risk free scenario to one associated with risk a "risk premium" measure is derived. Prior to this study, Batley (2007) extends the seminal works of Pratt (1964) in the context of total travel time and defines a "reliability premium". The reliability premium is the "delay to arrival time that the individual would be willing to pay in exchanging for eliminating unreliability in arrival time". This approach has been applied within this study, however instead of considering the elimination of the unreliability of the arrival time; the premium is measured relative to the exact knowledge of the delay time through the provision of online information.

Revealed preference data provides useful insights, however due to lack of control in the field it is extremely difficult to isolate the impact of information on risk attitudes. Therefore methods from experimental economics have been used to achieve this goal, through salient incentives that induce the value of the utilities. This property of experimental economics is well defined under Induced Value Theory (Smith, 1982). To this end, controlled laboratory experiments have been extensively used to study driving behaviour. In particular there have been studies relating equilibrium principles as well as individual travel behaviour (Rapoport et al., 2006, 2008; Nielsen, 2004; Gisches and Rapoport, 2010; Dixit and Denant-Boemont, 2013). There have also been a few studies which have investigated the impact of information on route choice with the use of laboratory experiments (Denant-Boèmont and Petiot, 2003; Ziegelmeyer et al., 2008; Selten et al., 2007; Ben-Elia et al., 2013; Chorus et al., 2013).

Experimental economics in transport has predominantly been used to explore equilibrium behaviour. Selten et al. (2007) conducted an experiment to study equilibrium properties in route choice behaviour and the impact of information. They concluded that provision of information was beneficial to the road users and reduced system costs. Ziegelmeyer et al. (2008) studied the impact of information on departure time behaviour, and concluded that information did not impact departure time behaviour. However, this can be attributed to a "stranger" design in their experiment where users were randomly assigned to cohorts after every round, and prior information would not have any value in such a setting.

Ben-Elia and Avineri, (2015a) provides a comprehensive review of experimental impacts of information, however, within this section of the paper only a few of the relevant studies are detailed. One of the first experimental economic studies evaluating the impact of information on traffic was conducted by Denant-Boèmont and Petiot (2003). The research investigated how individuals value information under different levels of information in the context of mode choice. Though the authors assumed risk neutrality, they found that individuals tended to pay a higher value for information as the risk increased, suggesting that risk attitudes could play a role. An interesting driving simulator study conducted by Chorus et al. (2013) found that travellers have intrinsic preferences for certain types of information over others, and these preferences do not necessarily relate to the economic value of the information. Further, Ben-Elia et al. (2008) found evidence that information seemed to increase risk seeking behaviour. In fact, the revealed preference study by Tseng et al. (2013) also suggested a change in behaviour with provision to information. These findings provided an impetus to the main focus of our study, to investigate whether information influences risk attitudes.

There lies a substantial gap in understanding how information in a choice set might affect risk attitudes. This understanding will provide insight into how individuals value information and reliability in a driving context. To study this, a controlled experiment was conducted using methods from experimental economics.

3. Experimental design

The experiment was designed to understand route choice behaviour with and without the presence of information within a choice set. The structure involved utilising four multiple price list (MPL) (Holt and Laury, 2002) lotteries considering:

- Two choice tasks without the presence of information but with tolls and

- Two choice tasks with the presence of information

MPL lotteries contain a series of paired lottery choices (normally 10), one being of greater risk than the other. The payoffs for each paired lottery remain the same for the series whilst the probability associated with each of the payoffs change. The participant selects which lottery he or she would prefer to play for each pair across the series. The concept behind the MPL lottery is that a participant would select the low risk lottery until the high risk lottery provides a greater probability of the higher payoff to occur, and when this occurs, the participant would cross over to the high risk lottery. An individual's risk preference can be measured by assessing when participants make this switch from the low risk lottery to the high risk lottery (Charness et al., 2013). The advantage of using MPL lotteries over other simpler risk elicitation methods is that the method can estimate parameters of a model (assuming a particular functional form for the utility of a person) corresponding to risk preferences (Charness et al., 2013). The ability to measure the degree of risk aversion is essential to understand the impact of the presence of information within the choice set on the risk attitudes of the participant pool.

In this study the lotteries were framed as route choice problems with uncertainty in travel times. The tasks required participants to choose between two competing routes, where each route contained 2 possible delay outcomes, across 10 separate lotteries presented to the participants as "decision scenarios". It is important to note that the free flow travel time on the routes presented were identical and these routes served as alternative options for users, the only difference is the level and likelihood of additional delay that could occur for each of the routes. One route option contained low variability between the delays (either a 5 minute or 6 minute delay) serving as the low risk option whilst the other option contained a higher variability between the delays (either a 9.75 minute or 0 minute delay) serving as the high risk option. The probabilities associated with the delay outcomes provide participants an indication to the historical performance of each route, depicting the experience road users (in particular commuting traffic) would naturally obtain from day to day travel. The decision scenarios were structured to describe the various driving conditions on the competing routes, as well as offering to identify the cross-over point between the high and low risk route options.

A comparison of the variances of each decision scenario across both routes is presented in Table 1 highlighting the difference in reliability of each route. The variance for each scenario is calculated using the formula: $E[X^2] - \left(E\left[X\right]\right)^2$, where X represents the delay outcomes. It is evident from Table 1 that Route B has a considerably higher variance to that of Route A, thus confirming that Route A is a relatively lower risk selection. Decision scenario 10 provides a sanity check for the experiment. In this case, Route A will definitely result in 5 minutes of delay whilst Route B for certain will have a 0 minute delay. Participants who understand the tasks and are aiming at maximising profit will always select Route B in this case. All participants selected Route B suggesting a sound understanding of the experiment procedure. A participant would initially select the lottery across each of the decision scenarios and the outcome of a specific scenario was dependent on the rolling of a die. Excerpts of two of the choice tasks presented to a participant are shown in Fig. 1 (without information) and Fig. 2 (with information). The MPL lottery task with the presence of information offered the opportunity for a participant to pay for information and realise the delay which will incur on both the routes. In this treatment, participants could select either Route A or Route B without purchasing any information or select the option to purchase information revealing the delay outcomes of each route. Given this information, a participant had the opportunity to guarantee minimisation of the delay incurred when travelling. It is vital to understand that selecting either Route A or Route B represents a simple lottery where

Table 1
Comparison of the variance across decisions scenarios and between lotteries.

Lottery 1 (Route A)				Lottery 2 (Route B)			
Decision	**Delay (minutes)**	**Probability**	**Variance**	**Decision**	**Delay (minutes)**	**Probability**	**Variance**
1	5	10%	0.09	**1**	0	10%	8.56
	6	90%			9.75	90%	
2	5	20%	0.16	**2**	0	20%	15.21
	6	80%			9.75	80%	
3	5	30%	0.21	**3**	0	30%	19.96
	6	70%			9.75	70%	
4	5	40%	0.24	**4**	0	40%	22.82
	6	60%			9.75	60%	
5	5	50%	0.25	**5**	0	50%	23.77
	6	50%			9.75	50%	
6	5	60%	0.24	**6**	0	60%	22.82
	6	40%			9.75	40%	
7	5	70%	0.21	**7**	0	70%	19.96
	6	30%			9.75	30%	
8	5	80%	0.16	**8**	0	80%	15.21
	6	20%			9.75	20%	
9	5	90%	0.09	**9**	0	90%	8.56
	6	10%			9.75	10%	
10	5	100%	0.00	**10**	0	100%	0.00
	6	0%			9.75	0%	

