Preferences for Intrinsically Risky Attributes

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Abstract:

Riskiness 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 the risk associated with vulnerability to drought or technological risks are treated as intrinsic since they cannot be plausibly disassociated from the water supply source. A risk task estimates participants' coefficient of constant relative risk aversion (CRRA), 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 – and not technology risk – is an important determinant of participants' choices.

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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, such as 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 utilize 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.

While we focus on risk preferences and intrinsic risk attributes, the methods can be generalized to link existing preferences to a wide range of intrinsic attributes. For example, conditional cooperation elicited in public goods games can be linked to the intrinsic attributes of public transit and carpooling versus driving alone in a travel mode choice experiment. Experimentally elicited preferences have been used to predict behavior in the field (Fehr and Leibbrandt, 2011; Cavalcanti et al., 2013; Gneezy et al., 2015), and our approach extends this to the stated preference setting. Though the research objectives are different from our setting, one research area that has incorporated experimental economics into stated preference research designs is the energy efficiency gap. Newell and Siikamäki (2014) and Newell and Siikamäki (2015) elicit individual discount rates to help assess if respondents in a choice experiment on buying a new hot water system trade off between upfront and operating costs in a cost efficient manner.

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. They 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 risk of failure as an explicit attribute 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 related 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 as 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” for electric cars, where consumers face an increase in the risk of being stranded from choosing an electric car over a petrol version (Hidrué 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.

Our application combines a fully incentivized risk task with a DCE to leverage variation in risk aversion as a driver of preference heterogeneity of unspecified intrinsic risk 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 were asked to choose amongst

six alternative sources of water to augment their city’s central water supply. In the DCE, alternative water sources vary with respect to water quality and cost to the household. 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. Therefore, public knowledge about centralized sources of water provision is high, making it likely that consumers’ have well-formulated beliefs regarding the intrinsic risks of different supply sources.

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 and improves the 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 of J alternative municipal water sources. Utility U of individual i from choosing water source j for choice occasion t is given by

$$U_{ijt} = V_{ijt} + \epsilon_{ijt}, \quad (1)$$

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:

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

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:

$$V = \beta_j \mathbf{X}_j + \beta_q \mathbf{X}_q + \beta_c C, \quad (3)$$

where β_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 β_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 technology working as envisaged. From the outset, we are agnostic about which type of risk may be important and test models with different types of risk identified by a dummy variable X_r . As before, it is assumed that each of these sources provides deterministic utility components from the respondents’ perspective 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.

Adapting equation (3) to accommodate the risk-related utility component yields:

$$V = \beta_j \mathbf{X}_j + \beta_q \mathbf{X}_q + \beta_c C + \beta_r f(X_r, \gamma_i), \quad (4)$$

where β_r determines the weight the participants put on the risky attribute. We denote the risky utility component associated with the dummy variable X_r using a non-linear constant relative risk aversion (CRRA) functional form, $f(X_r, \gamma_i) = \left(\frac{X_r^{1-\gamma_i} - 1}{1-\gamma_i} \right)$, 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 $\gamma_i > 0$.

$X_r = 2$ 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 .²

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 the three weather-dependent sources: 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 these 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

¹The 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 .

²This 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 $\beta_r f(X_r, \gamma_i)$, where X_r is supply risk.

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.³

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 start by completing an incentivized risk experiment, with earnings ranging from A\$0.60 to A\$23.10.

Next, respondents participated in a first DCE on the non-market benefits of local water management projects, described in more detail by Brent et al. (2014).⁴ The second choice task elicited water source preferences and is the focus of this paper.⁵ 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.⁶ 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

³By only interviewing owner-occupiers we ensured that all participants in the survey also receive water bills, as this is not the case for some tenants.

⁴While there are possibilities of order effects from the two choice tasks we do not believe it will affect our central hypothesis about intrinsic risk attributes.

⁵Some 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.

⁶The CRCWSC is an Australian research organization, which is funded by the federal government.

(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

Before commencing the DCE a subset of 167 respondents participated in a fully incentivized choice experiment over binary monetary lotteries that allows us to estimate their risk attitudes.⁷ 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 and Mellor, 2008). Full instructions and explanatory examples shown to participants are given in Appendix A.4. The experiment is based on Holt and Laury (2002) and consists of ten questions, each of which asks the participant to choose between two binary lotteries.

