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Socioeconomic Differences in Ambiguity Attitudes, Partial Ambiguity and A-insensitivity: Evidence from Real-World Decision Making under Uncertainty

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ABSTRACT: Using a nonlinear mixed logit model, this study investigates commuter choice behaviour in the presence of uncertain travel time. Within the proposed source-dependent extended expected utility framework, the uncertainty-risk gap is captured in the source function and the attitude towards ambiguity is measured over the full subjective probability distribution. Based on one revealed preference dataset, we structurally estimated observed heterogeneity in ambiguity attitudes in terms of socioeconomic covariates and unobserved between-subject heterogeneity in taste preferences, while controlling for risk attitude and allowing for the trade-off between attributes. In addition to revealed age and gender differences in ambiguity preferences, other important findings include partial ambiguity seeking in this type of loss domain and the existence of likelihood insensitivity under uncertainty (i.e., a-insensitivity). This systematic investigation of decision making under uncertainty in real-market settings would offer behaviourally realistic inputs into the evaluation of social effects and design of effective policies.

KEY WORDS: ***Ambiguity attitude, travel time uncertainty, subjective probability, source preference, socio-economic status, nonlinear mixed logit***

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1. Introduction

Many economic decisions in real markets are inevitably associated with uncertainty. Uncertainty is defined as "a quality depending on the amount, type, reliability and unanimity of information, and giving rise to one's degree of confidence in an estimate of relative likelihoods" (Ellsberg 1961, p.657). In the presence of uncertainty, information on the likelihoods of potential consequences is unavailable or incomplete. Therefore, decision makers have to assess these probabilities with some degree of ambiguity. In the existing literature, most studies have concentrated on risk with objective or known probabilities, rather than uncertainty associated with subjective or unknown probabilities (Croson and Gneezy 2009; Bouchouicha *et al.* 2017). Risk can be treated as a special case of uncertainty, that is, under the same belief for objective probabilities from risky sources and for subjective probabilities generated from uncertain sources. However, empirical evidence has revealed the remarkable distinction between risk and uncertainty. In a gain domain, the former may be often preferred, and this typical choice behaviour is called ambiguity aversion (Ellsberg 1961).

The role of ambiguity attitudes (or ambiguity preferences) in decision making under uncertainty has been investigated across various fields, for example financial economics (e.g., Dimmock *et al.* 2016 for stock market participation; Alary *et al.* 2013 for insurance behaviour), environmental economics (e.g., Millner *et al.* 2013 for climate change), health economics (e.g., Berger *et al.* 2013 for treatment choice), population economics (e.g., Hao *et al.* 2016 for migration) and technological economics (e.g., Barhama *et al.* 2014 for technology adoption). The common finding is ambiguity aversion for gains or ambiguity seeking for losses. A number of experimental studies covering both gains and losses also demonstrated a fourfold pattern of ambiguity preferences, that is, ambiguity aversion for moderate-high likelihood gains or low likelihood losses and ambiguity seeking in for low likelihood gains or of moderate-high likelihood losses (Baillon and Bleichrodt 2015; Bouchouicha *et al.* 2017; Kocher *et al*. 2018).

Travel times over repeated trips tend to vary due to inherent travel time uncertainty, that is, random fluctuations at the supply and demand sides such as accidents, traffic signals, road construction, extreme weather, traffic mix and driving behaviour. Therefore, before departing, travellers are faced with an uncertain context with an undefined likelihood of arriving earlier, later or on time, relative to a normal travel time. In the current study we focus on the repeated commuting trip, and suggest that an individual's willingness to make a judgment on this natural uncertain event depends not only on the degree of variability but also on its source (subjective probabilities vs. objective probabilities). However, in the field of transport economics, existing research has been focused on the elicitation of risk attitudes, and almost all experimental studies have employed risky events, in which the probabilities of different scenarios per choice alternative are assumed to be known and provided to the subjects (see Kemel Paraschiv 2013; Ramos *et al.* 2014 and Li 2018 for reviews).

To the authors' knowledge, there is no empirical evidence on travellers' ambiguity attitudes in the literature. The primary purpose of this study is to behaviourally measure ambiguity attitudes, using the revealed preference data collected by Hensher *et al*. (2015). This study investigates the way in which ambiguity attitudes can be built into an empirical travel choice model, along with taste preferences, nonlinear probability weighting and risk attitudes. More specifically, this study has identified mixed ambiguity seeking, neutrality and aversion but stronger ambiguity seeking among sampled Australian commuters in the presence of travel time uncertainty, along with overall risk-taking behaviour. An important perceptual phenomenon in uncertain decisions has also been found among some socioeconomic cohorts within this sample, that is, a-insensitivity. More importantly, these behavioural results under uncertainty were empirically identified within a nonlinear mixed logit while addressing three major research gaps (see the following review section) in modeling choice behaviour under uncertainty simultaneously, which has not, to our knowledge, be considered in the broader literature.

2. Behaviourally Measuring Ambiguity Attitudes: Research Gaps

A widely used approach to elicit structural parameters of utility or value functions is using incentivized games[1] such as lottery-choice tasks (Charness *et al.* 2013; Lönnqvist *et al.* 2015). Evidence shows that behavioural parameters inferred from lottery choices were associated with a significant degree of noise (Lönnqvist *et al.* 2015). Real-world decisions (e.g., relocation, migration, occupational and travel choices) are far more complex with multiple trade-offs than laboratory experimental games which mainly involved monetary calculation and may be irrelevant to real-life choice settings. (Levitt and List 2007; Charness and Gneezy 2012).