Decision	Motorway Route Choice A	Arterial Route Choice B	Toll for Motorway Route	Your Choice (Circle one)
1	5.00 min delay if throw of die is 1 6.00 min delay if throw of die is 2-10	0.00 min delay if throw of die is 1 9.75 min delay if throw of die is 2-10	$2.00	A B
2	5.00 min delay if throw of die is 1-2 6.00 min delay if throw of die is 3-10	0.00 min delay if throw of die is 1-2 9.75 min delay if throw of die is 3-10	$2.00	A B
3	5.00 min delay if throw of die is 1-3 6.00 min delay if throw of die is 4-10	0.00 min delay if throw of die is 1-3 9.75 min delay if throw of die is 4-10	$2.00	A B
4	5.00 min delay if throw of die is 1-4 6.00 min delay if throw of die is 5-10	0.00 min delay if throw of die is 1-4 9.75 min delay if throw of die is 5-10	$2.00	A B
5	5.00 min delay if throw of die is 1-5 6.00 min delay if throw of die is 6-10	0.00 min delay if throw of die is 1-5 9.75 min delay if throw of die is 6-10	$2.00	A B
6	5.00 min delay if throw of die is 1-6 6.00 min delay if throw of die is 7-10	0.00 min delay if throw of die is 1-6 9.75 min delay if throw of die is 7-10	$2.00	A B
7	5.00 min delay if throw of die is 1-7 6.00 min delay if throw of die is 8-10	0.00 min delay if throw of die is 1-7 9.75 min delay if throw of die is 8-10	$2.00	A B
8	5.00 min delay if throw of die is 1-8 6.00 min delay if throw of die is 9-10	0.00 min delay if throw of die is 1-8 9.75 min delay if throw of die is 9-10	$2.00	A B
9	5.00 min delay if throw of die is 1-9 6.00 min delay if throw of die is 10	0.00 min delay if throw of die is 1-9 9.75 min delay if throw of die is 10	$2.00	A B
10	5.00 min delay if throw of die is 1-10	0.00 min delay if throw of die is 1-10	$2.00	A B

DECISION ROW CHOSEN BY FIRST THROW OF THE DIE: ________

THROW OF THE DIE TO DETERMINE DELAY: __________

EARNINGS: ______________

Fig. 1. Excerpt of choice tasks without information.

the roll of the die determines the delay and ultimately the payoff for the participant. In contrast, the choice to purchase information constitutes a compound lottery where the final route choice is dependent on rolling the die for Route A and then Route B.

Experiments using monetary incentives provide a high degree of control in laboratory setting to study individual preferences (Dixit et al., 2014; Selten et al., 2007). The lottery tasks were incentivised to elicit preferences based on actual

Decision	Freeway Route Choice A	Arterial Route Choice B	Information Choice C	Your Choice (Circle one)
1	5.00 min delay if throw of die is 1 6.00 min delay if throw of die is 2-10	0.00 min delay if throw of die is 1 9.75 min delay if throw of die is 2-10	$2.00	A B C
2	5.00 min delay if throw of die is 1-2 6.00 min delay if throw of die is 3-10	0.00 min delay if throw of die is 1-2 9.75 min delay if throw of die is 3-10	$2.00	A B C
3	5.00 min delay if throw of die is 1-3 6.00 min delay if throw of die is 4-10	0.00 min delay if throw of die is 1-3 9.75 min delay if throw of die is 4-10	$2.00	A B C
4	5.00 min delay if throw of die is 1-4 6.00 min delay if throw of die is 5-10	0.00 min delay if throw of die is 1-4 9.75 min delay if throw of die is 5-10	$2.00	A B C
5	5.00 min delay if throw of die is 1-5 6.00 min delay if throw of die is 6-10	0.00 min delay if throw of die is 1-5 9.75 min delay if throw of die is 6-10	$2.00	A B C
6	5.00 min delay if throw of die is 1-6 6.00 min delay if throw of die is 7-10	0.00 min delay if throw of die is 1-6 9.75 min delay if throw of die is 7-10	$2.00	A B C
7	5.00 min delay if throw of die is 1-7 6.00 min delay if throw of die is 8-10	0.00 min delay if throw of die is 1-7 9.75 min delay if throw of die is 8-10	$2.00	A B C
8	5.00 min delay if throw of die is 1-8 6.00 min delay if throw of die is 9-10	0.00 min delay if throw of die is 1-8 9.75 min delay if throw of die is 9-10	$2.00	A B C
9	5.00 min delay if throw of die is 1-9 6.00 min delay if throw of die is 10	0.00 min delay if throw of die is 1-9 9.75 min delay if throw of die is 10	$2.00	A B C
10	5.00 min delay if throw of die is 1-10	0.00 min delay if throw of die is 1-10	$2.00	A B C

DECISION ROW CHOSEN BY FIRST THROW OF THE DIE: ________

IF CHOICE A or CHOICE B, THROW OF THE DIE TO DETERMINE DELAY: ___________

IF CHOICE C, THROW OF THE DIE TO DETERMINE DELAY:

Select FREEWAY DELAY ________ ARTERIAL DELAY ___________

EARNINGS: _______________

Fig. 2. Excerpt of choice task with information.

choices being made for real consequences. Thus, participants were given not only delay information but also the information about the consequence of the delay, imposing a value of time. The participants received an initial income of $10 for each task and were informed that 1.00 min of delay resulted in a $1.00 reduction in income. In other words, the value of time was assumed to be $1 per minute. The without information choice tasks involved a toll route (Motorway Route) for the lower risk lottery, which when selected incurred a further reduction in income in addition to the delay experienced. This resulted in the participant paying a toll for reduced variability. In the case of the information choice task, the toll was removed and a fixed cost was charged for the provision of information. The experiment was incentivised to align the participants' goal of profit maximisation from completing the tasks, with the rational driving behaviour characteristic of attempting to minimise expected delays when travelling.

The value of time discussed within the experiment is related to delay time and not the value of travel time. As explained earlier, the free flow travel times were equal for both routes and participants were faced with the decision of selecting a route based on the additional delay that could be experienced on either of the routes. It is acknowledged that value of time associated with the delay is considerably greater than that of conventional value of time estimates. The 2012 Austroads Guide to Project Evaluation: Part 4: Project Evaluation data indicates that the value for travel time as $13.17 per person hour (Austroads, 2012), consistent with a number of other studies (Litman, 2009; Carrion and Levinson, 2012). According to the Bureau of Infrastructure Transport and Regional Economics (BITRE) (2009) which uses data obtained from the 2008 Austroads Guide to Project Evaluation, the value of delay time in dollars/hour/vehicle varies between $30 and $87 in an urban metropolitan setting for private vehicles which is comparable to the applied rate within the experiment. This concept is reflected in the premium users' place on reliability (Brownstone and Small, 2005; Small, 1999; Small et al., 2005) where delays in addition to the budgeted travel time or free flow travel time are of greater value than the value associated with the travel time itself.

The payoffs for each participant were calculated at the completion of all four choice tasks, described at the beginning of Section 3. The payoffs for the choice tasks not involving the presence of information were determined by the participant rolling a die first to determine which decision scenario that would be selected for payment, and then rolling the die a second time to determine the delay on the route selected by the participant.

The choice tasks involving the provision of information required an additional consideration. If a participant chose to obtain information for a specific decision scenario, and if that scenario was selected for payment upon the first roll of the die, the exogenously assigned cost to obtain information is deducted from the income. The participant then rolled the die separately for each of the routes to determine the exact delays. This process resolved the uncertainty of delay on the routes. Based on this the participant would then select the route, and the cost of delay on the chosen route was deducted from the income.