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. The tenth question in Table 1 is a choice between receiving \$12.00 with certainty (option A) and \$23.10 with certainty (option B) and acts as a control question.⁸ Before the task commenced, it was explained that one of the 10 questions would be randomly selected for payment. A random draw was used to determine which outcome of the selected option was paid to the participant.

To allow for more flexibility in the estimation of individuals' risk attitudes and to address concerns about order effects, we depart from Holt and Laury (2002) by presenting each question separately and in a random order rather than displaying the questions

⁷Risk elicitation was a component of a randomized field experiment linked to the first choice task in the survey. As a result, it was not rolled out over the entire sample.

⁸A participant choosing option A for question 10 could imply that they do not wish to take money from the researcher or that they did not understand or engage with the task.

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

Option A	Option B	$EV_A - EV_B$	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	$1.37 < \gamma_i$

in a multiple price list format. This accommodates participants who display multiple switchpoints between lottery A and lottery B because they are indifferent between a number of lottery choices and thus their implied range of γ_i cannot be estimated as precisely as for respondents with single switchpoints (Andersen 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, his estimated γ_i value lies between $-1.71 < \gamma_i < -0.15$. Moreover, showing the lotteries to participants as a list (as in Holt and Laury, 2002) could lead to ordering effects that impact individuals' 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. To reduce the cognitive burden of respondents, all lottery payoffs and probabilities were presented using images as well as text (Dave et al., 2010), as shown in Figure 1.

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 Appendix A.5):

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

Figure 1: Risk preference experiment example of choice image.

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. Throughout the choice task the participants could refer to the summary information sheet, which is reproduced in Figure A.4 of Appendix A.5. 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).⁹ As shown

⁹While six alternatives may seem high in number for choice experiments, these are the six primary water sources available in Australia, and excluding any could introduce a bias into the respondents' choices. For example respondents may lump an omitted source together with one of the alternatives in

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

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

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 while the higher levels are 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. 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 this reflects the water quality most commonly supplied by these sources.

the choice set.

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).¹⁰ 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 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 2.¹¹ The second to last column of Table 2 shows the same data for the subsample of 137 respondents for whom we have observed risk attitudes.¹² 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 Appendix A.1.

¹⁰Forced 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.

¹¹Rainwater 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.

¹²Thirty of the 167 who were given the risk task were excluded, as explained in Section 3.2.1.

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

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.¹³ 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 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). We use a conservative approach to deal with issues of unboundedness and use a γ_i parameter value of -1.71 for people who selected option B in the first question and 1.37 for people who switched from option A to option B for the last question.¹⁴

Of the 167 participants who completed the risk task, we exclude 30 who chose option A for question 10 since they may not have understood the risk task.¹⁵ The 137 participants

¹³Answering lottery B for the first question of Table 1 is considered one switch.

¹⁴An alternative would be to assume a lower and upper bound based on the most extreme values found in the literature. Experimentation with this alternative approach did not yield material differences to the overall results of this study. Also, the majority of Danes in a similar field study were found to exhibit a CRRA parameter within the range of -1.71 and 1.37 (Harrison et al., 2007).

¹⁵The relatively large number of respondents included is likely due to our deviation from the multiple price list format, which we do in order to reduce single-switching bias.

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 is 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 β , and all variables for source j at time t into a single $\mathbf{X}_{jt}$. U_{ijt} can be modeled probabilistically, as it is a latent variable that determines each individual's choice of water supply source, j . Thus, assuming each individual has a unique β_i

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

$$= \Pr(\beta_i \mathbf{X}_{jt} + \epsilon_{ijt} > \beta_i \mathbf{X}_{kt} + \epsilon_{ikt}) \quad \forall j \neq k \quad (5b)$$

$$= \Pr(\epsilon_{ijt} - \epsilon_{ikt} < \beta_i \mathbf{X}_{kt} - \beta_i \mathbf{X}_{jt}) \quad \forall j \neq k. \quad (5c)$$

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 β in the following way:

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

Here, θ is a vector of distributional parameters, such as the mean and variance, estimated

using numerical simulation of maximum likelihood. To estimate the model, the researcher specifies the distribution of each element of β , and whether or not they are independently distributed, or correlated. Commonly normal, lognormal or triangular distributions are used. By allowing random distribution of β , the mixed logit can approximate any random utility model (Hensher and Greene, 2003; Train, 2009).

