Eliciting Risk Preferences for Intrinsic Attributes

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Abstract

Risk is an important attribute of goods, whereby the utility derived from that attribute is determined by one's attitude to risk. We develop a novel approach to leverage data on risk attitudes from a fully incentivized risk elicitation task to model intrinsic riskiness of alternatives in a choice experiment. In a door-to-door survey, 981 respondents participated in a discrete choice experiment to elicit preferences over alternative sources of municipal water, conditional on water price and quality. Additional source attributes, such as supply risks due to the water source being weather dependent or technology risks are treated as intrinsic as they cannot be plausibly disassociated from the water supply source. The risk task allows the estimation of a coefficient of constant relative risk aversion (CRRA) for an individual, which is incorporated into the preference estimation to test the hypotheses that supply risk and new technology risk are important intrinsic attributes for new water sources. Participants are not given information about supply or technological risks of the sources to avoid framing effects driving the results. Controlling for water quality and cost, we find that supply risk is an important determinant of participants' choices, while respondents are not concerned about technology risk.

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1 Introduction

Lancaster's (1966) theory of consumption states that utility is derived not from the good or service itself, but rather from its characteristics or attributes. Building on this premise, stated preference methods make predictions about changes in utility over alternatives that result from changes in their attributes. While the analyst has control over the extrinsic attributes for each alternative presented, specific alternatives may also have intrinsic attributes. One can think of intrinsic attributes as the residual attributes that are left unspecified in a choice experiment. Consider a travel mode choice experiment that offers the choice between public transit and automobile travel with attributes for the travel time, reliability, and cost. The unspecified intrinsic attributes for public transit may be inconvenience, the ability to read while commuting, and warm glow from making an environmentally friendly choice. In the empirical analysis of the choice experiment these intrinsic attributes are generally bundled into an alternative specific constant (ASC) that communicates the aggregate preferences for public transit relative to driving conditional on the extrinsic attributes.

In some settings, however, it may be desirable to assess individuals' preferences or beliefs for an attribute without explicitly defining it as an extrinsic attribute. For example, the risk of an accident can be presented as an attribute in the travel choice example, but it would not necessarily capture the respondents pre-existing beliefs about the risk of cars relative to transit, which are formed by idiosyncratic information unobservable to the analyst. Moreover, preferences for varying degrees of travel risk depend on the respondents' attitudes to risk that are similarly unobservable. Failing to allow for the respondents' perceptions of and preferences for intrinsic attributes can be problematic, for example, when the propensity to participate in a survey of preferences depends on risk attitudes in a systematic way. In this paper we show that leveraging information about risk attitudes from an incentivized field experiment to model preferences for unspecified intrinsic risk attributes improves model fit and yields significantly different estimates of marginal utilities. We utilitize data from a discrete choice experiment (DCE) on preferences for a new source of municipal water supply. The intrinsic risk attributes are not mentioned to participants at all; rather, we rely on their pre-existing perceptions about the intrinsic riskiness of each of the water sources.

There is a growing literature in environmental economics that focuses on risk attitudes within the contexts of flood insurance (Botzen and Van Den Bergh, 2012; Botzen and van den Bergh, 2012; Petrolia et al., 2013), investments in energy efficiency (Qiu et al., 2014), wildfire protection (Bartczak et al., 2015) and reducing health risks (Lusk and Coble, 2005; Anderson and Mellor, 2008; Cameron and DeShazo, 2013; Andersson et al., 2016). Botzen and Van Den Bergh (2012) analyze the role of increased flood risk from climate change on the market for flood insurance and investigate how consumers respond to low-probability risks and changes in risk as well the role of communicating risk probabilities in risk-related decisions. In a revealed preference setting Petrolia et al. (2013) elicit risk attitudes in order to investigate the role of risk aversion on flood insurance uptake. In most of these settings risk has a direct effect on the preferences for the good and is explicitly modeled as an attribute in a choice experiment (Botzen and Van Den Bergh, 2012; Botzen and van den Bergh, 2012; Petrolia et al., 2013), or as a driver of private purchase decisions (Petrolia et al., 2013).

Similarly, environmental projects and policies tend to have strong elements of risk and uncertainty regarding outcomes (Pindyck, 2007) and a recent focus of the DCE literature has been on improving the methodology to deal with outcome-related risk. For example, Glenk and Colombo (2013) add an explicit attribute of risk of failure for policy options aimed at increasing soil carbon in Scotland, and hence reducing greenhouse gas emissions. They use this data to estimate the preferences of their participants with regards to the level of uncertainty of policies and find the non-linear expected utility theory model performs best. Other DCE studies are concerned with outcome-related risk surrounding the level of environmental quality of a particular lake (Roberts et al., 2008), policies to improve fish numbers and size in popular angler spots (Wielgus et al., 2009) and policies to improve the environmental quality in the Great Barrier Reef (Rolfe and Windle, 2015). These studies demonstrate that the addition of an attribute that captures outcome releated risk alters the stated preferences compared with studies that do not explicitly allow for outcome related risks (Roberts et al., 2008; Wielgus et al., 2009).

Certain risks are central features of the good, such as the probability of a flood for flood insurance, and thus can be modeled explicitly. However, in settings such as the deployment of a new technology, where risk perceptions about the new technology are complex it may be preferable to consider risk to be an intrinsic attribute and allow respondents to communicate risk preferences through their choices. For example, risk averse people are less likely to purchase energy efficient appliances (Qiu et al., 2014) and take longer to adopt new farming technologies (Liu, 2013). Other examples relate to "range anxiety" and electric cars, where consumers face an increase in the risk of being stranded from choosing an electric car over a petrol version (Hidrue et al., 2011). The analyst cannot credibly decouple these risks as extrinsic attributes, and it is this type of intrinsic risk that is the focus of this paper.

Specifically, we combine a fully incentivized risk task with a DCE to leverage the variation in risk aversion to explain the heterogeneity of preferences over goods with unspecified intrinsic risky attributes. A risk task involving incentivized decisions over binary monetary lotteries (Holt and Laury, 2002), was randomly allocated to a subsample of 981 households that participated in a door-to-door survey, where householders are asked to choose amongst six alternative sources of water to augment their city's central water supply. The survey was conducted in Melbourne and Sydney, Australia, where residents frequently experience droughts that result in restrictions to household water use as well as controversial public investments to boost central water supply. With more water shortages being projected for the near future, public knowledge about centralized sources of water provision is high, making this an ideal case study for our research question. In the DCE, alternative water sources vary with respect to water quality and cost to the household. In addition, each water source has intrinsic attributes such as the impact on the environment and vulnerability to drought.

Ex ante we hypothesize that there are two sources of intrinsic risk affecting the choices made by participants. These sources of risk were intentionally *not* mentioned in the information materials provided to the participants of the DCE to ensure participants were not biased towards responding to these risks more than they would otherwise. First, some sources (a new dam, stormwater harvesting and interbasin transfer pipeline) are dependent on weather and therefore may not provide sufficient water security during periods of drought. We define this risk as a supply risk. Additionally, certain sources (stormwater harvesting and recycled water) provide water via new technologies that risk averse consumers may believe are unproven, which we term technological risk. We find supply risk to be an important intrinsic attribute and show that explicitly modeling risk aversion as part of the utility function has a significant effect on preference estimation as well as improving model fit.

The motivation behind the DCE in this paper stems from general concerns over security of municipal water supplies, particularly in regions susceptible to droughts. There are increasing demands for water and a diminishing number of unexploited sources of water for centralized water systems – for example, the number of viable locations remaining to build dams is decreasing (Duarte et al., 2014). Furthermore, climate change is already challenging existing water supply systems through changing rainfall patterns, and dry regions of the world are likely to see more frequent droughts over the course of the current century (IPCC, 2014). Decentralized alternatives to water supply, such as rainwater tanks, are increasingly being utilized as an important source of water. However, centralized water supply systems are still by far the main source of water provision, including on the world's driest inhabited continent, Australia (Mankad and Tapsuwan, 2011; ABS, 2013). Therefore, new sources of centralized water supply will probably continue to be built at considerable cost. It is important to understand public preferences for new water sources including risk attitudes towards supply security and deployment of new technologies.

The paper is organized as follows. The theoretical framework is outlined in the next section, followed by a brief description of the experimental design and summary statistics. Section 4 summarizes the empirical framework, Section 5 describes the main results and Section 6 concludes.

2 Theoretical Framework

We begin with a random utility model (McFadden, 1973) of householders' choices over a set J of alternative sources of additional mains water. Utility U of individual i from choosing water source j for choice occasion t is given by

$$U_{ijt} = V_{ijt} + \epsilon_{ijt}, \tag{1}$$

where V_{ijt} is a linear function of the observable source attributes, water quality and cost per kL consumed, and ϵ_{ijt} is a random component incorporating all other factors that may affect U_{ijt}. In particular, if V_{ijt} contains ASCs, these dummies incorporate attributes that are intrinsic to the water source such as the perceived taste, color or smell of the water (eg. Marks, 2006; Productivity Commission, 2011; Chen et al., 2013), aesthetic, environmental or ecological impacts (Productivity Commission, 2011), as well as risks. Individual i chooses water source j for choice t when:

$$U_{ijt} \geq U_{ikt} \quad \forall j, k \in J, j \neq k. \tag{2}$$

A standard empirical application of this model assumes the observable component, V_{ijt}, to be linear and additively separable in its elements. Thus, in our base model:

$$V = \boldsymbol{\beta}_j \mathbf{X}_j + \boldsymbol{\beta}_q \mathbf{X}_q + \beta_c C, \tag{3}$$

where $\boldsymbol{\beta}_j$ is a vector of the ASCs for each water source $\mathbf{X}_j$, with the omitted categorical dummy being "new dam". The vector of coefficients $\boldsymbol{\beta}_q$ is associated with the different levels of allowed use (or quality) $\mathbf{X}_q$ and β_c is the coefficient on cost per kL of water consumed.