Table 2 presents the structure of all four tasks. In addition to completing the above tasks, participants were required to fill out a demographic questionnaire. The questionnaire was completed after the first 2 choice tasks were administerd and prior to the second 2 choice tasks, to provide participants a break and ensure the separation of the two sets of tasks.[1] To control for order effects, the sequence of the four choice tasks were varied across the sessions. The experiments with the following sequences of tasks were conducted across different sessions.

- Order 0: Low-Toll (Task 1), High-Toll (Task 2), Low-Information (Task 3), High-Information (Task 4)
- Order 1: Low-Information (Task 3), High-Information (Task 4), Low-Toll (Task 1), High-Toll (Task 2)
- Order 2: High-Toll (Task 2), Low-Toll (Task 1), High-information (Task 4), Low-Information (Task 3)
- Order 3: High-information (Task 4), Low-Information (Task 3), High-Toll (Task 2), Low-Toll (Task 1)

3.1. Recruitment process

Participants were recruited using the University of New South Wales Australian School of Business (ASB) Experimental Research Laboratory. Individuals could register to be part of human-subject experiments conducted at the University and invitation emails were sent to registered individuals to take part in the study. Admission to participate in the study was contingent on respondents being at least 17 years old and holding a valid driver's licence to ensure that participants understood the meaning of route choice in a real driving scenario. The study was completed at the University of New South Wales within the laboratory of the ASB Experimental Research group.

3.2. Sequence of events

The study consisted of seven 2 h sessions of experiments with a total of 156 participants completing all tasks of the experiment. The sessions were held on the following days:

- 7 November 2012, 16 participants (Order 0)
- 15 November 2012, 11 participants (Order 0)

[1] A complete set of experiment instructions can be made available upon request.

Table 2
Structure of choice tasks.

	Description	Presence of Information
Choice task 1 (Low-Toll)	Participants are required to choose between a Motorway Route (Choice A) with low variability of travel time (and the presence of a \$2 toll) against an Arterial Route (Choice B) with higher variability of travel time and no toll.	No
Choice task 2 (High-Toll)	Participants are required to choose between a Motorway Route (Choice A) with low variability of travel time (and the presence of a \$4 toll) against an Arterial Route (Choice B) with higher variability of travel time and no toll.	No
Choice task 3 (Low-Information)	Participants are required to choose between a Freeway Route (Choice A) with low variability of travel time against an Arterial Route (Choice B) with higher variability of travel time. Neither of these routes contained tolls.	Yes (Cost = \$2)
Choice task 4 (High-Information)	Participants are required to choose between a Freeway Route (Choice A) with low variability of travel time against an Arterial Route (Choice B) with higher variability of travel time. Neither of these routes contained tolls.	Yes (Cost =\$4)

- 16 November 2012, 20 participants (Order 0)
- 20 November 2012, 24 participants (Order 0)
- 26 November 2013, 33 participants (Order 2)
- 28 November 2013, 23 participants (Order 3)
- 14 March 2014, 28 participants (Order 1)

Upon arrival at the study site, the driver's licences of the participants were verified. After which, the participants were assigned seating locations within the laboratory. An informed consent form and the study documentation were presented to the participants as per University of New South Wales regulations. The consent form briefly explained the rights and responsibilities of each participant as well as assurance of the confidentiality of the information obtained within the study. The study documentation remained face down on the desk until the study began.

4. Estimation of risk attitudes

The purpose of the study is to compare risk attitudes of road users with and without the presence of the choice to purchase information. The methodology for the estimation process was guided by the assessment of subjective risks presented by Dixit et al. (2014) as well as the study of risk attitudes across different regions (Dixit et al., 2013). Expected Utility Theory (EUT)[2] is used as the theoretical basis of the modelling used to infer the risk attitudes of the participants.

Two different utility of income functions were used for the estimation process; the Constant Relative Risk Aversion[3] (CRRA) function (1) and the power function (2), where "x" is the payoff obtained from the lottery and "r" is level of the risk aversion.

$$U(x) = \frac{x^{1-r}}{1-r} \tag{1}$$

$$U(x) = x^r \tag{2}$$

The CRRA utility function assumes that users have a constant attitude towards risk expressed as a proportion of the level of income they receive (Friedman and Savage, 1948). The function has been commonly used throughout experimental literature and has been effective in measuring of risk attitudes within the context of the EUT framework throughout a variety of fields including economics, psychology, health as well as transportation (Rasouli and Timmermans, 2014, Abellán-Perpiñán et al., 2006; Andersen et al., 2008; Holt and Laury, 2002).

Under CRRA utility, risk neutral behaviour corresponds to "$r = 0$", risk loving behaviour when "$r < 0$" and risk averse behaviour when "$r > 0$". Considering the power utility function, risk neutral behaviour is indicated when "$r = 1$", risk loving when "$r > 1$" and risk averse when "$0 < r < 1$". The risk attitude parameter was estimated using maximum likelihood estimators and a latent EUT structural model of choice. The model uses the selections of the participants, either the binary choice in the without information case or ternary choice in the with information case, as the observed data within the latent class model. In order to measure the inferred risk attitude parameter, a latent index was formulated based on the multinomial logit specification accounting for the potential for any behavioural errors.

In order to explain the concepts of EUT applied for the estimation of the risk attitudes, consider the case with k possible outcomes and probabilities (p_k). As explained in the experimental design, these probability values are communicated to the participants in the task instructions. Therefore, the expected utility for a particular route, 'i', (a particular lottery in the

[2] The choice of using the expected utility model rather than non-expected utility model was driven by the experimental design, in which we had a random payment protocol. Based on work by Cox et al. (2014), due to the compound lottery nature of the prospects using non –expected utility models such as Rank Dependent Utility is problematic and results in incorrect inferences.

[3] For robustness check, analysis was also conducted with Constant Absolute Risk Aversion utility function and the findings were similar.