Different ambiguity preferences were estimated from various lab experiments. For example, using the classic Ellsberg paradox in the gain domain, Ellsberg (1961) found ambiguity aversion; using an experiment in the loss domain, Wakker (2010) found ambiguity seeking. Zhou and Hey (2018, p.754) highlighted that "preferences are often constructed rather than merely revealed': that the strategy used to make a decision can be affected by the characteristics of the decision problem". Therefore, the ambiguity attitude of a decision maker may vary when facing different uncertain events, as well as the extent of ambiguity aversion or ambiguity seeking. In order to elicit behaviourally meaningful outcomes, the context of experiments need to be as similar as (Loomes and Pogrebna 2014) possible to or even the same as (Zhou and Hey 2018)[2] the real-world decision problems investigated.

Artificial laboratory events have been extensively used to behaviourally measure ambiguity attitudes. One of its drawbacks is a failure to engage subjects (Mata *et al.* 2018). The external validity or generalizability (i.e., whether the experimental findings can be extrapolated to the real world) is another concern for using artificial events.

[1] Another drawback of this approach is "that it is costly and difficult to perform with a large, representative sample, preventing large-scale studies" (Dohmen 2011, p.523).

[2] Zhou and Hey (2018) compared behavioural outcomes of different experimental methods (Holt–Laury price lists, pairwise choices, the Becker–DeGroot–Marschak method and allocation questions), preference functions under alternative theories (Expected Utility and Rank-Dependent Expected Utility) and utility specifications (constant absolute risk aversion and constant relative risk aversion), and found that only the context (i.e., the experimental or elicitation method) has a significant influence on the estimated risk attitudes. They suggested that researchers should focus on the design of experiment with the same context as the economic problem in reality and the elicitation of risk attitudes that best explain behaviour in that specific situation, rather that the choice of utility functional form.

There is no robust evidence that the elicited ambiguity attitudes from artificial events are capable of predicting actual economic decisions (Dimmock *et al.* 2016). The significance of using natural events has been highlighted by Heath and Tversky (1991), Levitt and List (2007), Ellsberg (2011), Page *et al.* (2014), Trautmann and van de Kuilen (2015) and Baillon *et al.* (2018b), among others. Baillon *et al.* (2018b) concluded that few studies have estimated ambiguity attitudes using natural events, given that, in real markets, it is rather difficult to observe revealed preference (RP) based probability beliefs, and moreover, symmetry and corresponding control associated with artificial events may be absent in natural events.

Another research gap is the lack of control for risk attitudes in the elicitation of ambiguity attitudes (see e.g., Kilka and Weber 2001; Baillon *et al.* 2018a). This control is crucial to demonstrate the uncertainty-risk gap in decision making, given that "ambiguity reflects what uncertainty comprises beyond risk" (Abdellaoui *et al.* 2011, p. 702). If ignored, the role of ambiguity attitude would be illustrated through a biased estimator. Last but not least, students were frequently recruited as subjects (see e.g., Abdellaoui *et al.* 2011; Trautmann and van de Kuilen 2015; Schneider *et al.* 2018). Few studies have investigated the ambiguity attitudes of the general population (Dimmock *et al.* 2016). For delivering behaviourally meaningful and externally valid outputs, relevant preferences and actual experiences of true decision makers are required, as well as sociodemographic variations of general populations. However, "The homogeneity of the university student population limits the ability of laboratory experiments to detect the preference heterogeneity that is present in the broader population" (Anderson *et al.*, 2010, p.223).

3. Strengths of this Study

As an example, Baillon *et al.* (2018b) used multiple ambiguity indexes to measure ambiguity attitudes concerning the Amsterdam stock exchange index performance. Baillon *et al.* addressed the first two major research gaps by using real-world events and controlling for risk attitudes. However, instead of true investors, they sampled 104 students from Erasmus University Rotterdam, and hence failed to accommodate the third gap. In our study, the context of the empirical application (see section 5) is directly related to decision makers' travel mode choices, in which the sampled subjects were 759 commuters in the field with relevant experiences of travel and perceptions of traffic conditions. Moreover, using this representative sample allows us to investigate a wider range of sociodemographic variations (e.g., income, age and occupation) in ambiguity attitudes, in addition to gender. Compared to Baillon *et al.* (2018b) using ambiguity indexes, this study offers a methodological difference, that is, using the nonlinear utility framework with expected utility, perceptual conditioning and source preference. We jointly estimated the parameters of interest (e.g., taste, risk and ambiguity preferences) based on the proposed functional form, utility specification, probability weighting and source function using a nonlinear mixed logit model. Existing applications of nonlinear mixed logit are all in the domain of risk (see e.g., Hensher *et al*. 2011; von Gaudecker *et al*. 2011; Anderson *et al.* 2012), this study is the first that applies this advanced model in the domain of uncertainty.