In addition to our base model, we propose an alternative model specification, to explicitly allow for heterogeneous risk attitudes toward a subset of water sources that may be perceived as being intrinsically risky. Such risk perceptions may be due to the source being dependent on weather or subject to a new and unproven technologies working as envisaged. From the outset, we are agnostic about which type of risk may be important and identify a set of dummy variables X_r, where r indexes these mutually exclusive risky sources. $X_r = 2$ indicates that water is provided via a risky source r, while $X_r = 1$ indicates that the provision is via a non-risky source.[1] The fact that these sources of risk were not mentioned to participants in information materials provided should alleviate concerns that framing bias is driving the risk parameter β_r. As before, it is assumed that each of these sources provides deterministic utility components from the perspective of respondents and enter the utility function in the standard linear form, $\beta_j X_j$. In addition, these sources have a utility component that is subject to perceived outcome risk that is unobservable by the researcher. It is anticipated that preferences will also be influenced by each individual's degree of risk aversion. The importance of risk attitudes for explaining heterogeneous preferences is our central hypotheses of interest.

We denote the risky utility component associated with X_r using a non-linear constant relative risk aversion (CRRA) functional form, $f\left(X_r, \gamma_i\right) = \left(\frac{X_r^{1-\gamma_i}-1}{1-\gamma_i}\right)$, that is assumed to be additively separable from other utility components. Thus the utility that is attributable to X_r depends on each individual's CRRA parameter, γ_i, that is estimated separately using an incentivized risk experiment. A risk loving individual is characterized by $\gamma_i < 0$, a risk neutral individual by $\gamma_i = 0$ and a risk averse individual has $\gamma_i > 0$. Adapting equation (3) to accommodate the risk-related utility component yields:

$$V = \boldsymbol{\beta}_j \mathbf{X}_j + \boldsymbol{\beta}_q \mathbf{X}_q + \beta_c C + \beta_r f\left(X_r, \gamma_i\right), \tag{4}$$

where β_r determines the weight the participants put on the risky attribute. This specification assumes that, given observed risk attitudes, intrinsic risk-related utility can be fully separated out from the ASCs. For example, it assumes the utility from the supply risk of a water source can be captured separately from the utility of choosing a particular water source by the term $\beta_r f\left(X_r, \gamma_i\right)$, where X_r is supply risk.

[1] The dummy variable $X_r \in \{1, 2\}$ is due to the form of the CRRA utility function. When $X_r = 1$, the attribute is in its non-risky state and thus the CRRA utility function is 0 for all levels of risk aversion. When $X_r = 2$, the attribute is in its risky state and the CRRA utility function varies by level of risk aversion, γ_i.

Whether a particular attribute is considered risky by participants and given a significant weight in determining their choice of a new water source is an empirical question, which we seek to answer using the data described in the next section. We consider supply risk and new technology risk to be the primary risks associated with new sources of water and test each hypothesis separately.

The first hypothesis is that supply risk is an important intrinsic attribute for new dams, stormwater harvesting and interbasin transfer pipeline. Thus if supply risk matters, we expect $\beta_r > 0$ when X_r is a dummy for weather dependent sources. The second hypothesis, following the literature on technology adoption and risk aversion (Liu, 2013; Qiu et al., 2014), is that new technology risk is an important intrinsic attribute of certain water sources. Recycled and stormwater harvesting are new technologies that are not widely used in Australia. All other sources have some well established and sizable capacity (Productivity Commission, 2011). Thus we define X_r as a dummy for new technology and test the null hypothesis $\beta_r \leq 0$ against the alternative that $\beta_r > 0$.

3 Survey Design and Data

3.1 Survey description

The discrete choice experiment (DCE) that elicits preferences for new water supply sources was part of a door-to-door survey on preferences for urban water management conducted in Melbourne and Sydney, Australia. In total, a random sample of 981 householders over the age of 18, who had owner-occupier status in 2013, were interviewed.

At the door, interviewers introduced themselves and asked the householder to participate in a survey about local water management. The interviewer then confirmed the individual's eligibility, and proceeded with the survey on an iPad. Before commencing the survey, the software randomly assigned whether or not the participant would complete an incentivized risk experiment, with earnings ranging from A$0.60 to A$23.10.[2]

Next, respondents participated in a first DCE on the non-market benefits of local

[2]Concerns over the cost of payouts for the risk task prevented eliciting risk preferences for the full sample.

water management projects, described in more detail by Brent et al. (2014). The second choice task elicited water source preferences and is the focus of this paper.[3] The survey ended with a set of demographic and water-relevant questions.

The survey was developed after a series of focus group meetings with researchers from different disciplines in the Cooperative Research Centre on Water Sensitive Cities (CRCWSC) in which appropriate attributes and levels were discussed.[4] A professional survey company was employed to conduct the survey and the interview team was carefully briefed by the authors with regards to the objective and details of the survey. The survey was then pre-tested in full length interviews with volunteer council employees, most of whom were not involved with water management in the council. A trained psychologist assisted the focus group interviews, conducted debriefing interviews with the participants and provided recommendations based on her assessment of the survey design (including wording, length, information content and cognitive demands). The revised survey was successfully tested in the field with a small sample of households before being rolled out.

The survey was conducted in the council areas of Manningham and Moonee Valley (within greater Melbourne) and Fairfield and Warringah (greater Sydney). The councils were selected on the basis that they had similar rainfall patterns, income, age composition and level of home ownership. The survey was undertaken from March to October, 2013, ensuring results were not driven by seasonality.

3.1.1 Incentivized risk elicitation task

A fully incentivized choice experiment over lotteries was given to a subset of participants in order to estimate their risk attitudes. These tasks are particularly useful for understanding how people make decisions involving risk (Charness et al., 2013) and have been utilized in areas such as understanding farmer adoption of new technology (Liu, 2013) and predicting health-related behaviors and preferences (Lusk and Coble, 2005; Anderson

[3]Some respondents were incentivized for this first task, whereas others were not. When comparing the responses of these treatment groups to the second choice task, we find no statistically significant differences. This is expected given that everyone faced the same hypothetical, non-incentivized choice sets for the second DCE. We also do not find any difference in responses between those who were given the risk task and those who were not.

[4]The CRCWSC is an Australian research organization, which is funded by the federal government.

Figure 1: Risk preference experiment example of choice image.

and Mellor, 2008). Full instructions and explanatory examples shown to participants are given in the Appendix. The experiment is based on Holt and Laury (2002) and consists of ten questions, each of which ask the participant to choose between two lotteries. Our departure from Holt and Laury (2002) is that rather than displaying the questions in a multiple price list format, where all questions are given to participants in order and simultaneously, participants were given each question separately and in a random order. We also included images to help participants understand the choices they were being asked to make (Dave et al., 2010), as shown in Figure 1.

The full set of questions are displayed in the first two columns of Table 1, which show the potential earnings and probabilities for each of the two lotteries. The third column of Table 1 shows the difference in expected value of lottery A and lottery B; the fourth gives the implied range for the coefficient of CRRA γ_i if the participant switches from Lottery A to B at that question. Before the task commenced, it was explained that one of the 10 questions would be randomly selected and then a random draw for that lottery would determine their payment based on the option they selected.

When a single switch point (given the order of questions in Table 1) from choosing lottery A to choosing lottery B is not recorded, a participant is considered indifferent between a wider range of lotteries, and thus the implied range of their γ_i is wider (Andersen

Table 1: Risk preference task questions, difference in expected values and coefficient of CRRA.