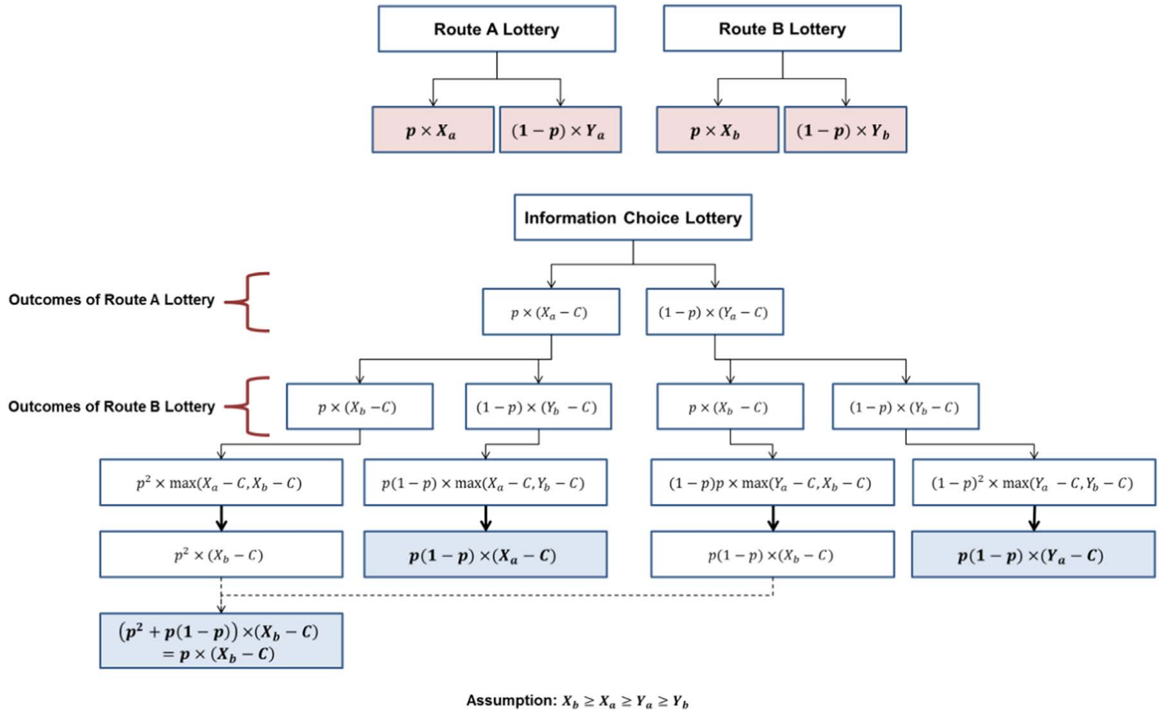

Fig. 3. Abstraction of the information lottery. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

context of MPL) can be described using Eq. (3):

$$EU_i = \sum_{k=1}^{K} (p_k \times U_k) \tag{3}$$

In the binary route choice case within the experiment, where participants can either choose route A or route B, each route had two different outcomes with complementary probabilities of 'p' and '$(1-p)$'. The users were given a fixed income (I) of \$10, while the toll (T) was either \$2 or \$4 (depending on the treatment). Therefore, given the assumption that the value of time is \$1 per minute, for a particular decision scenario, the expected utility accounting for tolls and delay outcomes can then be expressed as follows:

$$EU_{RouteA} = p \times U(I - T - 5) + (1-p) \times U(I - T - 6)$$
$$EU_{RouteB} = p \times U(I - 0) + (1-p) \times U(I - 9.75)$$

where $EU_X =$ expected utility of competing choices "X", ($X = RouteA, RouteB$)

$p =$ probability of delay outcome (5 minutes for motorway route and 0 minutes for arterial route).
$(1-p) =$ probability of alternative delay outcome (6 minutes for motorway route and 10 minutes for arterial route).
$I =$ Fixed income of \$10.
$T =$ Motorway toll (either \$2 or \$4 depending on the treatment).
$U(Y) =$ Utility of each monetary realisation "Y".

Fig. 3 presents the abstraction of the expected values of each lottery considered within the experiment and is useful to refer to whilst understanding the incorporation of information into the formulation. Within the diagram, the red shaded cells represent the expected value of the outcomes of the simple lotteries where participants select either Route A or Route B, while the blue shaded cells indicate the expected value of the compound lottery where participants have the option to purchase information.

In the case where purchasing information is in the choice set, a participant has three possible choices: Route A, Route B and purchase of information. If a participant chose to purchase information, the cost of information is deducted from his or her income and the participant was asked to roll the die to realise the delays incurred on Route A and then Route B. Upon receiving the delay information, the participant would choose the route with the lowest level of delay to maximise their profit. For example, consider that a participant selects the information choice for decision scenario 6. Firstly, the cost of information is deducted from the income; say in this case it is the low cost of information so the participant has a remaining income of \$8 (\$10–\$2). The participant then rolls the die to determine the delay on Route A and the die lands on 2 which results in a delay of 5 minutes. The participant rolls the die again to determine the delay on Route B and the die lands on 8 which results in a delay of 9.75 minutes. Knowing perfectly the delay outcomes for both routes, a payoff maximising participant would select Route A (5 minutes delay $<$ 9.75 minutes delay) and obtain a payoff of \$3. However, if the roll of the die to determine the delay for Route B was 5, the delay would have been 0 min and the participant would have selected Route B to obtain a payoff of \$8.

Accordingly, the expectation of the information scenario, for a participant choosing to purchase information, must consider the likelihood of each combination of delay outcomes observed for both routes as presented in Fig. 3. There are four feasible combination pairs within this experiment as shown in the third last row of Fig. 3. Since individuals minimise their travel costs and maximise their monetary payoffs (Fig. 3 is shown in the monetary domain), the four alternatives can be merged under the specific condition that $X_b \geq X_a \geq Y_a \geq Y_b$, (which is the case in this experiments lottery choices, whereX_b=\$10,X_a=\$5,Y_a=\$4,Y_b=\$0.25) to generate the final blue shaded cells at the bottom of Fig. 3.

Therefore, in a similar fashion, the expected utility for the information choice can be evaluated as a compound lottery of Route A and B. Based on Fig. 3, the expected utilities when information is present in the choice set, for a particular decision scenario, can be expressed as follows:

$$EU_{RouteA} = p \times U(I-5) + (1-p) \times U(I-6)$$
$$EU_{RouteB} = p \times U(I-0) + (1-p) \times U(I-9.75)$$
$$EU_{Information} = p \times U(I-0-C) + p(1-p) \times U(I-5-C) + (1-p)^2 \times U(I-6-C)$$

where EU_X = expected utility of competing choices “X”, (X=$RouteA$,$RouteB$,$Information$)

p=probability of delay outcome (5 min for motorway route and 0 min for arterial route).
$(1-p)$=probability of alternative delay outcome (6 min for motorway route and 10 min for arterial route).
I=Fixed income of \$10.
C=Exogenous cost of purchasing information (either \$2 or \$4 depending on the treatment).
$U(Y)$=Utility of each monetary realisation “Y”.

Similar to the without information case, Income (I) was fixed at \$10, the cost of information (C) is the exogenous cost to access information which was either \$2 or \$4 depending on the treatment. The expected utility (EU) for each lottery pair is calculated conditional on a participant's risk attitude ‘r’. To estimate the risk attitude we define a latent index (∇EU) as a multinomial logit specification, where individuals choose across the set of uncertain choices without information (Eq. (4)) and with information in the choice set (Eq. (4′)).

$$\nabla EU_J = \frac{eu_J}{eu_A + eu_B} \tag{4}$$

$$\nabla EU_J = \frac{eu_J}{eu_A + eu_B + eu_{Information}} \tag{4′}$$

where we define

$$eu_J = e^{\left[EU_J/\mu\right]} \tag{5}$$

In these equations, “J” represents the participant's choice of either route A or route B in the without information scenario and route A, route B or the purchase of information in the scenario offering information provision. This form of latent index allows for a link between the observed choices and the measure of risk attitude “r”. As presented in Eq. (5), for the fixed parameter estimation, a structural noise parameter, μ, is used to scale the latent index to account for behavioural errors (Hey and Orme, 1994).

Assuming that EUT and the utility function assumptions hold true, the likelihood of the observed responses depends on the estimates of ′r′ given the above statistical specification and the observed choices within the experiment. The risk attitudes ‘r’ are estimated by maximising the log-likelihood expressed as Eqs. (6) and (7), for the without information and with information scenarios respectively:

$$\ln L(r, \mu; y, \boldsymbol{X}) = \sum_i \left[\begin{array}{c} (\ln(\nabla EU_A) \times \boldsymbol{I}(y_i=0)) + \\ (\ln(\nabla EU_B) \times \boldsymbol{I}(y_i=1)) \end{array} \right] \tag{6}$$

$$\ln \mathrm{L}(r, \mu,; y, \boldsymbol{X}) = \sum_i \begin{bmatrix} (\ln\left(\nabla EU_A\right) \times \boldsymbol{I}(y_i{=}0))+ \\ (\ln\left(\left(\nabla EU_B\right)\times \boldsymbol{I}\left(y_i{=}1\right)\right)+ \\ \left(\ln\left(\nabla EU_{information}\right) \times \boldsymbol{I}(y_i{=}2)\right) \end{bmatrix} \tag{7}$$

where $\boldsymbol{I}(\cdot)$ is the indicator function, $y_i = 0,1,2$ denotes that the participant chose route A, route B or information respectively in driving Task i, and $\mathbf{X}$ is a vector of individual characteristics based on the demographic survey.