By accommodating these three major research gaps, this study presents new evidence on the distinction between risk and uncertainty. Using the actual decisions and subjective perceptions of sampled commuters, we found observed heterogeneity in ambiguity attitudes in terms of socioeconomic covariates and unobserved between-individual heterogeneity in taste preferences with respect to travel time and travel cost, as well as overall risk-taking behaviour in this type of loss domain. These behavioural findings were obtained within one dataset, using a structural modelling framework with nonlinearity in utility for capturing risk attitude, nonlinearity in probability weighting for accounting for perceptual conditioning and source preference for measuring the gap between risk and uncertainty (or ambiguity preference). This study uses natural events and actual decision makers while controlling for risk attitude and allowing for the trade-off between attributes within a nonlinear mixed logit model. In addition to age and gender differences in ambiguity preferences, other important findings of this study include partial ambiguity seeking and a-insensitivity.

4. Modelling Uncertain Decision Making: A Utility Approach with source preference

Ellsberg's paradox (Ellsberg 1961) found that an alternative with known probabilities was preferred over that with unknown probabilities. However, two alternatives would be indifferent under the sure-thing principle of Subjective Expected Utility Theory (Savage 1954). This choice behaviour, ambiguity aversion, highlights the important distinction between risk and uncertainty. Typically, the former refers to a circumstance where a decision maker has known/clearly-defined probabilities of possible outcomes, and the latter refers to a situation where a decision maker is not provided such information or such information is vague, and has to judge the probabilities of occurrence subjectively. Ambiguity preference represents the difference between beliefs for subjective probabilities generated from uncertain sources vs. those for objective probabilities from risky sources (Abdellaoui *et al.* 2011). Therefore, source preferences indicate ambiguity attitudes.

There are alternative approaches for behaviourally measuring ambiguity attitudes, for example ambiguity indexes (see e.g., Baillon *et al.* 2018b for a review and an empirical application). Smith (1969), Winkler (1991), Fox and See (2003) and Abdellaoui *et al.* (2011) suggested that using the utility function with probabilistic beliefs in the Ellsberg paradox is an appealing and preferred way to investigate source preference. Under this utility approach, Abdellaoui *et al.* (2011) highlighted three key components of modelling uncertain decision making: (1) the utility of outcomes, (2) choice-based probabilities for source of uncertainty and (3) source function. As the third component, the role of source function is to capture ambiguity attitudes rather than to modify probabilities (perceptual conditioning) or utilities (tastes). This study also uses this utility approach to quantify ambiguity attitudes, along with taste and risk preferences.

Following Fox and Tversky (1998), Fox and See (2003) proposed a structural modelling framework for decision making under uncertainty, which integrates two essential mechanisms: (i) the analysis of decision under risk including risk attitude and perceptual conditioning (or risky probability weighting) and (ii) the investigation of judgment under uncertainty including subjective probability and source preference (or ambiguity attitude). For the probability weighting process under uncertainty, the first step is to ask decision makers to provide their judged (subjective) probabilities of uncertain events. The second step is to weight those judged probabilities by using a nonlinear probability weighting function for risk (i.e., risky weighting function), and then a further transformation under the source function in the domain of uncertainty is applied. This systematic approach allows for ambiguity attitudes measured over the full probability distribution (also see e.g., van de Kuilen and Wakker 2011; Maafi 2011). The distinction between risk and uncertainty is captured in the source-dependent transformation. Fox and Tversky (1998) provided the formula for transforming risky probability weighting into ambiguity-attitude probabilities, given in equation (1). $\theta \neq 1$ is indicates the distinction between risk and uncertainty.

$$w_s(p)^{\theta \neq 1} = [w(sprob_m)]^{\theta} \quad (1)$$

$sprob_m$ is the subjective probability for the occurrence of the m^{th} outcome. θ is the estimated source preference parameter, which is the basis of an adjustment required in model estimation when an individual is initially offered 'given probabilities' in a choice experiment. Source preference can be defined empirically by a number of candidate constructs; however the notion of belief offers an appealing interpretation of ambiguity attitudes and aligns well with Ellsberg's contribution. If the uncertain alternative with subjective probabilities either judged or vaguely defined is preferred, relative to the risky alternative with objective probabilities either given or clearly defined, this choice behaviour implies ambiguity seeking. On the contrary, an ambiguity-averse decision maker would prefer the one with objective probabilities. In an uncertain decision-making environment, the source of probabilities (subjective vs. objective) would also have an impact on choice behaviour. $\theta \neq 1$ is uncertain probability weighting for ambiguity-attitude probabilities which has two components: risky probability weighting and source preference (ambiguity aversion or seeking). θ=1 implies ambiguity neutrality, that is, the same belief for probabilities generated from risky and uncertain sources, under which uncertain probability weighting would reduce to risky probability weighting.