Option A	Option B	$\mathrm{EV_A} - \mathrm{EV_B}$	CRRA if switch to B
10% of \$12.00, 90% of \$9.60	10% of \$23.10, 90% of \$0.60	\$6.99	$\gamma_i < -1.71$
20% of \$12.00, 80% of \$9.60	20% of \$23.10, 80% of \$0.60	\$4.98	$-1.71 < \gamma_i < -0.95$
30% of \$12.00, 70% of \$9.60	30% of \$23.10, 70% of \$0.60	\$2.97	$-0.95 < \gamma_i < -0.49$
40% of \$12.00, 60% of \$9.60	40% of \$23.10, 60% of \$0.60	\$0.96	$-0.49 < \gamma_i < -0.15$
50% of \$12.00, 50% of \$9.60	50% of \$23.10, 50% of \$0.60	−\$1.05	$-0.15 < \gamma_i < 0.15$
60% of \$12.00, 40% of \$9.60	60% of \$23.10, 40% of \$0.60	−\$3.06	$0.15 < \gamma_i < 0.41$
70% of \$12.00, 30% of \$9.60	70% of \$23.10, 30% of \$0.60	−\$5.07	$0.41 < \gamma_i < 0.68$
80% of \$12.00, 20% of \$9.60	80% of \$23.10, 20% of \$0.60	−\$7.08	$0.68 < \gamma_i < 0.97$
90% of \$12.00, 10% of \$9.60	90% of \$23.10, 10% of \$0.60	−\$9.09	$0.97 < \gamma_i < 1.37$
100% of \$12.00, 0% of \$9.60	100% of \$23.10, 0% of \$0.60	−\$11.10	$1.37 < \gamma_i$

et al., 2006; Charness et al., 2013). For example, if a participant records lottery A for his first choice, lottery B for his second, lottery A for his third and lottery B thereafter, the researcher estimates an γ_i value for him as $-1.71 < \gamma_i < -0.15$. While showing the lotteries to participants as a list (as in Holt and Laury, 2002) might lower the chances that a participant has more than one switch point, meaning less noisy data, it could lead to ordering effects that impact individual's choices (Harrison et al., 2005; Dave et al., 2010). The randomization of questions employed in this study may lead to noisier data, but is less likely to be biased.

The tenth question in Table 1 acts as a control question, ensuring understanding of the task. It is a choice between receiving \$12.00 with certainty (option A) and \$23.10 with certainty (option B). Therefore, if a participant chooses option A for question 10, it implies either that they do not wish to take money from the researcher or that they do not understand the task. We exclude 30 of the 167 participants who completed the risk task who chose option A for question 10 since they likely did not understand the risk task.

3.1.2 Discrete choice experiment over water sources

Preferences for a new water supply source are elicited through a discrete choice experiment (Carson and Louviere, 2011). The task was introduced to participants as follows (full instructions are shown in the Appendix):

When water shortages become more frequent, investments to increase urban water *supply need to be made. There are a number of options in terms of water source and technology that a city can invest in. These options differ with respect to the quality of water provided and therefore their allowed use, as well as the cost of water provision. It is possible to install a third water pipe to your house, so that your tap water will not be contaminated with potentially lower quality water from the new source. You would NOT have to pay for the installation of the third pipe.*

You will now be asked to make a series of 10 choices regarding your preferred additional water source, its allowed uses and the resulting cost of water. Assume that this would be the cost of your total water consumption per kiloliter in AUD. No other rates or charges would change.

Before starting the choice experiment participants received a brief explanation about the different water sources and attributes. The explanation did not mention risk to avoid altering participant's perceptions and thus allowing the estimation of respondents' inherent risk preferences over intrinsic attributes. The summary information sheet shown to participants is shown in Figure A.4 in the Appendix, which could be referred to throughout the choice task. Each participant was then given a sequence of ten separate questions, presented in a graphical format. Figure 2 provides an example. Each question asked for the participant's preferred new water supply source out of six possibilities: desalination, recycled, new dam, groundwater, stormwater or pipeline (interbasin transfer). As shown in Figure 2, the water supply source attributes vary in terms of allowed use and total cost per kiloliter on their water bill. Allowed use in the study has three levels – low risk outdoor use (non-potable outdoor, first two images, by descending order, in Figure 2); adding toilet, laundry and vegetable gardens (non-potable indoor, third image); and fully potable water (fourth image). Cost per kiloliter ranged from \$1.60 to \$3.20, in 20c increments. The lower cost levels were representative of water prices at the time of the survey and the higher levels were designed to stay within realistic bounds.

The D-efficiency criterion was applied to construct four blocks of ten choice questions using the the software package *Ngene*. Each participant was randomly assigned to one of the four blocks, and they saw the questions from their given block in a random order.

Figure 2: Example of image shown to participants for a water supply source choice.

Overall, the questions were balanced so that each water source was assigned each level of quality and cost approximately the same number of times. New dam and desalination were only assigned potable quality as they always produce high quality water.

The purpose of the survey is to determine community preferences for future centralized water supply projects, conditional on a new water supply source being built. Accordingly, this survey represents a forced choice, discrete choice experiment as there is no "status quo" option for participants – for example "no new water source" (Hensher et al., 2005; Louviere et al., 2010; Carson and Louviere, 2011).[5] A status quo option such as "no new water source" brings with it implicit assumptions on the part of the participant about water supply reliability compared with building a new source. These implicit assumptions are not known to the researcher, making the interpretation of the results problematic. Respondents may associate a type of new water source with a known project, but the

[5] Forced choice experiments are useful when considering situations such as preferences for the type of development in a place where a development is inevitable, and how residents value more conservation-friendly development (eg. Johnston et al., 2003; Duke et al., 2014). This study looks at a similar situation, asking participants to consider the inevitable situation in which not building a new water source is untenable.

potential impact on their local amenities of a particular water supply source is a relevant consideration for them to be making. Thus, the method chosen represents the best method to elicit community preferences about options for centralized water supply augmentation (Hensher et al., 2005; Louviere et al., 2010; Carson and Louviere, 2011).

3.2 Descriptive statistics

The demographics, flood risk perception, flood insurance ownership and rainwater tank ownership of the full sample of 981 participants are recorded in Table 2.[6] The second to last column of Table 2 shows the same data, but for the subsample of 137 who were randomly selected to do the risk task and who were not excluded from the analysis of the risk task. The rightmost column of Table 2 shows p-values, using the non-parametric Mann-Whitney test, comparing the distribution of each attribute between the risk subsample and those in the full sample who are not in the risk subsample. The p-values are all well above 0.1, indicating the risk subsample is not statistically different from the full sample. Thus, conclusions drawn from the risk sub-sample are relevant for the whole sample. The overall choices made in the DCE are given in Figure A.1 in the appendix.

3.2.1 Risk preference summary statistics

Table 3 shows the number of times each participant switched from the safe lottery A to the risky lottery B, using the order of questions in Table 1 as the order of lotteries. Answering lottery B for the first question of Table 1 is considered one switch. Switching twice implies the person switched from lottery A to B at some point, then back to A, then to B again. As shown in Table 3, about half of the participants switched more than once. This is to be expected given participants saw the choices in a random order and thus were not biased towards having a single switch point, but rather could express indifference between some options by switching more than once (Andersen et al., 2006; Charness et al., 2013). Multiple switching is not uncommon even when using the original Holt and Laury (2002) multiple price list format, with Anderson and Mellor (2008) reporting 21% switching more

[6]Rainwater tanks in urban Australia are not designed to replace mains water, but rather supplement outdoor water supply and are sometimes piped into laundry and toilets.

Table 2: Summary statistics.

	Full sample (%)	Risk subsample (%)	p-value
Gender			0.2943
Female	46.5	42.3	
Age			0.1355
Refused	0.2	0	
18 to 24	4.0	5.8	
25 to 44	24.5	31	
45 to 64	41.7	46.7	
65+	29.7	24.8	
Education			0.3215
Refused or other	4.0	1.5	
Year 10-12	27.3	24.8	
Certificate	15.3	16.8	
Associate	13.4	14.6	
Bachelor	23.8	21.2	
Graduate	16.3	21.2	
Income			0.3982
Refused	4.1	3.0	
Don't know	2.6	0.7	
Low	23.2	22.2	
Middle	60.1	61.5	
High	10.0	12.6	
Flood risk perception			0.9664
Refused	0.1	0	
Don't know	2.8	2.9	
1 in 2 years	7.2	4.4	
1 in 5 years	8.3	11.7	
1 in 10 years	8.4	9.5	
1 in 20 years	7.2	5.8	
Almost never	66.1	65.7	
Flood insurance			0.7389
Refused	0.3	0	
Don't know	22.2	19.0	
Yes	38.1	38.7	
No	39.4	42.3	
Own a rainwater tank			0.4536
Don't know	0.3	0	
Yes	28.1	25.6	
No	71.6	74.5	
Sample size	981	137	

Note: The p-values compare the risk sub-sample to the non-risk participants in the full sample, using the non-parametric Mann-Whitney test.

Table 3: Number of switches between lotteries A and B.

Number of switches from A to B	**% of participants**
1	49.6
2	33.6
3	13.1
4	3.6
Sample size	137

than once from their large sample of the general population in the USA.

To utilize the estimated coefficients of CRRA in the modeling approach of this paper, we allocate the midpoint of the estimated range for γ_i to each participant (see Andersen et al., 2006; Liu, 2013, as others who use this method). However, this study has a number of people whose γ_i is not bounded below (answered option B for the first question in Table 1; 27.0% of participants) or not bounded from above (answered option A for question 9 and switched to option B for question 10; 21.9% of participants). There are two potential approaches to deal with these participants. One is to assume a lower and upper bound based on the most extreme values found in the literature. The second, more conservative approach is to use the values of -1.71 and 1.37 as the bounds. The second approach is adopted here; the majority of Danes in similar field study on the public fall within these extremes (Harrison et al., 2007). Some experimentation with the first approach did not yield material differences to the overall results of this study.

The 137 participants for whom risk attitude is observed are a random subsample of the full 981 participants, as already shown in Table 2. The mean and standard deviation of the observed coefficient of CRRA is 0.10 and 0.88 respectively. This shows that people are on average risk averse, as it commonly found in field experiments on risk attitudes of the public in developed countries (eg. Anderson and Mellor, 2008; Harrison et al., 2007; Dave et al., 2010).