Heterogeneity amongst the participants' choices is present within the experimental data. Thus, in order to account for the heterogeneity within the estimation, a non-linear mixed logit approach is applied (Andersen et al., 2012). This methodology is described in detail within the paper by Andersen et al. (2012), with the key advantage being that the method offers a random parameter estimation. Thus, the estimate of 'r' is based on hyper-parameters which describe a distribution of values for the risk attitude parameter. The latent index for the non-linear mixed logit approach is shown in Eqs. (8) and (8′), where 'θ' is a vector defining the hyper-parameters of the distribution of the risk attitude parameter, 'r'.

$$\nabla EU_J = \int \left(\frac{eu_J}{eu_A + eu_B} \right) f(r \mid \theta).\ dr \tag{8}$$

$$\nabla EU_J = \int \left(\frac{eu_J}{eu_A + eu_B + eu_I} \right) f(r \mid \theta).\ dr \tag{8′}$$

It should be noted that for the random parameter estimation, the CRRA function faces numerical issues when r approaches the value of 1 and as such a more flexible power function was assumed to complete the analysis accounting for heterogeneity. Furthermore, substitution of (8) within the log-likelihood formulation (Eqs. (4)–(7)) results in a problem which cannot be solved analytically. Thus, the random parameter estimation was conducted using methods of maximum simulated likelihood identical to what is shown in Andersen et al. (2012).

5. Results

A total of 155 participants completed all four tasks of the experiment as well as the demographic survey. Table 3 presents a summary of the key participant characteristics observed throughout all the sessions. In general, there was almost equal representation of male and female participants with a slight male domination of 53.5% of the total sample. More than 56% of the participants had greater than two years experience in driving a vehicle suggesting that there was a certain level of understanding in relation to route choice and driving. Given that the participants were recruited from a University staff and student pool, it is acknowledged that the average age of the participants is young at 23.2 years. However, it should be noted that 26% of the participant pool were above the age of 24 indicating that this study did not focus exclusively on undergraduate student behaviour and there was a degree of diversity.

Each task provided 10 data points and there were 4 tasks in each session, therefore a total of 6200 data points were used in the estimation. The estimation and analysis were carried out using a statistical software package, STATA. The first step was to explore existence of order effects across the sessions. To study the impact of order effects the fixed parameter estimation considering the CRRA utility function was assessed. A dummy variable for each order and the different treatments were included in the EUT model, as shown in Table 4. The estimation results are presented as *"order_n"* for the particular case of an order without the presence of information within the choice set, and *"info_ord_n"* for the case with the presence of information, where "n" is the specific order used for a session. The results indicate that information has an impact on the measured risk attitudes. The value of the risk attitude parameter (r) is consistently greater without the presence of information within the choice set across all orders considered. Without the presence of information, the value of r lies between 0.3977 and 0.4861, however, the addition of information in the choice set reduced the r values to a range between 0.1281 and 0.2018. The results for the risk attitudes without information are consistent with earlier studies (Dixit et al., 2013; Andersen et al., 2010). The presence of order effects were investigated by evaluating statistical differences between the coefficients using a conventional "Z-test" (Paternoster et al., 1998). The findings of the statistical assessment indicated that there were no statistically significant differences in the coefficient estimates between the orders considered

Table 3
Summary of participant characteristics.

Characteristic	Values
Gender (Male/Female)	83/72
Driving experience (> 2 years/ < 2 years)	87/68
Average age	23.2
Range of ages	17–41

Table 4
Estimation results of EUT for each order.

Parameter	Coeff	Std errorμ	z	P > |z|
r				
Order_0	0.4726	0.0335	14.13	0
Order_1	0.4794	0.0591	8.12	0
Order_2	0.3977	0.065	6.12	0
Order_3	0.4861	0.0632	7.69	0
Info_ord_0	0.2018	0.0468	−5.79	0
Info_ord_1	0.1281	0.0824	−4.26	0
Info_ord_2	0.193	0.0781	−1.72	0.085
Info_ord_3	0.1519	0.0969	−3.45	0.001
LNμ				
Order_0	0.0763	0.1219	0.63	0.532
Order_1	0.2038	0.22	0.93	0.354
Order_2	0.4377	0.206	2.12	0.034
Order_3	−0.232	0.1843	−1.26	0.208
Info_ord_0	−0.468	0.1571	−2.98	0.003
Info_ord_1	−0.299	0.2755	−1.08	0.278
Info_ord_2	−0.896	0.2523	−3.55	0
Info_ord_3	0.1326	0.2697	0.49	0.623

Table 5
Summary of estimation results.

Parameter	Coeff	Std error	z	P > |z|
Fixed parameter estimation of EUT model: CRRA utility function				
r				
Noinfo	0.4605	0.0249	18.49	0
Info	0.1938	0.0231	8.39	0
LNμ				
Noinfo	0.1425	0.0871	1.64	0.102
Info	−0.302	0.0693	−4.35	0
Fixed parameter estimation of EUT model: power utility function				
r				
Noinfo	0.5395	0.0249	21.66	0
Info	0.8062	0.0231	34.88	0
LNμ				
Noinfo	−0.475	0.1252	−3.79	0
Info	−0.517	0.0931	−5.55	0
Random parameter estimation of EUT model: power utility function				
r_μ ***(Hyper-parameter defining the mean)***				
$r_{\mu,noinfo}$	0.7145	0.0189	37.84	0
$r_{\mu,info}$	0.9555	0.0126	75.63	0
r_σ ***(Hyper-parameter defining the standard deviation)***				
σ_{noinfo}	0.1102	0.0128	8.63	0
σ_{info}	0.1711	0.0219	7.79	0
$\sigma_{noinfo,info}$	0.0695	0.0416	1.67	0.095

for a confidence level of 95%. Based on these results, the participants show lower risk aversion when provided with the choice of information.

As order effects were not statistically significant, the model was re-estimated with only the information treatment effect to consider the average risk attitudes across the sample of observations. In addition, the power utility function was also used to carry out estimations for both fixed and random risk attitude parameters. The results of the entire estimation procedure are presented in Table 5.

There is a consistent trend across all the estimation results. The value of the risk attitude parameter "*r*" reduces from 0.4605 to 0.1938 when information is present, for the fixed parameter estimation considering the CRRA utility function, as shown in the top one-third of Table 5. The difference between the risk attitude parameter estimates is statistically significant with a Z-score in excess of 7.8 (greater than the critical value of 1.96) indicating significance at a 95% confidence level. This suggests a reduction in risk attitude with the presence of information.

