Preferences for Intrinsically Risky Attributes

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January 30, 2017

Abstract

Incentivized experiments are commonly viewed as substitutes for, rather than complements to stated preference methods. While the former are founded in revealed behavior, the latter are able to characterize preferences in situations that cannot be directly observed. We leverage the distinct strengths of each approach to model preferences in a situation where the utility derived from a risky attribute of a good is determined by one's tolerance for risk. Our novel approach leverages risk preferences by combining a fully incentivized risk experiment in the field with a stated preference survey to model utility for intrinsic risk. A door-to-door survey of 981 participants in a drought-prone region elicits preferences for alternative sources of municipal water, conditional on water price and quality. Participants' estimated coefficients of constant relative risk aversion (CRRA) are incorporated into preference estimation to test the hypotheses that supply risk (vulnerability to drought) and new technology risk are important intrinsic attributes for new water sources. 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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The authors are grateful for helpful comments from Ian Bateman, Gaurav Datt, Lata Gangadharan, Robert Johnston, Paul Raschky, John Rolfe, Michael Ward, and participants at the 2016 AARES and EAERE conferences that greatly improved the paper. Funding from the Cooperative Research Centre for Water Sensitive Cities (CRC grant number 20110044) is acknowledged. This project has been approved by the Monash University Human Research Ethics Committee; MUHREC#: CF12/2511 2912001358.

1 Introduction

Experimentally elicited preferences are widely utilized to predict behavior in the field (Fehr and Leibbrandt, 2011; Cavalcanti et al., 2013; Gneezy et al., 2016). A key strength of fully incentivized experiments is that preference elicitation is founded in revealed behavior; in contrast, stated preference methods are able to characterize preferences in situations that cannot be directly observed. Thus, while there are opportunities for combining revealed and stated methods (Adamowicz et al., 1994; Whitehead et al., 2008), incentivized experiments are more likely to be seen as substitutes rather than complements to stated preference methods. For example, consumer preferences for food are elicited using either stated choice methods (Scarpa et al., 2012; Meas et al., 2015) or experiments in the laboratory and in the field (Melton et al., 1996; Lusk and Coble, 2005). In other instances, incentivized experiments are used to validate the results of stated preference methods (List and Shogren, 1998). In this article we leverage the distinct strengths of each approach and use information on respondents' attitudes from an incentivized lab-in-the-field experiment to augment the estimates in a stated choice study, thereby gaining additional insights about the respondents' preferences for intrinsic attributes that would otherwise remain hidden.

Our approach relates to Lancaster's (1966) theory of consumption, which states that utility is derived not from the good or service itself, but rather from its characteristics or attributes. Building on this premise, stated choice 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 stated choice experiment. Consider a travel mode choice experiment that offers the choice between public transit and automobile travel with extrinsic 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. An important example of this is when the propensity to participate in a survey depends on risk attitudes in a systematic way. In this article we show that leveraging information about risk attitudes to model preferences for unspecified intrinsic risk attributes improves the model fit and yields significantly different estimates of marginal utilities.

Our application combines a fully incentivized risk experiment with a a stated preference approach. The risk experiment, involving incentivized decisions over binary monetary lotteries (similar to Holt and Laury, 2002) is randomly allocated to a subsample of 981 households that participated in a door-to-door survey, where respondents were asked to choose among six alternative sources of water to augment their city's central water supply. The survey uses a discrete choice experimental design (DCE), where alternative water sources vary with respect to allowed water use and cost to the household. The survey is 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.[1] 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 are intentionally *not* mentioned in the infor-

[1] There is an extensive literature on the acceptance of various forms of water supply in Australia, see Fielding et al. (2015) and the papers cited for more information.

mation materials provided to the participants of the DCE to ensure participants are 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 term this risk 'supply risk'. Additionally, certain sources (stormwater harvesting and recycled water) provide water via new and somewhat unproven technologies, which may be of concern to some consumers. We label this intrinsic attribute 'technology risk'. We argue that Australian households have well-formed perceptions of these two risks based on the extensive public discourse surrounding water supply augmentation during the Millennium Drought. For example, Dolnicar et al. (2014) show that only 28% of respondents believe that the current, reservoir-sourced tap water can save Australia from drought, whereas they are much more confident about the ability of desalination (77%) and recycled water (83%) to sustain water supplies during a drought. While 90% of Australian respondents believe their current water is safe to drink, only 54% think this is true of recycled water, which is, according to 73% of respondents, also prone to technological failure. These findings by Dolnicar et al. (2014) motivate our hypotheses that supply and technology risks may be important determinants of preferences for different water sources.

The article is organized as follows. The next section positions this study within the revealed and stated preference literature on risk and risk attitudes. The theoretical framework is outlined in Section 3, followed by a brief description of the experimental design and summary statistics. Section 5 summarizes the empirical framework, Section 6 describes the main results and Section 7 concludes.

2 Risk in Preference Elicitation

Agricultural and environmental 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 extrinsic 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 extrinsic 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). Our results complement these findings in that we also find an effect on estimated preferences when allowing for intrinsic risk attributes in a stated choice setting. Moreover, we find that this effect varies systematically with the respondent's risk attitude.