4 Empirical Specification

This paper employs the mixed logit to estimate the utility function given by equations (3) and (4). An advantage of the mixed logit is that it allows for preference heterogeneity amongst participants, by incorporating both fixed and random coefficients.

To simplify notation we group all coefficients into a single vector $\boldsymbol{\beta}$, and all variables for source j at time t into a single $\boldsymbol{X}_{jt}$. U_{ijt} can be modeled probabilistically, as it is a latent variable which determines each individual's choice of water supply source, j. Thus, assuming each individual has a unique $\boldsymbol{\beta}_i$

$$\Pr(Y_{it} = j) = \Pr(U_{ijt} > U_{ikt}) \quad \forall j \neq k \tag{5a}$$

$$= \Pr(\boldsymbol{\beta}_i \boldsymbol{X}_{jt} + \epsilon_{ijt} > \boldsymbol{\beta}_i \boldsymbol{X}_{jt} + \epsilon_{ikt}) \quad \forall j \neq k \tag{5b}$$

$$= \Pr(\epsilon_{ijt} - \epsilon_{ikt} < \boldsymbol{\beta}_i \boldsymbol{X}_{jt} - \boldsymbol{\beta}_i \boldsymbol{X}_{jt}) \quad \forall j \neq k. \tag{5c}$$

As the objective is to compare models that explicitly allow for water source specific risks with those that do not and for which the error terms would be correlated, we reject the IID assumption and specify a mixed logit functional form for equation (5c). The mixed logit model allows for individual heterogeneity in $\boldsymbol{\beta}$ in the following way:

$$\Pr(Y_t = j) = \int \frac{\exp(\boldsymbol{\beta} \boldsymbol{X}_{jt})}{\sum_{k \in J} \exp(\boldsymbol{\beta} \boldsymbol{X}_{jt})} f(\boldsymbol{\beta} | \boldsymbol{\theta}) d\boldsymbol{\beta}. \tag{6}$$

Here, $\boldsymbol{\theta}$ is a vector of distributional parameters such as mean and variance, estimated using numerical simulation of maximum likelihood. The researcher can choose which elements of $\boldsymbol{\beta}$ are randomly distributed and thus assumed to vary across the population, and which elements are fixed and thus identical across the population. To estimate the model, the researcher must specify the distribution of each element of $\boldsymbol{\beta}$, and whether or not they are independently distributed, or correlated. Commonly normal, lognormal or triangular distributions are used. By allowing random distribution of $\boldsymbol{\beta}$, the mixed logit can approximate any random utility model (Hensher and Greene, 2003; Train, 2009).

5 Results

The mixed logit models are estimated using maximum simulated likelihood with 400 Halton draws for the sample of 860 people and 500 draws for the smaller sub-sample, a sufficient number to ensure stability of estimates for this dataset and specification of models (Hensher and Greene, 2003; Train, 2009). The main results are presented in Table 4.

Model 1 in the first column of Table 4, is based on equation (3) and is the mixed logit estimation of the explicit attributes presented in the DCE. It is estimated from a subsample of 860 people so that it uses the same subsample as Models 3 and 5. The first two coefficients in descending order are fixed coefficients for allowed use - non-potable outdoor and non-potable indoor, relative to potable quality.[7] The results confirm findings in other studies that people dislike non-potable indoor water. Chen et al. (2013) accredit this aversion to concerns over smell and color of this type of water, given it is used for toilets and laundering. While other specifications were tested, the goodness of fit measures of AIC and BIC indicate Model 1 fits best when the coefficients for these variables are fixed.

The next set of variables of Model 1 in Table 4 are the means of the random ASC coefficients for water source, relative to new dam. The coefficients on these variables are in line with the overall choices (see Figure A.1 in the appendix): they are all negative as new dam is the most popular option. They are also in order of popularity, with desalination being the largest coefficient as it is next most popular after new dam and groundwater is the smallest as it is the least popular. The water source coefficients are all assumed to be normally distributed.

The final mean random coefficient is cost. It is negative and statistically significant, as expected. It is assumed to follow a symmetric triangular distribution, as this distribution does not assume small numbers of people have extreme parameter values, like a normal or lognormal distribution (Hensher and Greene, 2003). Thus, sensitivity to cost remains

[7] The assumption behind fixed coefficients is that they are the same for all participants.

Table 4: Mixed logits models without and with risky attributes; errors are bootstrapped for Models 3 and 5.

	(1)	(2)	(3)	(4)	(5)
Fixed Coefficients & Means					
Fixed Coefficients					
Non-potable outdoor	0.0265	−0.0583	0.0259	−0.0587	0.0259
	(0.0470)	(0.1080)	(0.0496)	(0.1080)	(0.0481)
Non-potable indoor	−0.1452***	−0.2595**	−0.1471***	−0.2601**	−0.1455***
	(0.0514)	(0.1202)	(0.0531)	(0.1201)	(0.0498)
β_r (supply risk)		0.2247	0.7115*		
		(0.2729)	(0.3847)		
β_r (new technology risk)				−0.1209	−0.3891
				(0.2759)	(0.4581)
Random Coefficients					
Desalination	−0.7724***	−0.4354	−0.0546	−0.6748***	−0.7746***
	(0.0879)	(0.3400)	(0.4014)	(0.1783)	(0.1021)
Recycled	−1.6845***	−1.0638***	−0.9622**	−1.1771***	−1.2903***
	(0.1109)	(0.3551)	(0.3995)	(0.3528)	(0.4823)
Groundwater	−2.5589***	−1.9428***	−1.8375***	−2.1664***	−2.5616***
	(0.1207)	(0.3707)	(0.4047)	(0.2538)	(0.1331)
Stormwater	−0.9977***	−0.7071***	−0.9998***	−0.5778*	−0.6053
	(0.0788)	(0.1558)	(0.0845)	(0.3283)	(0.4747)
Pipeline	−2.2565***	−1.6346***	−2.2534***	−1.6342***	−2.2554***
	(0.0980)	(0.1771)	(0.0992)	(0.1774)	(0.1074)
Cost	−0.1118***	−0.1543	−0.1086	−0.1528	−0.1138
	(0.0425)	(0.1107)	(0.0927)	(0.1112)	(0.0912)
Standard Deviation or Spread					
Standard Deviation					
Desalination	2.1183***	1.6085***	2.0923***	1.6400***	2.1244***
	(0.0961)	(0.2009)	(0.1025)	(0.1991)	(0.1068)
Recycled	2.2761***	1.6101***	2.2593***	1.5955***	2.2716***
	(0.1083)	(0.2144)	(0.1205)	(0.2099)	(0.1223)
Groundwater	1.6403***	1.2825***	1.6346***	1.2624***	1.6458***
	(0.1013)	(0.2359)	(0.1276)	(0.2339)	(0.1334)
Stormwater	1.6482***	1.1648***	1.6516***	1.1628***	1.6520***
	(0.0729)	(0.1428)	(0.0940)	(0.1431)	(0.0877)
Pipeline	1.3142***	0.7937***	1.3092***	0.7921***	1.3118***
	(0.0910)	(0.1925)	(0.1321)	(0.1942)	(0.1306)
Spread					
Cost	0.2639***	0.2502	0.2549**	0.2462	0.2701**
	(0.0981)	(0.2700)	(0.1005)	(0.2719)	(0.1058)
AIC	23795.0	4129.5	23787.7	4130.0	23794.2
BIC	23893.8	4207.8	23893.6	4208.3	23900.1
Observations	8600	1370	8600	1370	8600
Individuals	860	137	860	137	860
Coefficient; (Standard Error); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.					

Notes: The coefficient for cost follows a triangular distribution. All other random coefficients are normally distributed.
For all variables, standard errors are clustered at the respondent level. CRRA data is imputed for 723 individuals for Models 3 and 5; thus standard errors are bootstrapped for Models 3 and 5, with 500 repetitions. Quality variables are relative to low quality, water source variables are relative to new dam.

within a reasonable range.[8]

The next section of the table shows the standard deviation or spread of the random coefficients. The estimated standard deviation for the new sources of water coefficients are large and significant. They indicate, for example, that less than one half of a standard deviation above the mean coefficient for desalination, participants prefer desalination over new dam. Thus, preferences for new water source are highly heterogeneous. The spread of the cost coefficient is also significant, indicating a range of cost sensitivities amongst respondents.

5.1 Supply risk preferences

Model 2 in Table 4 adds the fixed coefficient β_r, which is the parameter for supply risk. It is estimated using the subsample of 137 for whom risk attitude is observed. The first hypothesis of this paper (in Section 2) states that if supply risk in an important intrinsic attribute for preference, then β_r should be positive and statistically significant. Model 2 shows $\beta_r > 0$, but it is not statistically significant. This result is using just 137 of the survey respondents. Given the positive value of β_r, we impute risk attitudes for the full sample to utilize as many respondents' data as possible to test whether the lack of statistical significance is a due to the small sample size. Details on the imputation are presented in Section 5.3.