In equation (1), w is some probability weighting function. This study uses the functional form proposed by Tversky and Kahneman (1992), given in equation (2), in which γ is the probability weighting parameter to be estimated.

$$w(p_m) = \frac{p_m^{\gamma}}{[p_m^{\gamma} + (1-p_m)^{\gamma}]^{\frac{1}{\gamma}}} \quad (2)$$

The empirical application in this study (introduced the next section) is the decision makers' views on what they believe are likely (i.e., subjectively perceived) travel times under repeated commuter trip making behaviour, in which probability judgements are used to account for decisions under uncertainty. This approach accommodates source preference, while maintaining the segregation of belief and taste preferences. In the current study, source preference is captured in a binary model framework with the choice variable being commuting mode (car vs. PT), and its utility expression associated with each alternative that accounts for source preference and risk attitude for travel time is given in equations (3) & (4). The proposed source-dependent extended expected utility framework (EEUT_s) extends Hensher *et al.* (2011)'s Extended EUT

(EEUT) modelling framework for risky choices with objective probabilities, and further measures ambiguity attitudes generated by subjective probabilities through the source preference parameter (θ).

$$U = EEUT_s(U) + \sum_{z=1}^{Z} \beta_z S_z \tag{3}$$

where $EEUT_s(U) = \beta_x [w(p_1)^\theta x_1^{1-\alpha} + w(p_2)^\theta x_2^{1-\alpha} + ... + w(p_R)^\theta x_R^{1-\alpha}] / (1-\alpha)$ (4)

x is the uncertain attribute (travel time in this study). A general power specification under constant relative risk aversion (CRRA) is used as the nonlinear utility specification, in which the value of (1-α) indicates the attitude towards risk; θ is the source preference parameter that identifies deviations of uncertainty from risk with $\theta \neq 1$ illustrating different source preferences with respect to objective probabilities and subjective probabilities, where the value of θ implies ambiguity attitude; and β_x is the marginal disutility or taste parameter for travel time. There are also a number of other variables in the utility expression are added in as linear in parameters. The presence of α, γ and θ in equations (3) and (4) results in an embedded attribute-specific treatment in the overall utility expression associated with each alternative, with nonlinearity in a number of parameters. Within this framework, risk attitudes are controlled for when eliciting ambiguity attitudes. This segregation is important for an unbiased measure of ambiguity.

5. Empirical Application: Mode Choice Under Travel Time Uncertainty

The conventional and dominant approach to travel time variability research is the use of stated preference experiments, in which a subject is asked to make a choice among different routes or modes and their attributes levels are designed by the analyst. If the probabilities of different travel outcomes were exogenously introduced to subjects, the induced decision-making context is under risk with objective probabilities, rather than the true travel context with vaguely judged subjective and endogenous probabilities. In order to imitate mode choice under uncertainty, we developed a fully subjective approach to investigate uncertain travel decision making with a primary focus ambiguity attitudes, in which our sampled commuters were asked to indicate the perceived and judged levels and corresponding probabilities of attributes associated with a chosen and a non-chosen alternative, similar to the revealed preference method.

In March 2014, a group of car and public transport commuters in the Sydney metropolitan area were sampled, with a focus on subjects who are regular users of car as a driver or public transport (single modal or multimodal of bus, train and ferry). To be eligible for the survey, at least one public transport (PT) option must be available to car commuters for commuting if they wanted to use it and *vice versa* for PT commuters. Each commuter was asked to report three perceived commuting times and the judged likelihood of experiencing each travel time. Instructions were provided to help commuters judge the likelihood of the three possible outcomes based on their recent experience (for those who have used alternative mode to commute) or perceptions of what it is likely to be. The survey also included questions relating to travel cost, number of times using car and public transport for commuting in the last two months, as well as socio-economic characteristics such as age, income, occupation and household car ownership. A screen shot of the survey instrument is given in Figure 1. For detailed information on this data, see Hensher *et al.* (2015).

994 qualified commuters (a response rate of 25%) were obtained for this study. A process of cleaning and validating the data reduced the sample to 759 usable observations. Inconsistencies between reported household size and household structure and between public transport fares and toll costs of different travel outcomes are the main reasons for removing observations from the final dataset. For the sampled 759 Australian car commuters, the average income was Au$77,433 in the year of 2014 and the average age was 39.7, in which 56.6% of the sample were female.