The value of "*r*" is affected in a similar fashion when applying the power utility function. The fixed parameter estimation shows an increase in the risk attitude parameter from 0.5395 to 0.8062 when information is introduced in the choice set (refer to middle section of Table 5). As described in Section 4, risk seeking behaviour increases as the value of "*r*" increases

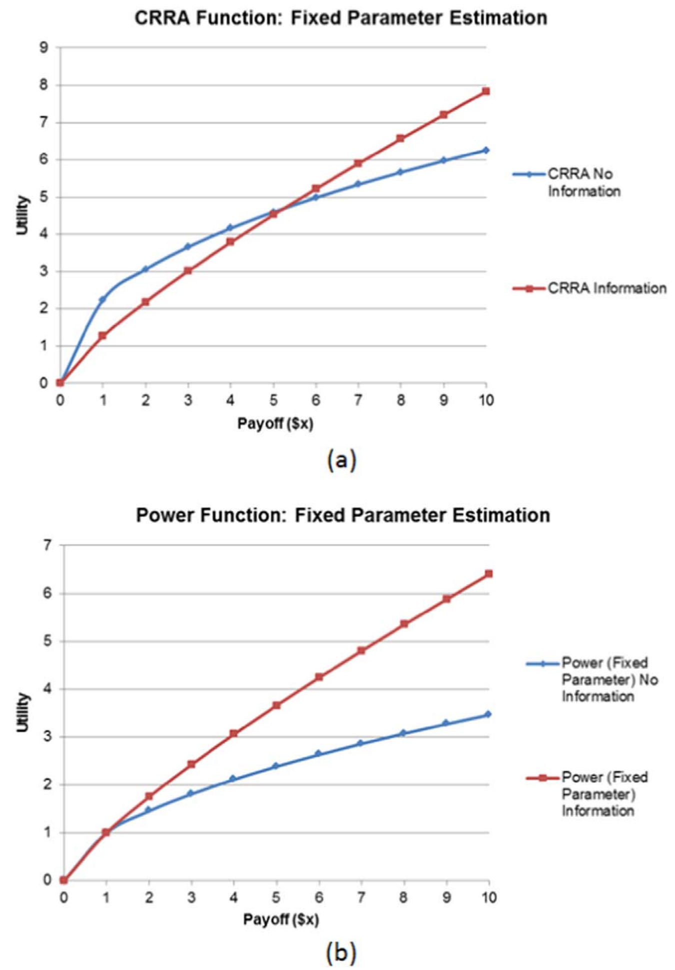

Fig. 4. Comparison of utility functions with and without the presence of information, (a) CRRA function: fixed parameter estimation, (b) power function: fixed parameter estimation. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

for the power utility function. Again these results are statistically significant with a Z-score exceeding 7.8 (greater than the critical value of 1.96).

Incorporating heterogeneity of choice in the estimation process also yielded comparable results, as shown in the bottom-third of Table 5. The random parameter estimation using the power function indicated an increase in the estimated mean of the population distribution of '*r*' from 0.7145 to 0.9555 again highlighting a reduction in risk aversion when information is included in the choice set. Similar to before, the result is significant at a 95% confidence interval, with a Z-score exceeding 9.5 (greater than the critical value of 1.96). The estimated standard deviation of the population distribution of '*r*' increases from 0.1102 to 0.1711 when information is present in the participants choice set. This suggests a greater variability in risk attitudes in the information treatment, highlighting that there are degrees in the level of risk taking across the sample with some participants potentially behaving similar to the no-information treatment while others exhibiting greater risk seeking opportunities. However what is evident from the mean value of the risk attitude parameter is that information has a tendency to reduce risk aversion.

Fig. 4 graphically describes the variation in utility for each estimation procedure. Further emphasising the numerical results, it is clear that the risk aversion characteristics of the participants reduce when the purchase of information is introduced into the choice set. This is the case as the red "information" curves are considerably more linear than that of the blue "no information" curves highlighting a greater degree of risk neutrality.

In addition, it is observed that the Fechner error is lower in situations where purchase of information enters the choice set than when it does not exist in the choice set (which is statistically significant at a 95% significance level). This implies that there are relatively smaller variances due to behavioural errors when information is present in the choice set. Based on these results, it is evident that the provision of information which resolves the uncertainty of a travel outcome reduces the risk aversion and behavioural error when making a travel decision.

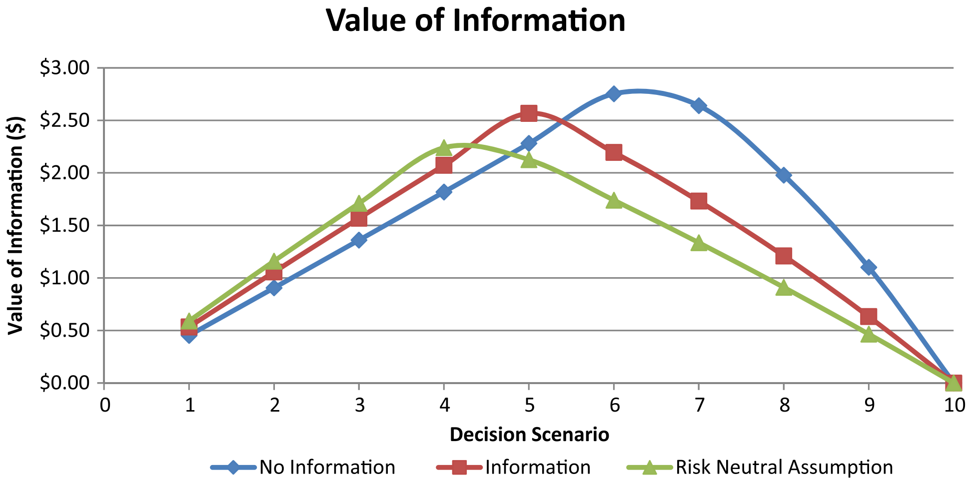

Fig. 5. Calculated maximum willingness to pay for information considering the EUT model.

5.1. Value of information

As mentioned throughout the paper, risk attitudes play an important role in the value people associate to information, in other words, determining how much people would pay for information to resolve the risk associated in travelling on either route. To better understand the impact of differences in risk attitudes when information is in the choice set, we calculate the value of information (v) for each of the 10 route choice lotteries, with the assumption that the value of time is $1/min. Given that under all the estimation procedures, it was evident that risk aversion increases in the presence of information, this analysis uses the results of the fixed parameter estimation using the CRRA utility function to present the potential impact on the valuation of information. As mentioned earlier, the CRRA based estimation was used for further analysis due to its prevalence throughout literature (Dixit et al., 2015).

The value of information (v) is determined by the value 'v', that an individual' would be willing to pay such that the expected utility of information is equal to the maximum expected utility of the competing routes (Eqs. (10) and (11), for the CRRA function). It must be noted that the value of p_i and $1-p_i$ are provided to the subjects in the experiment, while the risk attitude 'r' was estimated from their choice data. Therefore the value of information can be calculated by solving Eq. (8) for each lottery pair 'i' (decision scenario) while considering the risk attitudes. The value of information, 'v', is solved by using Eq. (10). In order to clarify the terms of Eq. (10), it is important to reiterate that the participants received an income of $10 for each decision scenario. Route A had two delay scenarios which resulted in a loss of either $5 or $6 while Route B had two delay scenarios which resulted in a loss of either $0 or $9.75. As mentioned in Section 3, the inclusion of information resulted in a reduction of income and 'v' represents the amount a person would be willing to pay for information in the both treatments (without information and with information).