Model 3 shows the results for the full subsample of 860, with level of risk aversion imputed for those with unobserved risk attitude. The 121 respondents that are excluded from the full sample are excluded as risk attitude could not be imputed for them. With the larger sample size, β_r is both positive and statistically significant. Furthermore, the model fit improves over the model without risk attitude, Model 1, using both AIC and BIC criteria.

Inference in Model 3 uses bootstrapped standard errors based on Shao and Sitter

[8] While bounded triangular distributions are often used for cost (Hensher and Greene, 2003; Johnston and Ramachandran, 2014), we do not bound the distribution to avoid placing unnecessary restrictions on our models. Other authors use bounded triangular distributions in order to correctly calculate willingness to pay (Daly et al., 2012), which is not a concern for us. Sensitivity to cost is often low when using realistic values for water given these costs are low compared with a total household budget (Olmstead, 2010); an unbounded triangular distribution allows more flexibility to account for this fact.

(1996), which is robust regardless of imputation method and statistical model. Bootstrapping is undertaken for all models that use imputed data in order to account for the uncertainty from the imputation stage. More details on the bootstrapping procedure are given in Section 5.3.

The other important feature of Model 3 to note is the mean coefficients for new water source. Mixed logit coefficients cannot be directly compared between models without accounting for scale differences, but Models 1 and 3 are also different in terms of interpretation of the coefficients. Because supply risk is an intrinsic attribute, preferences for a given water source is a combination of both the water source coefficient and β_r in Model 3.

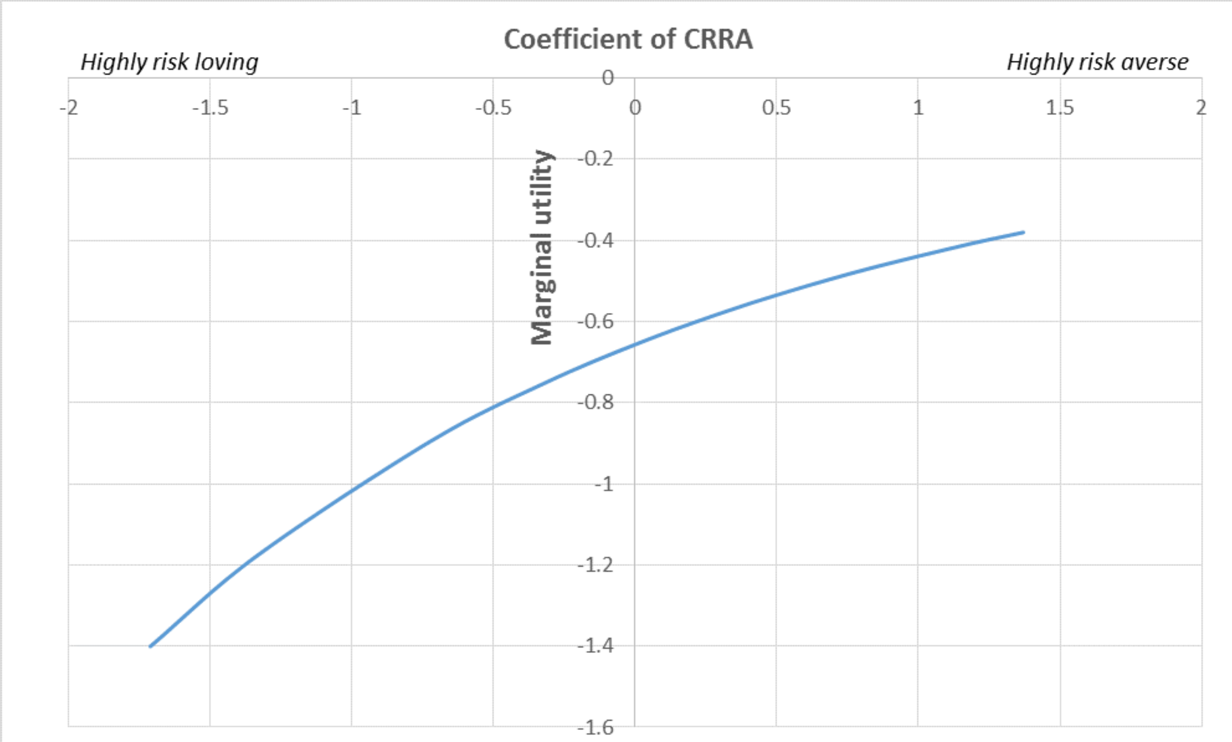
The utility an individual at the mean receives from choosing desalination over new dam in Model 1, *ceteris paribus*, is given by the estimated mean coefficient for desalination, $\hat{\bar{\beta}}_D$. In Model 3, as follows from equation (4), the estimated utility an individual at the mean receives from choosing desalination over new dam, becomes:

$$\begin{aligned}\hat{\bar{U}}_{iD} - \hat{\bar{U}}_{iND} =& \hat{\bar{\beta}}_D + \hat{\beta}_r \left(\frac{1^{1-\gamma_i} - 1}{1-\gamma_i}\right) - \hat{\beta}_r \left(\frac{2^{1-\gamma_i} - 1}{1-\gamma_i}\right) \qquad (7a)\\ =& \hat{\bar{\beta}}_D - \hat{\beta}_r \left(\frac{2^{1-\gamma_i} - 1}{1-\gamma_i}\right). \qquad (7b)\end{aligned}$$

Thus, for this case, Model 3 includes the marginal utility from moving from a source with supply risk to a source without supply risk, $-\beta_r\left(\frac{2^{1-\gamma_i}-1}{1-\gamma_i}\right)$. Therefore, when comparing preferences for sources in Model 3, β_r must be taken into account if the sources have different types of supply risk.

Figure 3 plots Equation (7) by individual level of risk aversion, γ_i. Given the marginal utility is always negative, an average participant still prefers the new dam no matter what their level of risk aversion. However, given the coefficient on desalination is random and with a large standard deviation, there will be some participants for whom their level of risk aversion does impact whether they prefer new dam to desalination or not. Figure 3

Figure 3: Mean marginal utility of switching from new dam to desalination, by level of risk aversion, Model 3 (Equation (7)).



assumes allowed use and cost are the same for both new dam and desalination for the purpose of comparison.

5.2 New technology risk preferences

The second hypothesis stated in Section 2 is in regards to new technology risk. Table 4 also presents Model 4, which assumes the sources of stormwater and recycled are perceived as new technology. Model 4 is otherwise the same specification as Model 2. Model 5 is the same as Model 4, but utilizes the larger subsample of 860. The estimated coefficient of β_r for new technology risk in both Models 4 and 5 is negative and statistically insignificant. Thus, based on this result, the hypothesis that β_r for new technology risk is positive is rejected. Overall, using the AIC and BIC criteria, Model 3 has a superior fit to the data compared with Model 5.

Table 5 helps complete the overall picture of the drivers of the results. It shows 6 models, with each source classed separately as risky. All models use the full 860 observations available with imputed data, and have bootstrapped standard errors. New dam generates a positive but non-statistically significant coefficient for β_r. Desalination has a negative and highly significant coefficient for β_r; all the other sources have non-significant coefficients, which are all negative. Thus, the result that supply risk is a significant intrinsic attribute is driven largely by new dam. Importantly though, it is in the inclusion of all sources with a supply risk in the risk attribute dummy X_r that leads to a positive and statistically significant parameter for B_r (supply risk) in Model 3.

5.3 Imputing risk attitudes for the full sample

Table 6 displays the tobit model that is used to impute risk attitudes for the full sample. The fitted values from this model are used to impute the risk attitudes for those without observations for this variable. In order to more accurately impute risk attitudes, both demographics and indicators of attitudes to risk are included.[9] The attitude to risk variables are flood risk perception, owning flood insurance, not knowing whether or not they own flood insurance, and an interaction between owning flood insurance and flood risk perception. The flood risk perception question is as shown in Table 2. In the tobit model it is treated as a Likert-type scale from 1 to 5, with 1 equating to "Almost never" and 5 being "1 in 2 years". As already mentioned, the locations chosen for the survey had similar rainfall patterns, so differences in responses should not be a reflection of differences in actual flood risk; rather they should reflect differences in perceived flood risk. The interaction between owning flood insurance and flood risk perception is positive and statistically significant, as expected.

The first demographics included in Table 6 are age, gender and education. Next is dummies for middle and high household income (relative to low income) as self-identified by participants. This variable is used for income as subjective data can be useful as explanatory variables to explain behavior (Bertrand and Mullainathan, 2001). Furthermore, more people were willing to answer this question about their household income than giv-

[9]The model is estimated from 124 of the 137 people with observed risk attitudes as the other 13 do not have a full set of right-hand side variables due to answering "Don't know" or refusing to answer to some of the survey questions.

Table 5: Mixed logits with each source separately classed as risky.