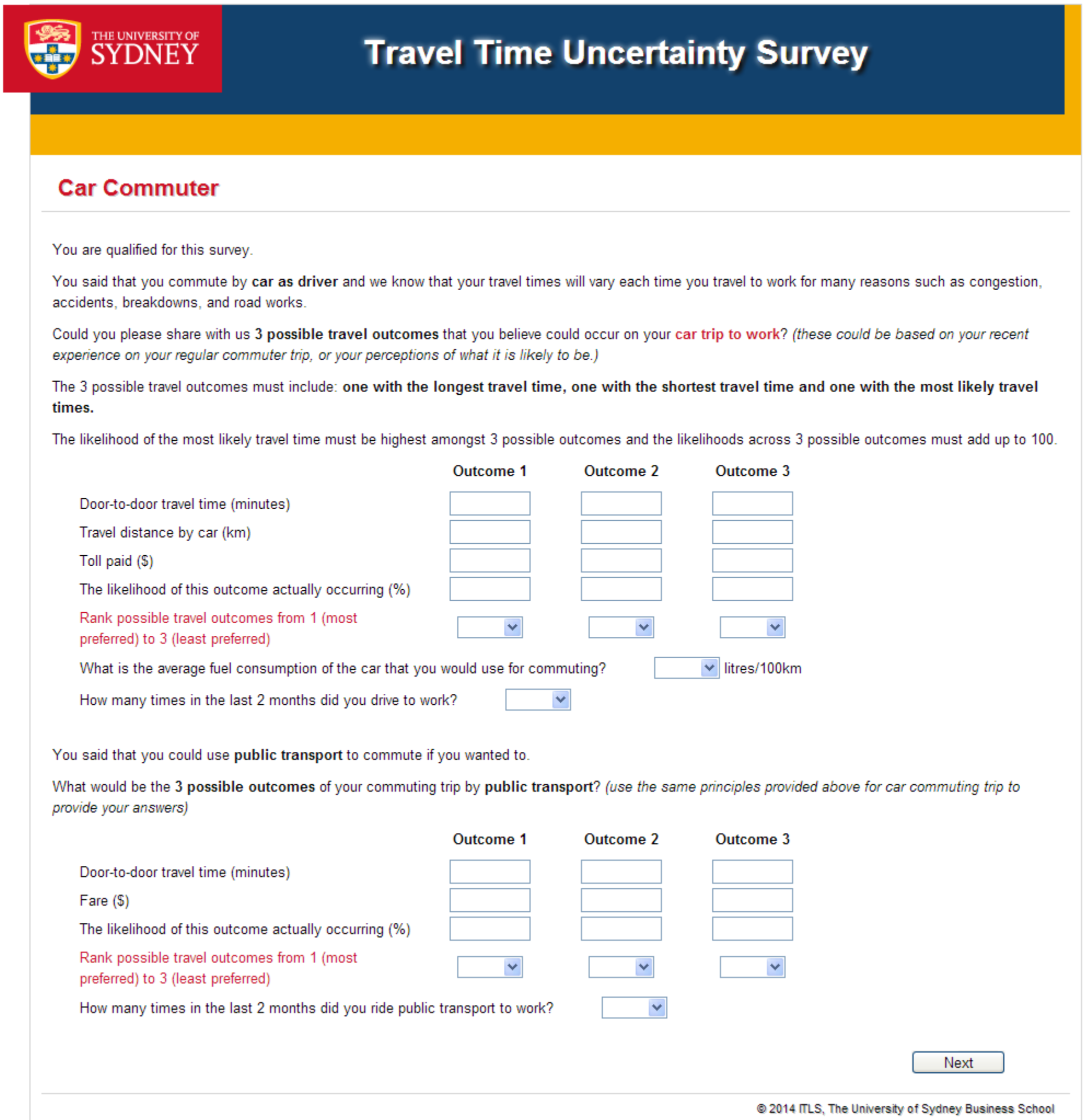


Figure 1: A screen shot of the travel time uncertainty survey for car commuters

6. Model Estimation and Empirical Results

The advanced nonlinear mixed logit model is employed to account for unobserved between-individual taste heterogeneity in travel time and travel cost parameters across the sampled commuters. Compared to the simple choice model (e.g., multinomial logit) assuming preference homogeneity, its main advantage is the capture of unsystematic differences in preferences at the individual level using random parameters or distributions. The possible impacts of socioeconomic characteristics on ambiguity attitudes such as gender, age and income were also investigated within this nonlinear utility framework. After testing different combinations of unobserved and observed heterogeneity, the final model with significant unobserved heterogeneity in taste preferences (time and cost) and observed heterogeneity in ambiguity attitudes (with only age and gender being significant influences) is given in Table 1.

Table 1: Nonlinear mixed logit model with socioeconomic differences in ambiguity attitudes (estimated using Nlogit 6)

Variable	Parameter	*t*-Ratio
Non-random parameters:		
Car constant	-1.406	-9.64
Alpha (α)	0.731	6.05
Nonlinear probability weighting (γ)	0.633	3.96
Source preference (θ)	1.553	7.62
Gender effect (Dummy variable: male=0, female=1) on source preference	-0.406	-1.92
Age effect (Dummy variable: younger=0, older=1) on source preference	-0.552	-2.68
Means for random parameters:		
Travel time (β_{Time})	-0.890	-2.01
Travel cost (β_{Cost})	-0.479	-10.09
Standard deviations for random parameters:		
Travel time (β_{Time})	0.890	2.01
Travel cost (β_{Cost})	0.479	10.09
No. of observations (N)	759	
Akaike information criterion (AIC)/N	0.763	
Rho-squared	0.465	
Log-likelihood	-281.381	

For taste preferences captured by two triangular distributions[3], the parameter estimates for *Travel time* and *Travel cost* are of the expected sign, and their unconditional mean estimates are negative as reported in Table 1, as well as their conditional mean estimates for the sampled 759 commuters at the individual level. The conditioning occurs at the

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

individual level based on the subject's choices and attribute levels. These mean estimates are based on repeated draws (500 Holton draws used in this mixed logit model) from the estimated model for the parameters of interest. For the sampled 759 commuters, the conditional mean estimates at the individual level varies from -0.525 to -1.425 for *Travel time* and from -0.171 to -0.579 for *Travel cost*, with unobserved between-subject taste heterogeneity (see Figure 2). Using Tversky and Kahneman's one-parameter function (equation 2), the estimated nonlinear probability weighting parameter (γ), statistically significant from one ($\frac{0.633-1}{s.e.=0.160}=$ -2.30 where *s.e.* is its standard error), is 0.633, which would overweight low probabilities and underweight medium to high probabilities (see Figure 3).