$$\max\left(EU_{i,RouteA}, EU_{i,RouteB}\right) = EU_{i,Information} \tag{9}$$

$$\max\left\{\left(p_i\frac{(10-5)^{1-r}}{(1-r)} + (1-p_i)\frac{(10-6)^{1-r}}{(1-r)}\right), \left(p_i\frac{(10-0)^{1-r}}{(1-r)} + (1-p_i)\frac{(10-9.75)^{1-r}}{(1-r)}\right)\right\}$$
$$= p_i\left[\frac{(10-v-0)^{1-r}}{(1-r)}\right] + p_i(1-p_i)\left[\frac{(10-v-5)^{1-r}}{(1-r)}\right] + (1-p_i)^2\left[\frac{(10-v-6)^{1-r}}{(1-r)}\right] \tag{10}$$

Fig. 5 compares the value of information in the presence of information in the choice set and no information being present. The greatest level of uncertainty regarding the outcome of each pair of lotteries occurs between decision scenario 4 and decision scenario 6 where there is close to an equal likelihood of the favourable and unfavourable outcomes for both lotteries. Thus, participants would value information far more in these scenarios relative to the initial and latter scenarios where either an unfavourable or favourable outcome is known with a 70% or greater probability. This explains why the value of information increases and decreases across the decision scenarios. The results of the different information treatments are found to be remarkably different. It is clear that, if the observed difference in risk attitude is not explicitly incorporated, the value of information tends to be overestimated in less risky situations, i.e. decision scenarios 6 onwards, where the probability of the favourable delay outcome of both routes is greater or equal to 60%. This means that when users are faced with a route in a road network that for a majority of time performs as expected or with minor delays, the post implementation value of an information system is less than pre implementation if we assume a static risk attitude during appraisal. It is clear that neglecting to incorporate this fundamental difference could result in inaccurate feasibility and cost benefit analysis of the implementation of information systems that would ultimately lead to misguided policy decisions. The implication could include the overpricing of information or inappropriately allocating funds for information systems by assuming high information costs.

It should be noted that ignoring the impact of risk attitudes biases the estimates of the value of information. Further, the presence of information was found to significantly impact risk attitudes and consequently the value of information. To be precise, people behave in a less risk averse manner in the presence of information. This is an interesting and a novel behavioural finding that would impact the evaluation of information provision schemes.

5.2. Value of reliability

As discussed in the introduction and literature review, it is well known that risk attitudes influence how individuals value reliability. The more risk averse an individual is, the more an individual would be willing to pay for reliability. The results of the maximum likelihood estimation indicate that information reduces the degree of risk aversion. However, in both cases, with and without information, participants remained risk averse with values for the parameter "r" being greater than zero for the estimation involving the CRRA function and less than 1 for the estimations using the power function.

Though several studies have used standard deviation of travel time to measure value of reliability (Bates et al., 2001; Lam and Small, 2001; Brownstone and Small, 2005), an alternative way to measure value of reliability is to evaluate the risk premium (Batley, 2007; Beaud et al., 2012) and this study further purses the risk premium approach.

Similar to the analysis surrounding the value of information, the value of reliability is calculated considering the results of the fixed parameter estimation using the CRRA utility function. For the purposes of this analysis, a risk premium is defined as the difference between the expected value and certainty equivalent of the risky lottery.[4] The certainty equivalent is the certain amount at which an individual is indifferent to the risky lottery. In the context of travel time, or in the case of this experiment the additional delay time, this would imply:

$$EU_{lottery} = EU_{certain}$$

$$\int_0^\infty U(t)f(t)dt = U(t_{CE})$$

$$t_{CE} = U^{-1}\left(\int_0^\infty U(t)f(t)dt\right)$$

$$VOR = Risk\ Premium = EV - t_{CE} = \int_0^\infty tf(t)dt - t_{CE}$$

In the case of this specific experiment with discrete state transforms, the above calculation of the risk premium for a Route J can be written as follows:

$$EV_{routeJ} = \sum_i p_i x_i;\ EU_{routeJ} = \sum_i p_i U(x_i);\ U(x_i) = \frac{(x_i)^{1-r}}{(1-r)} \tag{11}$$

$$EU_{routeJ} = U(x_{certain}) \rightarrow x_{certain} = \left((1-r)\sum_i p_i U(x_i)\right)^{\frac{1}{1-r}} \tag{12}$$

$$VOR = EV_{routeJ} - x_{certain} = \sum_i p_i x_i - \left((1-r)\sum_i p_i U(x_i)\right)^{\frac{1}{1-r}} \tag{13}$$

The expected value and expected utility for each route and each decision scenario can be determined using Eq. (11), where "x" represents the payoff an individual would obtain. Eq. (12) describes the condition for certainty equivalence, and is used to calculate the certainty equivalent ($x_{certain}$). Finally, Eq. (13) presents the calculation of the Value of Reliability (VOR) which is the risk premium and is defined as the difference between the expected value of taking the uncertain route and the certainty equivalent. It must be noted that under risk neutral conditions, ($r = 0$), the VOR and risk premium is equal to zero.[5] The analysis presented throughout the paper is focussed on presenting a comparison between a no information case and a with information case accounting for the impact of differing risk attitudes between the scenarios.

The VOR reduces as the level of risk aversion reduces in the presence of information (see Figs. 6 and 7). This result is consistent with the theory that the more risk averse an individual is, the more they are willing to pay for reliability. The variation of the VOR described within the figures is consistent with the structure of the experiment, where the most

[4] Lottery here is used in a context free manner and could involve situations where travel times are the consequences.

[5] In a risk neutral scenario ($r=0$ in CRRA), the expected utility collapses to the expected value. Therefore, preferences are not affected by the standard deviation of the travel time or travel delay and the VOR is zero.

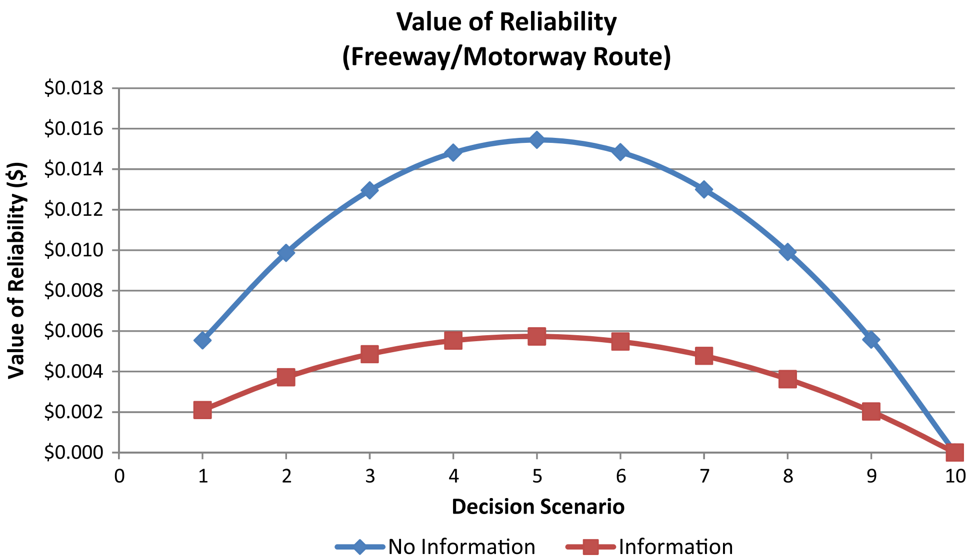

Fig. 6. Value of reliability for the motorway route (Route A) in the experiment.