5 Results

The base model 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 on a subsample of 860 people using maximum simulated likelihood with 400 Halton draws, to ensure stability of estimates for this dataset and model specification (Hensher and Greene, 2003; Train, 2009).¹⁶ The first two coefficients in descending order are fixed coefficients for allowed use – non-potable outdoor and non-potable indoor, relative to potable quality. 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 that the quality coefficients should be fixed.

The next set of variables in column (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 Appendix A.1): they are all negative as new dam is the most popular option. Desalination, with the largest mean ASC, is the next most preferred source and the groundwater ASC is the smallest indicating that it is the least popular source. All water source coefficients are assumed to be normally distributed.

The final mean random coefficient is cost. It is negative and statistically significant, as expected. Using a symmetric triangular distribution, we find that sensitivity to cost is low

¹⁶The subsample of 860 is used so that it the same subsample as the models in columns (3) and (5) of Table 4, which arises as a result of the imputation process. This is explained in detail in Appendix A.2. All models estimated with 860 participants were estimated using 400 Halton draws.

Table 4: Mixed logit regression results

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

Note: Standard errors clustered at the respondent level are in parentheses. CRR data is imputed for 723 individuals for columns (3) and (5), and thus the standard errors are bootstrapped for these models. The coefficient for cost follows a triangular distribution. All other random coefficients are normally distributed. Quality variables are relative to low quality, water source variables are relative to new dam.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

but within a reasonable range. 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). We use an unbounded triangular distribution that allows more flexibility to account for this fact.

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

Column (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 and using 500 Halton draws. The first hypothesis of this paper (in Section 2) states that if supply risk is an important intrinsic attribute for preference, then β_r should be positive and statistically significant. Column (2) shows $\beta_r > 0$. Given the positive value of β_r , we impute risk attitudes for the full sample to utilize the choice from as many respondents as possible to test whether the lack of statistical significance is due to the small sample size. The imputation involves regressing demographic variables and indicators of attitudes to risk on the observed CRRA parameter. These are jointly significant at the 1 per cent level. The fitted values from this model are used to impute the risk attitudes of the 723 people who did not participate in the risk task and for whom we have observations on all the relevant variables for the imputation. The mean CRRA parameter value and standard deviation of the full dataset of 860 respondents with either observed or imputed CRRA parameter values, is 0.08 and 0.58 respectively. This compares favourably to the mean and standard deviation of 0.10 and 0.88 for the observed sample. The results of the imputation and further details are presented in Appendix A.2.

Column (3) runs the same model as column (2) with the full 860 respondents. With the larger sample size, β_r is both positive and statistically significant at the 10% level. Furthermore, the model fit improves over the base model without risk attitude using both AIC and BIC criteria. Inference in column (3) uses bootstrapped standard errors. Bootstrapping is undertaken for all models that use imputed data in order to account for the uncertainty from the imputation stage. We use Shao and Sitter (1996) to bootstrap the standard errors, as it is robust to the 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 and we sample each separately, with replacement. This split bootstrap sampling is done to reflect the original survey design. Because of the random allocation of the risk task amongst the survey participants, this split bootstrap sampling process does not impact the robustness of the estimated standard errors.

The interpretation of column (3) coefficients for new water source differs from column (1). 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 estimated in column (3) of Table 4. The utility an individual at the mean receives from choosing desalination over new dam in the model of column (1), *ceteris paribus*, is given by the estimated mean coefficient for desalination, $\hat{\beta}_D$. Following from equation (4) the estimated utility an individual at the mean receives from choosing desalination over new dam, becomes:

$$\hat{U}_{iD} - \hat{U}_{iND} = \hat{\beta}_D + \hat{\beta}_r \left(\frac{1^{1-\gamma_i} - 1}{1 - \gamma_i} \right) - \hat{\beta}_r \left(\frac{2^{1-\gamma_i} - 1}{1 - \gamma_i} \right) \quad (7a)$$

$$= \hat{\beta}_D - \hat{\beta}_r \left(\frac{2^{1-\gamma_i} - 1}{1 - \gamma_i} \right). \quad (7b)$$

Thus, for this case, column (3) includes the marginal utility from moving from a source with supply risk to a source without supply risk, with the net effect being equal to

Figure 3: Mean marginal utility of switching from new dam to desalination by level of risk aversion.