	(6)	(7)	(8)	(9)	(10)	(11)
Fixed Coefficients & Means						
Fixed Coefficients						
Non-potable outdoor	0.0261	0.0270	0.0255	0.0265	0.0264	0.0265
	(0.0474)	(0.0486)	(0.0479)	(0.0478)	(0.0507)	(0.0485)
Non-potable indoor	-0.1450^{***}	-0.1462^{***}	-0.1467^{***}	-0.1452^{***}	-0.1448^{***}	-0.1452^{***}
	(0.0513)	(0.0498)	(0.0498)	(0.0510)	(0.0537)	(0.0510)
β_r (new dam)	0.4709					
	(0.3675)					
β_r (desalination)		-1.1747^{***}				
		(0.4283)				
β_r (recycled)			-0.6705			
			(0.5847)			
β_r (groundwater)				-0.1140		
				(0.4452)		
β_r (stormwater)					-0.2766	
					(0.4777)	
β_r (pipeline)						-0.0081
						(0.3501)
Random Coefficients						
Desalination	-0.2959	0.4052	-0.7751^{***}	-0.7724^{***}	-0.7733^{***}	-0.7723^{***}
	(0.3851)	(0.4319)	(0.1025)	(0.1013)	(0.1035)	(0.1021)
Recycled	-1.2051^{***}	-1.6768^{***}	-1.0100^{*}	-1.6836^{***}	-1.6857^{***}	-1.6845^{***}
	(0.3899)	(0.1247)	(0.6016)	(0.1244)	(0.1258)	(0.1199)
Groundwater	-2.0815^{***}	-2.5584^{***}	-2.5596^{***}	-2.4417^{***}	-2.5612^{***}	-2.5589^{***}
	(0.3976)	(0.1333)	(0.1334)	(0.4638)	(0.1415)	(0.1340)
Stormwater	-0.5240	-0.9999^{***}	-0.9975^{***}	-0.9979^{***}	-0.7189	-0.9977^{***}
	(0.3796)	(0.0901)	(0.0843)	(0.0843)	(0.4885)	(0.0863)
Pipeline	-1.7821^{***}	-2.2562^{***}	-2.2547^{***}	-2.2566^{***}	-2.2563^{***}	-2.2483^{***}
	(0.3873)	(0.1020)	(0.1042)	(0.1086)	(0.1051)	(0.3722)
Cost	-0.1130	-0.1062	-0.1120	-0.1120	-0.1133	-0.1119
	(0.0938)	(0.0946)	(0.0953)	(0.0928)	(0.0939)	(0.0971)
Standard Deviation or Spread						
Standard Deviation						
Desalination	2.1037^{***}	2.0879^{***}	2.1220^{***}	2.1180^{***}	2.1205^{***}	2.1183^{***}
	(0.1054)	(0.1040)	(0.1021)	(0.1074)	(0.1059)	(0.1104)
Recycled	2.2666^{***}	2.2640^{***}	2.2680^{***}	2.2758^{***}	2.2810^{***}	2.2761^{***}
	(0.1206)	(0.1218)	(0.1225)	(0.1158)	(0.1203)	(0.1231)
Groundwater	1.6348^{***}	1.6372^{***}	1.6466^{***}	1.6366^{***}	1.6422^{***}	1.6403^{***}
	(0.1237)	(0.1316)	(0.1267)	(0.1341)	(0.1292)	(0.1356)
Stormwater	1.6469^{***}	1.6434^{***}	1.6565^{***}	1.6476^{***}	1.6481^{***}	1.6482^{***}
	(0.0905)	(0.0896)	(0.0844)	(0.0875)	(0.0885)	(0.0919)
Pipeline	1.3133^{***}	1.3167^{***}	1.3112^{***}	1.3137^{***}	1.3139^{***}	1.3141^{***}
	(0.1355)	(0.1372)	(0.1360)	(0.1330)	(0.1326)	(0.1418)
Spread						
Cost	0.2679^{***}	0.2487^{**}	0.2644^{**}	0.2644^{**}	0.2685^{***}	0.2640^{***}
	(0.1008)	(0.1006)	(0.1065)	(0.1045)	(0.0997)	(0.0989)
AIC	23789.3	23787.2	23794.3	23796.9	23796.1	23797.0
BIC	23895.2	23893.1	23900.2	23902.8	23902.0	23902.9
Observations	8600	8600	8600	8600	8600	8600
Individuals	860	860	860	860	860	860

Coefficient; (Standard Error); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: The coefficient for cost follows a triangular distribution. All other random coefficients are normally distributed.
For all variables, standard errors are clustered at the respondent level. CRRA data is imputed for 723 individuals; thus standard errors are bootstrapped, with 500 repetitions. Quality variables are relative to low quality, water source variables are relative to new dam.

Table 6: Tobit for imputing coefficient of CRRA.

	Tobit
Constant	-0.4976
	(0.7710)
Flood risk perception	-0.0916
	(0.1109)
Own flood insurance	-0.0225
	(0.2435)
Don't know flood insurance	-0.3901
	(0.2498)
Flood insurance*Flood risk percep	0.3412**
	(0.1503)
Age	-0.0089
	(0.0061)
Female	0.0810
	(0.1840)
Education (yrs)	0.0591
	(0.0452)
Middle income	-0.2087
	(0.2376)
High income	-0.1150
	(0.3547)
Fairfield	0.6196**
	(0.2870)
Moonee Valley	0.3039
	(0.2558)
Manningham	0.6336**
	(0.2644)
σ	0.9600***
	(0.0729)
Pseudo R-squared	0.0798
P-value	0.0047
N	124

Coefficient; (Standard Error); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: Middle and high income are dummies relative to low income. Dummies for Fairfield, Moonee Valley and Manningham are relative to Warringah.

ing a more precise indication of its monetary value. Finally, the dummy variables for the council areas of Fairfield, Moonee Valley and Manningham are included, and are relative to Warringah. The differences in risk attitudes by location likely reflect the different mix of ethnicities and cultural backgrounds, owing to immigration patterns, of the different council areas.

As shown in the last rows of Table 6, the model overall has a good statistical fit. Even if most of the coefficients are not individually significant, the low p-value of 0.005 for the full model shows that they have a high level of joint significance. The mean and standard deviation of the full dataset used, after imputing for 723 people for whom all relevant variables are observed, is 0.08 and 0.58 respectively. This compares favourably to the figures of 0.10 and 0.88 for the observed sample.

Figures A.2 and A.3 in the Appendix show the predicted probability of choosing each source by level of risk aversion, according to Model 1. Figure A.2 uses observed risk aversion, and Figure A.3 uses the full sample, with imputed risk aversion. The two sets of data produce similar results, providing support for the imputation method.

Standard errors for all mixed logit models estimated using imputed values are boost-rapped. Boostrapping is neccessary to take into account the uncertainty in the imputation process. We use Shao and Sitter (1996) to bootstrap the standard errors, as it is robust to imputation method. It requires the full imputation procedure to be completed for each bootstrap replication, to allow for the uncertainty in the imputation stage. As a slight departure from Shao and Sitter (1996), we split the sample into those 137 individuals with observed risk attitudes and those 723 individuals with unobserved risk attitudes for the bootstrap sampling. This split sampling is done to reflect the fact that a random subsample of a predetermined size was given the risk elicitation task in the design of the survey. If the sample were pooled we would be getting some bootstrapped replications which impute risk attitudes off a very small number of individuals (or perhaps even from 0 individuals) with observed risk attitudes, which we would never do in practise. Furthermore, by design the data is missing completely at random, so this split bootstrap sampling process does not impact the robustness of the estimated standard errors.

6 Conclusion

Preferences drive choices, and incorporating parameters such as risk attitudes into choice modeling produces a more comprehensive picture of preferences in a given setting. In this paper we demonstrate how data on risk preferences can disentangle the importance of specific intrinsic attributes in driving preferences for a particular type of good.

When using DCEs to elicit community preferences for non-market goods, risk often plays a central role in determining the optimal allocation of resources, particularly for environmental projects. Some recent studies include risk explicitly in the DCE (Botzen and Van Den Bergh, 2012; Botzen and van den Bergh, 2012; Petrolia et al., 2013; Qiu et al., 2014); however, this method has its limits. Though it is well suited to eliciting preferences for extrinsic attributes, some attributes cannot be plausibly varied across alternatives. Additionally, there is a limit to how many attributes can be included in a DCE experiment before cognitive limits are reached. This is important because there are settings where the researcher wants to uncover the respondents' underlying risk perceptions and preferences associated with an alternative instead of imposing structure by modeling risk as an extrinsic attribute. This approach can be generalized to account for other preferences such as discount rates as conducted in a different context by Newell and Siikamäki (2014). While identifying the importance of all the intrinsic attributes may not be possible, we demonstrate that properly measuring important related attitudes can identify specific intrinsic attributes driving preferences.

We utilize fully incentivized choices over binary monetary lotteries to accurately elicit risk attitudes of respondents in order to model the intrinsic risk perceptions and preferences over new water supply sources. We did not prompt participants with information about the intrinsically risky attributes of the water sources to ensure the results are not driven by framing effects. However, public knowledge of these risky attributes is high in our case study, given regular restrictions imposed by water shortages and many high profile public debates regarding water supply augmentation options. By augmenting a basic random utility model to incorporate observed and imputed risk attitudes, we are able to test whether water supply risk and new technology risk are important to participants. We find that we cannot reject the hypothesis that water supply risk is an important driver of preferences and that including supply risk improves model fit. This is an important finding to water managers who want to utilize green infrastructure for water management but are concerned about public perception of alternative supply sources.