Similarly, there is a growing literature 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), or as a driver of private purchase decisions (Petrolia et al., 2013). In our specific setting where risk is an intrinsic characteristic of the good we also find that risk attitudes matter to consumer choices.

Where risk is a central feature of the good, such as the probability of a flood for flood insurance, it 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, self reported data reveals that 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 (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 article.

The research that is closest to our own from a methodological perspective is Newell and Siikamäki (2014) and Newell and Siikamäki (2015). Those studies experimentally elicit individual discount rates to help assess if respondents in a stated choice experiment on buying a new hot water system trade off between upfront and operating costs in a cost efficient manner. In contrast, our focus is on eliciting preferences for intrinsic attributes by leveraging information on risk preferences. Importantly, our approach can be generalized to link existing preferences to a wide range of intrinsic attributes, thereby helping to improve the estimation of stated preference models. For example, conditional cooperation elicited in public goods games can be linked to the intrinsic attributes of public transit and car pooling versus driving alone in a travel mode choice experiment.

3 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

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

where V_{ijt} is a linear function of the observable source attributes, allowed use (quality level) 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 supply or technology 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 $\mathbf{X}_j$, relative to the source that is represented by the omitted categorical dummy. The vector of coefficients $\boldsymbol{\beta}_q$ is associated with the different levels of allowed use, $\mathbf{X}_q$, 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 that explicitly allows for heterogeneous risk attitudes toward a subset of water sources that may be perceived as intrinsically risky. In particular, a subset of sources may be perceived as risky if their supply depends on exogenous factors such as rainfall or if the technology that is used to provide water is new and unproven. From the outset, we are agnostic about which type of risk may be important and test models where a dummy variable X_r describes different types of risk. As before, it is assumed that, independently of allowed use and cost, each water source provides some utility that is certain from the respondents' perspective. This component enters the utility function in the standard linear form, $\beta_j X_j$. An additional utility component is linked to the perceived riskiness of particular sources. Because of its intrinsic nature, the risk-related component of utility only enters the utility function through an interaction with risk-preferences. Therefore, in most studies that do not estimate risk preferences, this component of utility is not observable. The importance of risk attitudes for explaining heterogeneous preferences is our central hypothesis of interest.

Retaining the additively-separable specification of equation (3) the risk-related utility component is accommodated as follows,

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

where the sign of $\beta_{r,h}$ indicates whether the participants perceive source(s) $h \subset J$ as risky. The magnitude of $\beta_{r,h}$ represents the weight of this intrinsic risk on utility. $X_{r,h}$ is the risk variable that takes on the value 2 if the source(s) is affected by risk relative to all sources assigned a value of 1. The parameter γ_i denotes each individual's constant relative risk aversion (CRRA) in the non-linear specification $f\left(X_{r,h}, \gamma_i\right) = \left(\frac{X_{r,h}^{1-\gamma_i}-1}{1-\gamma_i}\right)$.[2] This parameter is estimated independently using an incentivized lab-in-the field risk experiment. Thus, the utility that is attributable to $X_{r,h}$ depends on each individual's CRRA parameter. A risk loving individual is characterized by $\gamma_i < 0$, a risk neutral individual by $\gamma_i = 0$ and a risk averse individual has $\gamma_i > 0$.[3]

To illustrate the differences between the base model and risk-augmented model we compare the marginal utility implied by each model from choosing a water source j relative to source k with the same level of quality and cost. In the base model without risk preferences, the marginal utility of choosing source j over source k is $\beta_j - \beta_k$, which is the utility derived from the ASC for water source j. In the extended model, the marginal utility from choosing source j over source k takes into account both utility components: the deterministic change in utility, β_j, as well as the change in utility that is due to the relative riskiness of each source and is described by the non-linear combination of $\beta_{r,j}$ and γ_i. Assuming $X_{r,j} = 2$ and $X_{r,k} = 1$, the marginal utility of choosing source j over source

[2]The definition of the risk variable $X_{r,h} \in \{1, 2\}$ in conjunction with the CRRA functional form ensures that the risk-related component of utility is zero when $X_{r,h} = 1$, while varying continuously in the degree of risk aversion for $X_r = 2$.

[3]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 $\beta_{r,h} f\left(X_{r,h}, \gamma_i\right)$, where $X_{r,h}$ is supply risk.

k is given by

$$U_{ij} - U_{ik} = \beta_j + \beta_{r,j}\left(\frac{2^{1-\gamma_i}-1}{1-\gamma_i}\right) - \beta_k - \beta_{r,k}\left(\frac{1^{1-\gamma_i}-1}{1-\gamma_i}\right) \tag{5a}$$

$$= (\beta_j - \beta_k) + \beta_{r,j}\left(\frac{2^{1-\gamma_i}-1}{1-\gamma_i}\right). \tag{5b}$$

The sign of $\beta_{r,j}$ contains information about the relative riskiness of the two sources as perceived by the respondents. Table 1 shows how the sign of $\beta_{r,j}$ interacts with risk aversion parameter to impact utility, assuming equality of all non-risk related attributes. Importantly, Table 1 shows how the sign of $\beta_{r,j}$ yields information about how respondents perceive the riskiness of source j relative to source k. This allows us to test for intrinsic risk preferences for various water supply sources.