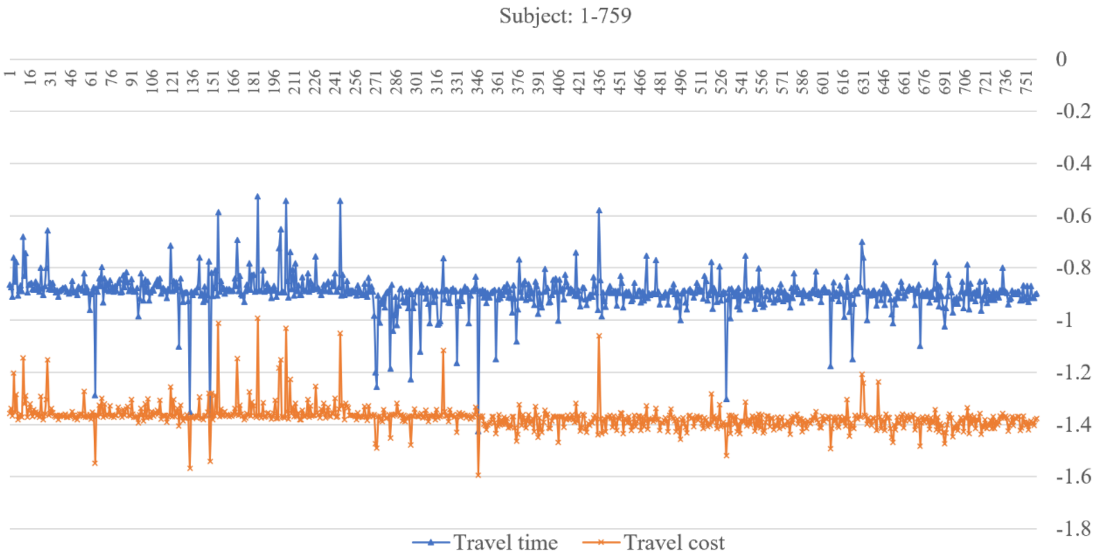


Figure 2: Conditional mean taste parameter estimates for sampled 759 subjects

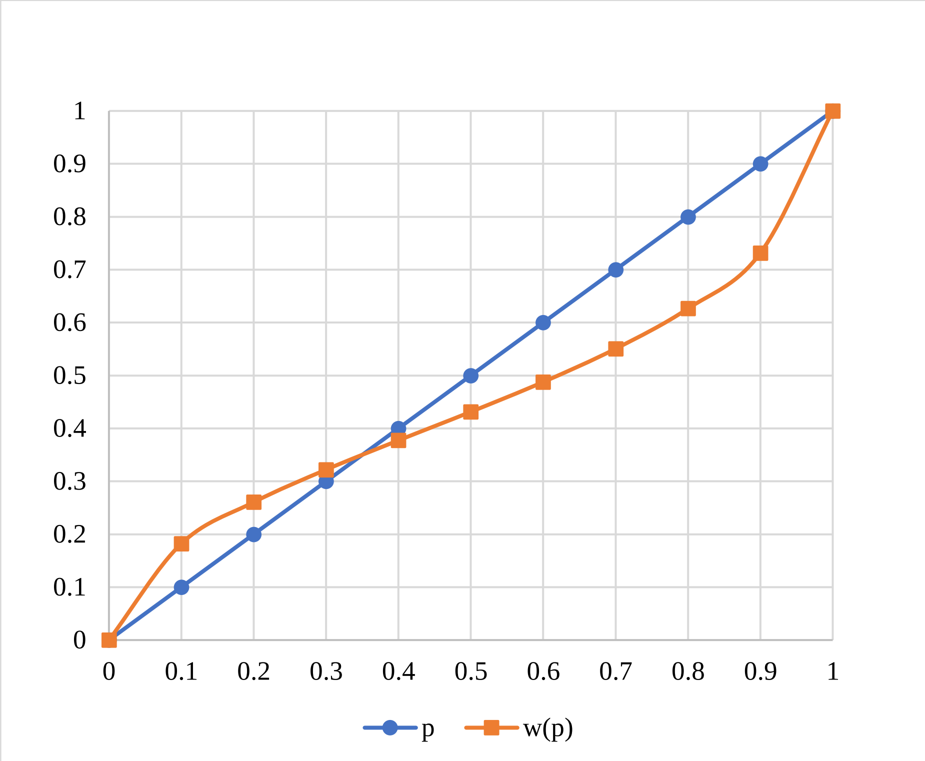


Figure 3: Nonlinear probability weighting (Gamma=0.633)