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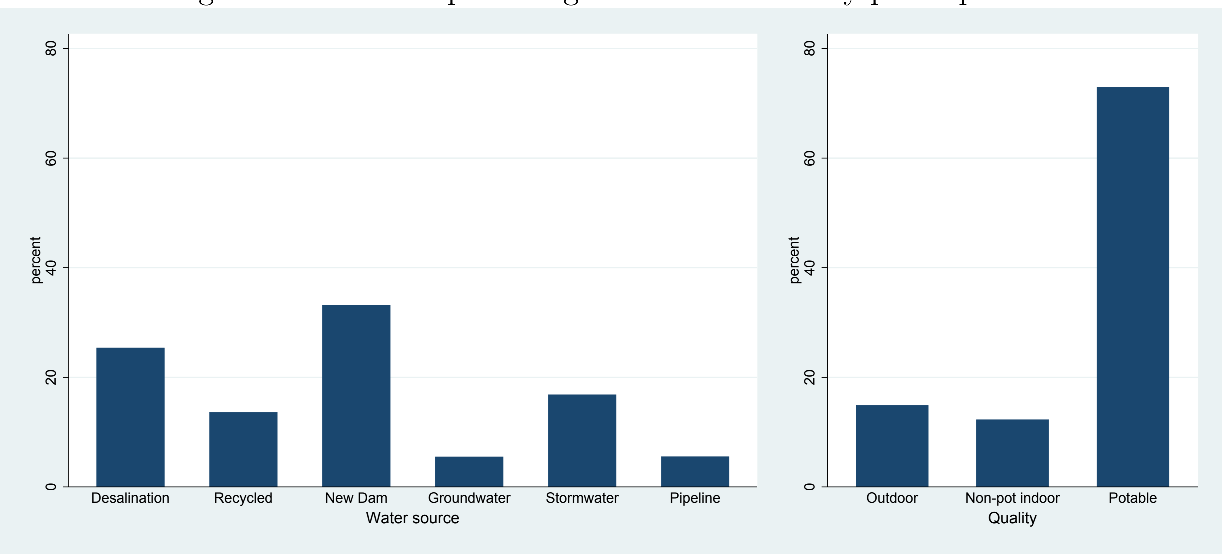
A Appendix

A.1 Overall DCE choices

Figure A.1 shows the overall results from the DCE, with new dam and desalination being the most preferred options, and groundwater and pipeline the least preferred. It is important to remember that desalination and new dam always had potable water, whereas the other four water sources had a balanced mix of quality levels. Therefore, if ensuring water is potable is a concern for individuals, then desalination and new dam never had to be ruled out on the basis of quality. The rightmost section of Figure A.1 shows the aggregate choices for allowed use, regardless of cost and water source. Potable is by far the most popular allowed use at 72.9%, followed by non-potable outdoor (14.9%) and non-potable indoor (12.3%).

Figure A.1: Overall percentage of choices made by participants.



A.2 Predicted probability and risk aversion

Figures A.2 and A.3 show predicted probability of choosing each water source by level of risk aversion. Figure A.2 shows this for observed risk aversion and Figure A.3 shows this for the full dataset with risk aversion imputed. The figures are produced by predicting the probability of choosing each source for each individual, given their observed choices and the overall population distributions estimated by Model 1, Table 4. These predicted probabilities are calculated by the method outlined by Train (2009). A fractional polynomial model is used to fit the lines shown in the graphs, with a 95% confidence interval around the graphs.

Figure A.2: Predicted probability of choosing each water source by risk aversion (observed), using Model 1 estimates, fixing cost at $2.40 and quality at high.

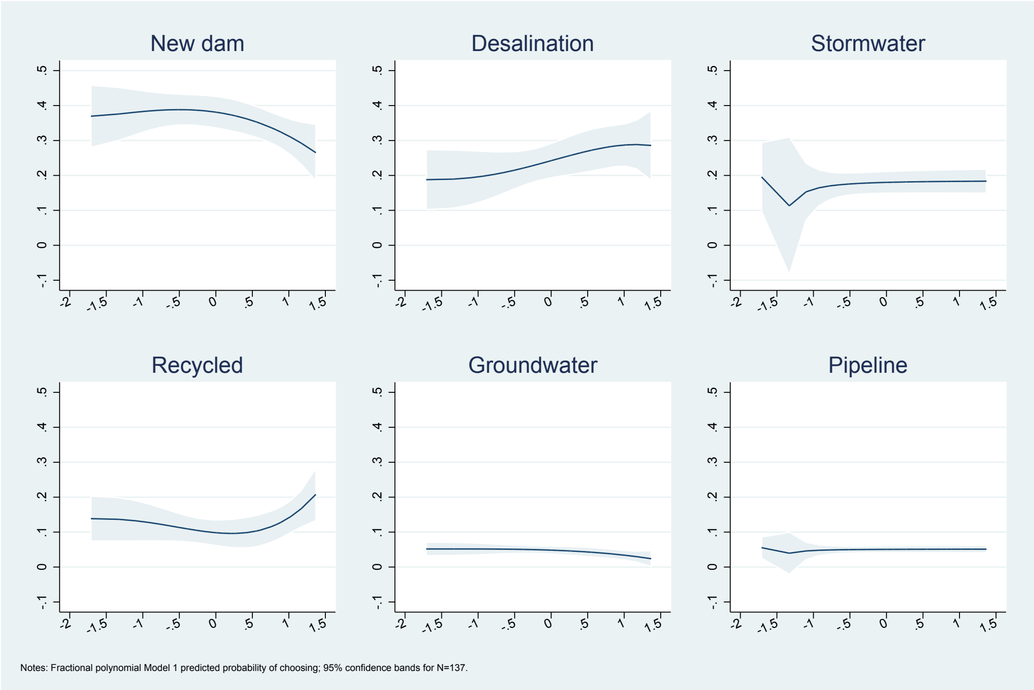
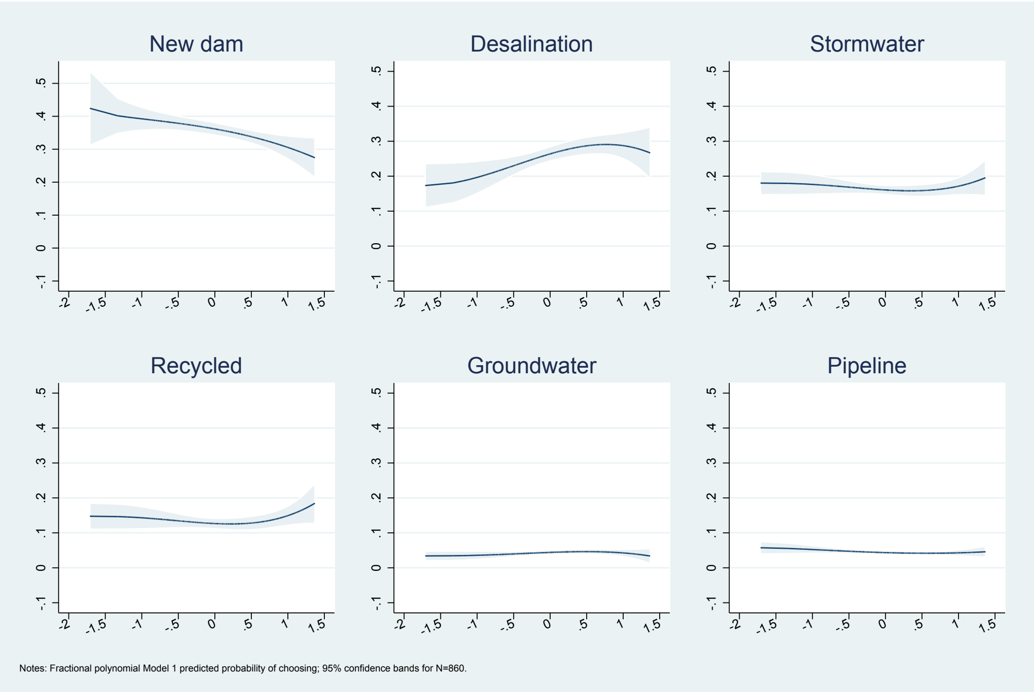


Figure A.3: Predicted probability of choosing each water source by risk aversion (observed and imputed), using Model 1 estimates, fixing cost at $2.40 and quality at high. Compare with Figure A.2.