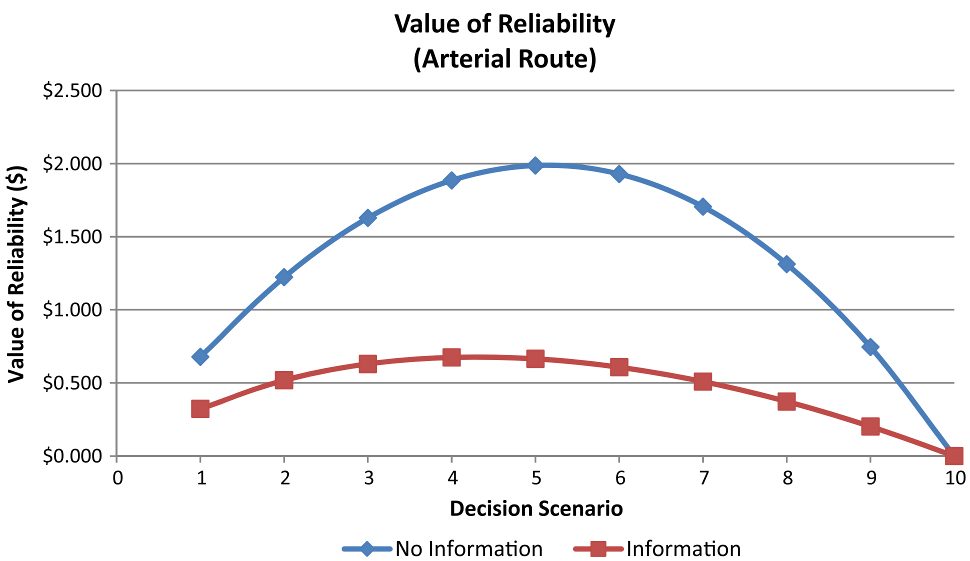

Fig. 7. Value of reliability for the arterial route (Route B) in the experiment.

uncertain scenario, being scenario 5, coincides with the peaks of the curves. Furthermore, it is clear that the willingness to pay for reliability is considerably less for the relatively reliable motorway (freeway) route as compared with the arterial route. The maximum value is less than $0.016 for the motorway route for all decision scenarios while the arterial route has a value approaching $2.00 for the 5th decision scenario. This is also an intuitive result, as individuals would be more willing to pay for reliability on less reliable routes (which in this experiment was the arterial route).

6. Discussion, limitations and future work

The results of the experiment and the subsequent estimation of risk attitudes present the following key findings;.

- Risk attitudes change when information is placed in a users' choice set. The degree of risk aversion reduces with the presence of information. The trend is also observed when accounting for heterogeneity using a random parameter estimation process
- The effect of the differences in risk attitudes without and with the presence of information has an impact on the valuation of information by users.

- In scenarios where the likelihood of unfavourable delay outcomes are low (probability of 40% or less, depicted by decision scenario 6 onwards) users overvalue information sources prior to implementation. In the opposite scenario where unfavourable delay outcomes are prevalent, users marginally undervalue the benefits of information.
- The value of reliability is greater in the scenario without the provision of information as information reduces or at best resolves uncertainty, such as in this experiment.

The contribution of the study stems from the controlled experimental approach and the discovery of the changes in risk attitudes between information regimes. The findings imply that the evaluation of online information infrastructure, such as the implementation of Variable Message Signs and other ATIS systems, needs to be considered carefully based on the likelihood of the delay outcomes observed in the field. Information is undervalued when there is a greater likelihood of incidents and disruptions creating relatively unfavourable delay outcomes. However, if these scenarios are not prevalent, users tend to overvalue information systems prior to implementation potentially resulting in a redundant system post implementation. Traffic engineers, transport planners and government authorities alike must be aware of and account for this phenomenon whilst appraising information infrastructure on road networks.

The authors acknowledge that there are limitations within this study. The fundamental abstraction from reality is that delay time and information regarding delay time was the only criteria used by participants in deciding on the route choice. Route choice decisions are in general multi-objective where travellers do think about travel time, reliability, tolls, road hierarchy and other factors that could affect their decisions. In saying this, from an experimental perspective, it was necessary to simplify this complex behaviour to isolate the impact of online information on risk attitudes. The other main limiting factor of the study is the use of a University based participant pool which can be argued provides a skewed behavioural experiment. The justification for the use of University pools is based on the experimental work which has been completed throughout literature. Previous studies have yielded incredible insight and a fuller understanding of user behaviour in transport systems that have been applicable to the wider community. However, ideally this experiment should be replicated across a wider demography to confirm the differences in risk attitude.

Extensions of this study are numerous. This experiment provided the user perfect information allowing for a resolution of the uncertainty in delays on both routes. The availability of perfect information within a transport system is limited and a similar experiment with imperfect information should be conducted to observe if a similar variation in risk attitude is observed. Furthermore, online information is one source of information that affects route choice. Users are exposed to experiential, and prescriptive sources of information in addition to the descriptive form discussed in this study (Ben-Elia and Avineri, 2015b). Incorporation of other forms of information into a similar experimental framework can be used to identify which form of information affects risk attitudes the most. For an example a repeated game involving two treatments, with and without information could be formulated to assess the experiential information acquisition of users in combination with exogenous information provision, extending the efforts of studies such as Ben-Elia et al. (2008). It is acknowledged that experiential information or overt experience is a key factor which affects the risk characteristics and decision making of individuals (Bogers et al., 2005; Ben-Elia et al., 2008; Neuman et al., 2010). Thus, investigation into experiential information would be an important next stage of this research effort. Finally, this experiment focussed specifically on travel time delays and the impact online information had on resolving uncertainty surrounding delay. An interesting adaptation of the experiment could be a focus on pre-trip information considering total travel times and departure time decisions for competing routes and assessing the impact of pre-trip information on the risk attitudes. This type of study would follow the work of (De Palma et al., 2012) but from an experimental economics perspective.

7. Conclusions

Information systems, within road transport networks, are used to guide the behaviour of road users in their decision making, in particular their route choice. This study was motivated by the question of whether risk attitudes are different when information exists in the choice set.

This question was investigated by conducting a controlled laboratory experiment based on the methods of experimental economics. A series of four Multiple Price List (MPL) lottery tasks were formulated and presented to the participants in order to measure their risk attitudes with and without the presence of information in their choice set. A model derived from Expected Utility Theory (EUT) was then used to quantitatively infer risk attitudes of the participants.

To the best of the authors' knowledge, this study is the first to explore the impact of information on risk attitudes. The results of the experiment indicate that when information is present in the choice set, there is a reduction in risk aversion. In order to account for the heterogeneity of choices made by the participants, a non-linear mixed logit estimation procedure was carried out to determine a random risk attitude parameter. This non-linear estimation reinforced the initial fixed parameter results further emphasising the reduction in risk aversion in the presence of information. This implies that the value of information and reliability could be overestimated if the risk attitudes are not properly calibrated within a transport model. In addition, the presence of perfect information, which can resolve the uncertainty of a travel outcome, is found to reduce the Fechner error, or behavioural error when making route choice travel decisions. These findings are fundamental, and have not been predicted by theory to date and therefore it is critical to explicitly recognise this within behavioural models that are essential to the effectiveness of transport models.

This paper demonstrates that the reduction in risk attitudes translates to a reduction in people's valuation of information. Neglecting to recognise this can lead to an overestimated value of information and reliability in the presence of information. Accordingly, valuations of civil infrastructure projects involving the provision of online information must take into consideration the changes in risk attitude in order to correctly assess the costs and benefits of the project. It is evident that this study has far reaching implications in the application of information systems for traffic management and planning.

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