This type of decision making is in a loss domain; if the estimated risk attitude parameter being less than one (<1), it indicates decreasing marginal disutility over the attribute of travel time with a negative parameter estimate, under which the level of disutility incurred by the alternative associated with probabilities of occurrence would be lower and hence it would be chosen, suggesting risk seeking. On the contrary, the estimated risk attitude parameter greater than one (>1) implies risk aversion (i.e., increasing marginal disutility), under which, the sure alternative would induce a lower level of disutility. In this study, the calculated risk attitude parameter is 0.269 (=1-*Alpha*), suggesting that our sampled commuters tend to be risk seeking in this type of loss domain, which is consistent with the existing findings (see Li 2018 for a review). Decision making under risk involves a trade-off between hope and fear, which would induce risk seeking for losses (Lopes 1987). Risk-seeking behaviour has also been found in other loss domains such as reduced wealth (Loubergé and Outreville 2001) and natural disasters (Eckel *et al.* 2009). A specific comment is required on how we interpret risk attitude in the current study, given that the data is a single cross-section, albeit with a data twist. The justification for including risk attitude (more commonly used in repeated experiments) is reflected in the repeat nature of travel time which engenders a meaning in terms of how the commuter treats travel time each time they undertake a trip. This is different to how they perceive the levels of travel time associated with each commuting trip (Hensher 2015). Thus, some risk takers are more prepared, *ceteris paribus*, to accept greater variability in travel time; in contrast a risk-averse commuter prefers less varied travel time.

Having controlled for the attitude towards risk, ambiguity attitudes then can be implied by the estimated source preference parameters. The estimated source preference parameter (θ) is statistically different from one ($\frac{1.553-1}{s.e.=0.204}=2.71$), suggesting a significant preference difference between uncertainty and risk. Among the candidate socio-demographics, only *Gender* and *Age*[4] in terms of dummy variables have a statistically significant influence on source preferences or ambiguity attitudes. Therefore, the whole sample is divided into four cohorts, and the corresponding ambiguity attitude parameter is 1.553, 1.147, 1.001 and 0.594 for sampled younger males (Cohort 1), older males (Cohort 2), younger males (Cohort 3) and older females (Cohort 4) respectively. The findings suggest that Cohorts 1, 2 and 4 would treat risk and uncertainty differently; while Cohort 3 tend to be ambiguity neutral.

An ambiguity-seeking decision maker would prefer the uncertain alternative with subjective probabilities over the risky one with objective probabilities, and *vice versa* for ambiguity aversion. After controlling for risk attitude (a common component for both risky and uncertain choices), if θ<1, for an equivalent subjective probability, the transformed probability under uncertainty (ambiguity-attitude probability: $w_s(p)^{\theta\neq1}$) would be higher than the transformed probability under risk (risk-attitude probability: $w(p)^{\theta=1}$) given that $w(p)$ is bounded between zero and one. In this study, the estimated taste parameter for *Travel time* (i.e., a source of disutility) is negative and $(1-\alpha)>0$, and therefore, the level of "disutility" (see equation 4 for its formation) induced by the uncertain alternative would be higher (more negative utility) than the risky one, implying ambiguity aversion. Contrariwise, if θ>1, the transformed probability under uncertainty ($w_s(p)^{\theta\neq1}$) would be lower than the transformed probability under risk ($w(p)^{\theta=1}$), and therefore, the uncertain alternative with less disutility would be preferred, that is, ambiguity seeking. For sources of utility (e.g., wealth), the implied ambiguity attitudes would be opposite, given that the corresponding taste preference parameters are expected to be positive. These behavioural implications are highlighted in Table 2. Given that the empirical application of this study is in a loss domain, the hypothesis is that our sampled commuters tend to be ambiguity seeking.

Table 2: Implied ambiguity Attitudes: Sources of utility and disutility

	Source preference parameter < 1	Source preference parameter =1	Source preference parameter >1
Source of utility (e.g., wealth)	Ambiguity seeking	Ambiguity neutral	Ambiguity averse
Source of disutility (e.g., travel time)	Ambiguity averse	Ambiguity neutral	Ambiguity seeking

The model outputs (see Table 1) revealed less ambiguity seeking for female subjects, as well as for older subjects. Within this sample, a fourfold pattern of ambiguity attitudes is identified across socio-demographics and summarised in Table 3, with two cohorts being ambiguity-seeking (younger males and younger females), ambiguity neutrality for older males and ambiguity aversion for older females. In the existing literature, empirical evidence on socioeconomic differences in between-individual ambiguity attitudes is rare, with the majority of theoretical studies assuming universal

[4] In this study, *Age* was divided into two groups, and over 40 years (i.e., the average age) is defined as *Older*.

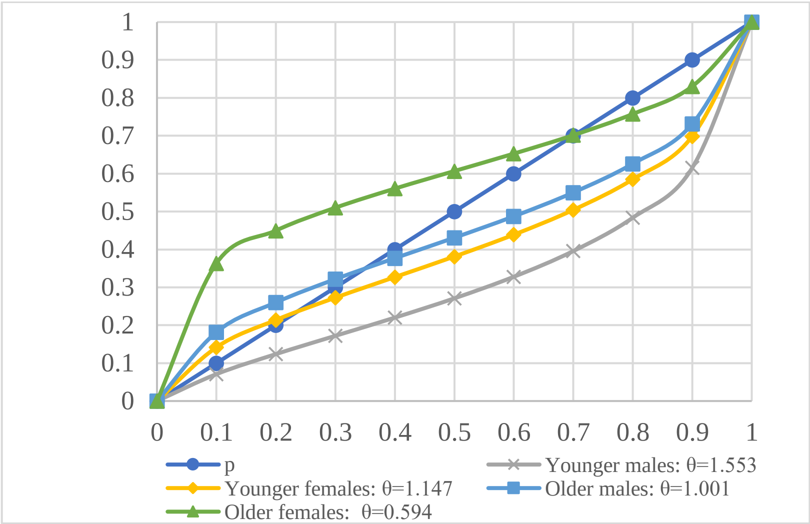
ambiguity aversion and most empirical studies revealing ambiguity averse for gains or ambiguity seeking for losses (Viscusi and Chesson 1999; Wakker 2010; Kocher *et al*. 2018). Among a few studies that have investigated this important topic, Sutter *et al*. (2013), Dimmock *et al.* (2016) and Baillon *et al*. (2018b) found no significant relations between sociodemographic characteristics and ambiguity attitudes. Using a field experiment conducted in China, Hao *et al.* (2016) found that their sampled male migrants tend to more ambiguity seeking than females and younger subjects would be more ambiguity seeking than older ones. Our empirical findings are consistent with Hao *et al.*'s evidence.