Note: The marginal utility is calculated using equation (7) and the estimated parameters from column (3) of Table 4. The dotted lines show the confidence interval at the 10% level, calculated using the delta method.

$-\beta_r \left(\frac{2^{1-\gamma_i} - 1}{1-\gamma_i} \right)$. Therefore, when comparing preferences for sources in column (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 .¹⁷ Given the marginal utility is always negative, the average participant still prefers the new dam no matter what their level of risk aversion. However, the large standard deviation of the coefficient on desalination means that for some participants their risk attitude will determine whether they prefer a new dam to desalination or not.

5.2 New technology risk preferences

The second hypothesis stated in Section 2 is in regards to new technology risk. Columns (4) and (5) in Table 4 test this hypothesis by assuming stormwater and recycled are perceived as new technology. These are regarded as alternative decentralized water systems

¹⁷For the purpose of comparison it is assumed that allowed use and cost are the same for both new dam and desalination.

that are not yet widespread in Australia. The models presented in columns (4) and (5) correspond to models in columns (2) and (3) except we replace supply risk with technological risk. Column (4) presents the results for the sample with risk data and column (5) presents model with imputed risk preferences. The estimated coefficient of β_r for new technology risk in both models 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, the models that incorporate supply risk fit the data slightly better than models incorporating technological risk.

Table 5 helps complete the overall picture of the drivers of the results. It shows six models, with each source separately classified as risky. All models use the full 860 observations available with imputed data, and have bootstrapped standard errors. New dam generates a positive but statistically insignificant coefficient for β_r . Desalination has a negative and highly significant coefficient for β_r ; all the other sources have negative insignificant coefficients. Given our specification of how risk enters into the utility function, supply sources with negative values for β_r are more attractive to risk averse respondents relative to risk loving respondents. Put simply, a negative value communicates that the supply source is not considered risky by respondents. In any regression the parameters need to be compared relative to each other. The positive value of β_r for new dam and the negative value for desalination, help with the interpretation of the supply risk coefficient in columns (3) and (4) of Table 4, indicating that this difference is an important driver of our result on supply risk. This is intuitive because new dam is currently the primary water source, which has historically been vulnerable to droughts, while desalination is the most robust drought-resistant supply source. The other four sources all have negative and statistically non-significant β_r coefficients, meaning that none of these sources stand out in terms of water supply or technology risk. Hence it is the combination of all three weather-dependent sources relative to the weather-independent sources that leads to the significant and positive parameter on supply risk in Table 4. The results in Table 5 largely support our specifications of supply and technological risk presented in Table 4.