A.3 Instructions - incentivized risk task

-------------------------------- [NEW SCREEN] --------------------------------

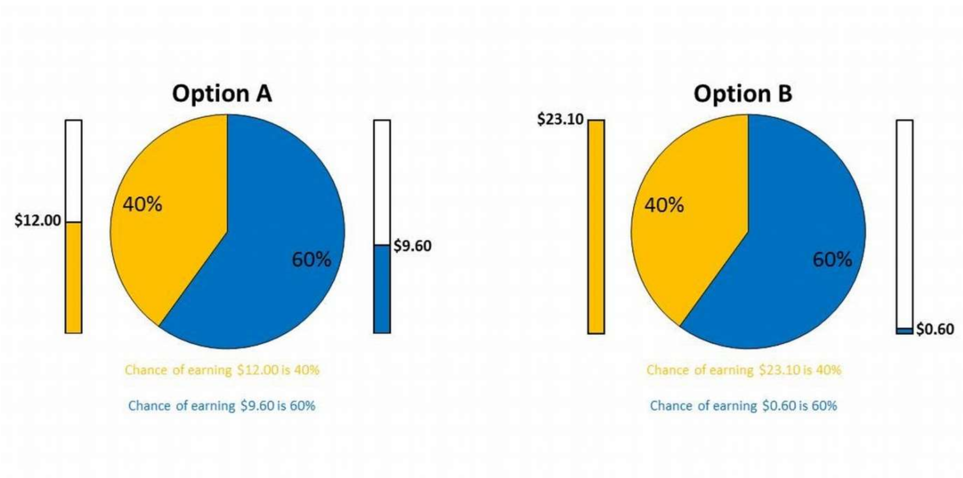
ACTIVITY 1

Explanation

Water management in Australia is influenced by weather and many other uncertain factors. Therefore, as a first step, we would like to get a better understanding how Australians make decisions related to uncertainty. There are standard techniques to make responses comparable between individual respondents. We are using one of these techniques here, to understand how important uncertainty is to you, by asking you to make a series of 10 choices in simple decision problems, in which you will earn some money. How much you receive will depend partly on **chance** and partly on the **choices** you make. The decision problems are not designed to test you. The only right answer is what you really would choose.

For each decision problem, please state whether you prefer option A or option B. After answering all 10 decision problem, **one of the 10** decision problems will be randomly selected and its chance outcome will be given to you as payment. As any of the decisions can be chosen for payment, you should pay attention to the choice you make in every decision screen.

Example1a: Here is an example of one choice that you may see on the screen.



- If Option A was chosen, there is a 40% chance that you will be paid $12.00 and a 60% chance that you will be paid $9.60.
- If Option B was chosen, there is a 40% chance that you will be paid $23.10 and a 60% chance that you will be paid $0.60.

Example1b: Here is an example of one choice that you may see on the screen.

- If Option A was chosen, there is a 70% chance that you will be paid $12.00 and a 30% chance that you will be paid $9.60.
- If Option B was chosen, there is a 70% chance that you will be paid $23.10 and a 30% chance that you will be paid $0.60.

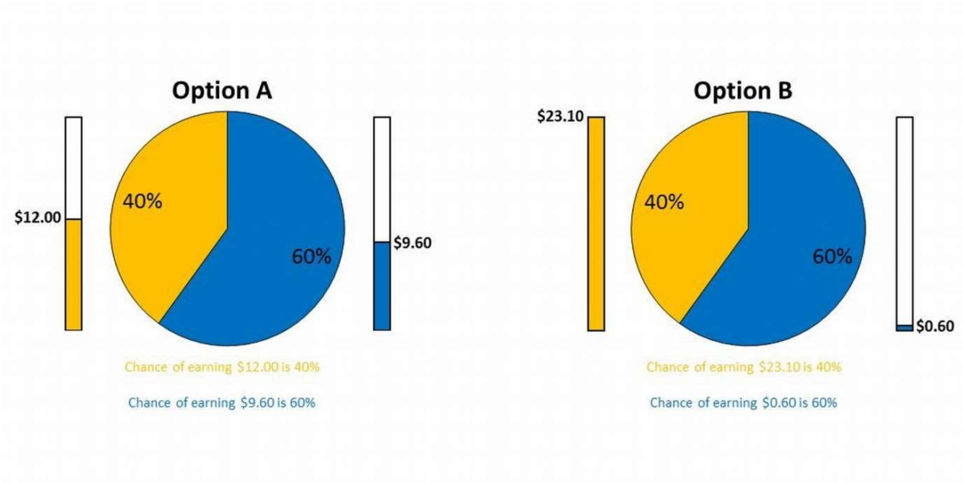
In short, this activity is trying to explore how you respond to risk.

How will you be paid?

As previously mentioned prior to the examples, you will earn some money depending on **choices** you made, and through **chance**.

After you have completed the 10 decision problems for this activity you will be shown a random number generator where you will be prompted to click “Stop!!” button. The generated random number will determine which of the 10 decision problems to focus on. If the random generator number was a 7, the “decision problem” to focus on will the 7th shown decision problem.

After a random number has been generated, you will be asked to draw another random number through the random number generator. The second random number generator will determine how much you will earn.



Referring back to the earlier examples, we mentioned the scenario below.

- If Option A was chosen, there is a 40% chance that you will be paid $12.00 and a 60% chance that you will be paid $9.60.
- If Option B was chosen, there is a 40% chance that you will be paid $23.10 and a 60% chance that you will be paid $0.60.

If in the above example, you had chosen Option A, and the number drawn from the second random number generator was between 1 and 4, then you earn $12.00. If the number drawn was between 5 and10, then you earn $9.60.

If in the above example, you had chosen Option B, and the number drawn from the second random number generator was between 1 and 4, then you earn $23.10. If the number drawn was between 5 and10, then you earn $0.60.

All earnings are in cash and are in addition to the $30 initial endowment that you receive as compensation for your time and effort in this and the following parts of this study. The interviewer will pay you the final balance of your earnings when all parts of the study are completed.

PLEASE TAKE IN TO CONSIDERATION THAT THERE ARE NO CORRECT OR WRONG DECISIONS. WE ARE ONLY TRYING TO EXPLORE DEPENDING ON THE DECISION PROBLEMS GIVEN HOW YOU RESPOND TO RISK.

A.4 Instructions - discrete choice experiment.

------------------------------- [NEW SCREEN] -------------------------------

ACTIVITY 2

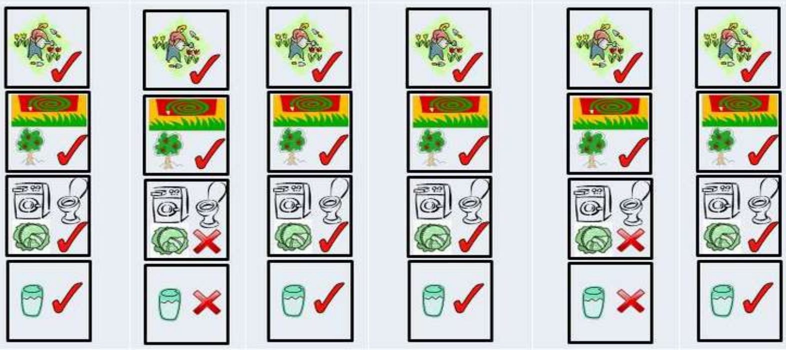
When water shortages become more frequent, investments to increase urban water supply need to be made. There are a number of options in terms of water source and technology that a city can invest in. These options differ with respect to the quality of water provided and therefore their allowed use, as well as the cost of water provision. It is possible to install a third water pipe to your house, so that your tap water will not be contaminated with potentially lower quality water from the new source. You would **NOT** have to pay for the installation of the third pipe.

You will now be asked to make a series of 10 choices regarding your preferred additional water source, its allowed uses and the resulting cost of water. Assume that this would be the cost of your total water consumption per kilolitre in AUD. No other rates or charges would change.

PLEASE TAKE IN TO CONSIDERATION THAT THERE ARE NO CORRECT OR WRONG DECISIONS. THESE DECISION PROBLEMS ARE NOT DESIGNED TO TEST YOU AND YOUR RESPONSE WILL NOT RESULT IN YOU PAYING MORE FOR YOUR WATERBILL.

[USE INSTRUCTIONS CHOICE SET 2 HERE AND EXPLAIN DIFFERENT ATTRIBUTE LEVELS]

Example 2: **Here is an example of one choice set that you may see on the screen.**

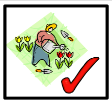
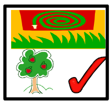
	Desalination	Recycled	New Dam	Groundwater	Stormwater	Pipeline
Allowed Use						
Price/Kl	$2.80	$1.60	$2.20	$2.80	$3.20	$1.60

You can choose between one of the six additional water sources. If the water from your preferred source is not supplied at drinking water quality, assume that a third water line has been installed to your home at no additional cost other than the new water price per kl of water you consume.

Do you have any questions?

Figure A.4: Information sheet provided for participants of discrete choice experiment.

Source of Additional Water	**Explanation**
Desalinisation	Desalinated sea water
Recycled	Recycled grey water
New Dam	Water drawn from new dam in the catchment
Groundwater	Water drawn from underground aquifers
Stormwater	Locally harvested and treated stormwater by your council
Pipeline	Water transported via pipelines from outside the catchment, for example from rural areas.

Allowed uses	**Explanation**	**Levels**
Note that: 1) any additional water sourced may be used to water non-edible garden plants (Class D). 2) Technological solutions exist to bring water from any source up the highest (fit for drinking) standard.	**Limited Outdoor** water receives lowest treatment of all classes. May only be used for non-food garden plants (**ornamental plants and flowers, no lawns**). Other outdoor uses that do not involve human contact permitted. (Class D)	
	Outdoor: in addition to the **limited outdoor** uses listed above, outdoor water may be used to **water lawns and fruit trees** grown over a meter high (Classes B and C).	
	Indoor water may be used for **all outdoor** uses (including the watering of vegetable gardens) and for **limited indoor**, including for clothes washing and closed system toilet flushing.	
	Potable water is of drinking quality and **allowed for any use**.	
Price/kl	This is the price you would be charged per kilolitre of your total, billed water consumption.	\$1.60-\$3.20