Table 3: A fourfold pattern of ambiguity attitudes within the sample

	No. of subjects	Sociodemographics	Ambiguity attitude	Source preference parameter
Cohort 1	211 (27.80%)	Younger & male	Ambiguity seeking	1.553
Cohort 2	283 (37.29%)	Younger & female	Ambiguity seeking	1.147
Cohort 3	118 (15.55%)	Older & male	Ambiguity neutral	1.001
Cohort 4	147 (19.37%)	Older & female	Ambiguity averse	0.594

This fourfold pattern suggested partial but stronger ambiguity seeking while rejecting the common assumption of universal ambiguity seeking for losses. In this type of loss domain, all sampled younger commuters (Cohorts 1&2), 494 out of 759 sampled subjects, tend to be ambiguity seeking; while 118 older male subjects are ambiguity neutral and 147 older female subjects are ambiguity averse. Chew *et al*. (2017) also revealed partial ambiguity, using an ambiguous lottery experiment in which 188 undergraduate students were recruited. They found a mix of ambiguity aversion (97 subjects), ambiguity neutrality (69) and ambiguity seeking (22), without linking this partial ambiguity with socio-demographics. Chew *et al*. (2017), in a gain domain, found stronger ambiguity aversion (i.e., 51.60% of their sample). This study, in a loss domain, revealed stronger ambiguity seeking (i.e., 65.09% of this sample). The findings from two studies suggest that ambiguity attitudes may be heterogeneous (within-study evidence) and ambiguity attitudes may be context dependent (between-study evidence: gain vs. loss).

The transformed probabilities under uncertainty for the four socioeconomic cohorts are plotted in Figure 4. Except for younger males, the other three cohorts display inverse S-shape weighting, suggesting that they would treat subjective probabilities as 50-50. This phenomenon that may occur in uncertain decisions is referred to as a-insensitivity in the literature; that is, likelihood insensitivity generated by uncertainty (Abdellaoui *et al.* 2011; Trautmann and van de Kuilen 2015; Dimmock *et al*. 2016). In this study, a-insensitivity would imply the lack of sensitivity to regular travel scenarios and reinforce ambiguity seeking for medium likelihood losses. To the authors' knowledge, a-insensitivity has been identified mainly by laboratory experimental studies in which students were used as subjects, with the exception of Dimmock *et al*. (2016) that revealed this perceptual phenomenon in stock market participation. This study adds non-laboratory evidence on a-insensitivity by revealing this latent component of economic decision making among the sampled younger female commuters and older commuters.



X-axis: Subjective probability	Y-axis: Ambiguity-attitude probability			
	Younger male commuters	Younger female commuters	Older males commuters	Older female commuters
0.10	0.07	0.14	0.18	0.36
0.20	0.12	0.21	0.26	0.45
0.30	0.17	0.27	0.32	0.51
0.40	0.22	0.33	0.38	0.56
0.50	0.27	0.38	0.43	0.61
0.60	0.33	0.44	0.49	0.65
0.70	0.40	0.50	0.55	0.70
0.80	0.48	0.58	0.63	0.76
0.90	0.62	0.70	0.73	0.83

Figure 4: Ambiguity-attitude probabilities

7. Conclusions

Although travel time uncertainty is embedded within congested transport systems, the psychological aspect of behavioural response to uncertainty is in the mind of the traveller. Using real-market decisions, this paper has presented empirical evidence on the role of ambiguity attitudes in commuting mode choice behaviour. The choice model jointly accommodated unobserved between-subject heterogeneity in taste preferences, nonlinearity in utility under CRRA, risky probability weighting and source functions. In addition to some common findings such as stronger ambiguity seeking in the loss domain, we also find significant age and gender differences in ambiguity attitudes, partial ambiguity in terms of mixed ambiguity seeking, neutrality and aversion and the lack of sensitivity to regular events (i.e., a-insensitivity) under uncertainty.

By using actual events with embedded uncertainty, controlling for risk attitude and sampling real decision makers, this study has addressed an important research gap in the literature.. Abdellaoui *et al.* (2011, p.701) highlighted that a-insensitivity is “not a statistical artifact, but a perceptual phenomenon that occurs in actual decisions”. Therefore, it is important to investigate uncertain decision making in real-market settings. Moreover, the investigation of systematic co-variations with socio-demographics would provide valuable information for evaluating social effects and designing effective policies to mitigate the psychological effect of ambiguity induced by travel time uncertainty.

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