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

	New dam (1)	Desalination (2)	Recycled (3)	Groundwater (4)	Stormwater (5)	Pipeline (6)
Fixed Coefficients & Means						
<i>Fixed Coefficients</i>						
Non-potable outdoor	0.0261 (0.0474)	0.0270 (0.0486)	0.0255 (0.0479)	0.0265 (0.0478)	0.0264 (0.0507)	0.0265 (0.0485)
Non-potable indoor	-0.1450*** (0.0513)	-0.1462*** (0.0498)	-0.1467*** (0.0498)	-0.1452*** (0.0510)	-0.1448*** (0.0537)	-0.1452*** (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)
<i>Random Coefficients</i>						
Desalination	-0.2959 (0.3851)	0.4052 (0.4319)	-0.7751*** (0.1025)	-0.7724*** (0.1013)	-0.7733*** (0.1035)	-0.7723*** (0.1021)
Recycled	-1.2051*** (0.3899)	-1.6768*** (0.1247)	-1.0100* (0.6016)	-1.6836*** (0.1244)	-1.6857*** (0.1258)	-1.6845*** (0.1199)
Groundwater	-2.0815*** (0.3976)	-2.5584*** (0.1333)	-2.5596*** (0.1334)	-2.4417*** (0.4638)	-2.5612*** (0.1415)	-2.5589*** (0.1340)
Stormwater	-0.5240 (0.3796)	-0.9999*** (0.0901)	-0.9975*** (0.0843)	-0.9979*** (0.0843)	-0.7189 (0.4885)	-0.9977*** (0.0863)
Pipeline	-1.7821*** (0.3873)	-2.2562*** (0.1020)	-2.2547*** (0.1042)	-2.2566*** (0.1086)	-2.2563*** (0.1051)	-2.2483*** (0.3722)
Cost	-0.1130 (0.0938)	-0.1062 (0.0946)	-0.1120 (0.0953)	-0.1120 (0.0928)	-0.1133 (0.0939)	-0.1119 (0.0971)
Standard Deviation or Spread						
<i>Standard Deviation</i>						
Desalination	2.1037*** (0.1054)	2.0879*** (0.1040)	2.1220*** (0.1021)	2.1180*** (0.1074)	2.1205*** (0.1059)	2.1183*** (0.1104)
Recycled	2.2666*** (0.1206)	2.2640*** (0.1218)	2.2680*** (0.1225)	2.2758*** (0.1158)	2.2810*** (0.1203)	2.2761*** (0.1231)
Groundwater	1.6348*** (0.1237)	1.6372*** (0.1316)	1.6466*** (0.1267)	1.6366*** (0.1341)	1.6422*** (0.1292)	1.6403*** (0.1356)
Stormwater	1.6469*** (0.0905)	1.6434*** (0.0896)	1.6565*** (0.0844)	1.6476*** (0.0875)	1.6481*** (0.0885)	1.6482*** (0.0919)
Pipeline	1.3133*** (0.1355)	1.3167*** (0.1372)	1.3112*** (0.1360)	1.3137*** (0.1330)	1.3139*** (0.1326)	1.3141*** (0.1418)
<i>Spread</i>						
Cost	0.2679*** (0.1008)	0.2487** (0.1006)	0.2644** (0.1065)	0.2644** (0.1045)	0.2685*** (0.0997)	0.2640*** (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

Note: Standard errors clustered at the respondent level are in parentheses. CRRA data is imputed for 723 individuals, and thus the standard errors are bootstrapped for these models. The coefficient for cost follows a triangular distribution. All other random coefficients are normally distributed. Quality variables are relative to low quality, water source variables are relative to new dam.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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 that allow risk to vary explicitly find that risk matters for preferences. However, what matters may be perceptions of riskiness, which may or may not be related to the defined risk levels in a DCE. Moreover, if an attribute is truly intrinsic, it 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. We demonstrate that measuring attitudes towards intrinsic attributes can help to identify which and to what extent intrinsic attributes drive preferences. This approach can be generalized to account for other experimentally-elicited preferences such as conditional cooperation and trust.

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 extending 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 Imputing risk attitudes for the full sample

Table A.1 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.¹⁸ 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 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 A.1 are age, gender and education. Next are 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 giving a more precise indication in dollar values. 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 A.1, 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.

Figures A.2 and A.3 in Appendix A.3 show the predicted probability of choosing each source by level of risk aversion, according to the model in column (1), Table 4. 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

¹⁸The 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 A.1: 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

Note: Standard errors are in parentheses. Middle and high income are dummies relative to low income. Dummies for Fairfield, Moonee Valley and Manningham are relative to Warringah.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

imputation method.

A.3 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 in column (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 the model in column (1), Table 4, 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 the model in column (1), Table 4, fixing cost at \$2.40 and quality at high. Compare with Figure A.2.

A.4 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 be 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 and 10, 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 and 10, 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.5 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						
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
Desalination	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
<p>Note that:</p> <p>1) any additional water sourced may be used to water non-edible garden plants (Class D).</p> <p>2) Technological solutions exist to bring water from any source up the highest (fit for drinking) standard.</p>	<p>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)</p>
	<p>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).</p>
	<p>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.</p>
	<p>Potable water is of drinking quality and allowed for any use.</p>
Price/kl	This is the price you would be charged per kilolitre of your total, billed water consumption.	\$1.60-\$3.20