Table 1: Interpreting the coefficient on $\beta_{r,h}$ for source $j \in h$ relative to source $k \notin h$

	Risk Loving $\gamma_i < 0$	Risk Neutral $\gamma_i = 0$	Risk Averse $\gamma_i > 0$	Perception of Source j
$\beta r, h > 0$	$U_j > U_k$	$U_j = U_k$	$U_j < U_k$	Relatively Risky
$\beta r, h < 0$	$U_j < U_k$	$U_j = U_k$	$U_j > U_k$	Relatively Safe

This assumes that the all other non-risk related attributes are for sources j and k are equal such as the ASC, cost, and quality. This follows the notation in equation (5) where $X_{r,j} = 2$ and $X_{r,k} = 1$.

To help clarify how risk is incorporated into our model we graphically illustrate the marginal utility for switching from source k to source j for different levels of risk aversion given the value of $\beta r, j$.[4] Figure 1 illustrates that when $\beta_{r,j}$ is positive the water source j is perceived as *riskier* than source k: a switch from source k to this riskier, but otherwise equally preferred, source j brings positive utility to risk loving individuals and negative utility to risk averse individuals.[5] In contrast, a negative coefficient ($\beta_{r,j} < 0$) in equation (5) indicates that source j is perceived to be *safer* than source k, so that the switch from source k to the safer, but otherwise equal, source j brings negative utility to risk loving individuals and positive utility to risk averse individuals. The marginal utility as

[4] Similar to Table 1, Figures 1 and 2 follows the notation in equation (5) where $X_{r,j} = 2$ and $X_{r,k} = 1$.

[5] For the two sources to be equally preferred when disregarding risk requires for equation (5) that $\beta_j = -\beta_{r,j}\left(\frac{2^{1-0}-1}{1-0}\right) = -\beta_{r,j}$.

a function of risk aversion when $\beta_{r,j} < 0$ is shown in Figure 2. As seen in both Figures 1 and 2 the risk component of utility is zero for a risk neutral consumer ($\gamma_i = 0$).

Figure 1: Marginal utility of switching from source k to source j where source j is considered riskier than source k and $\beta_{rj} > 0$

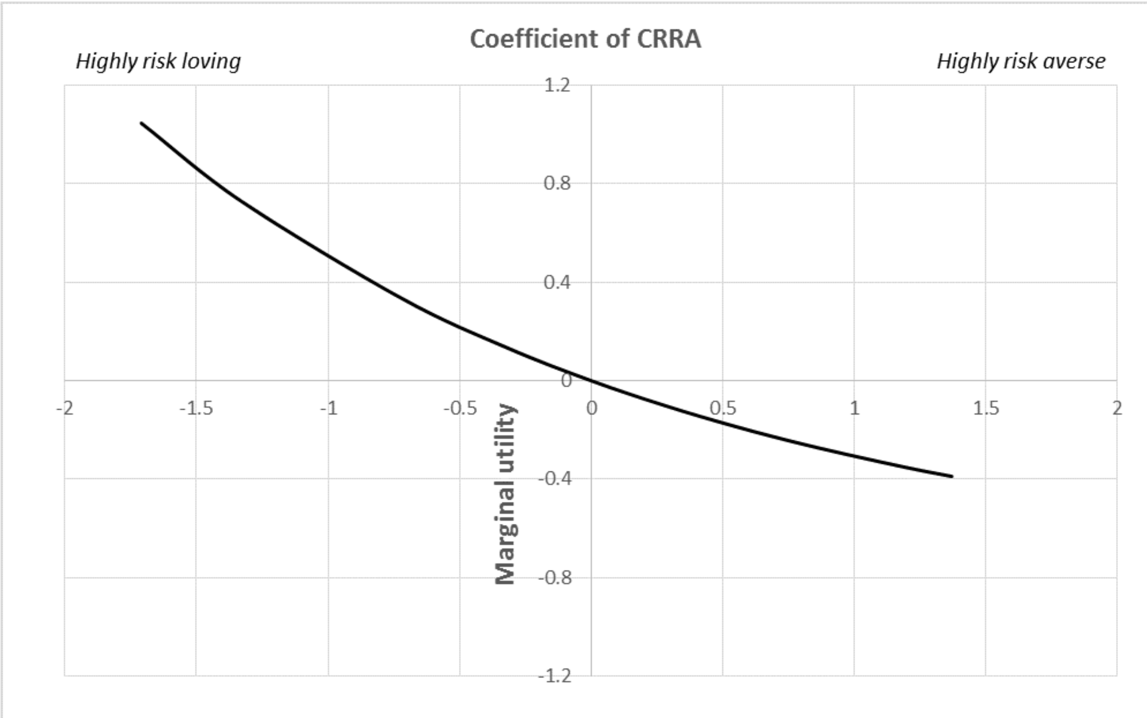
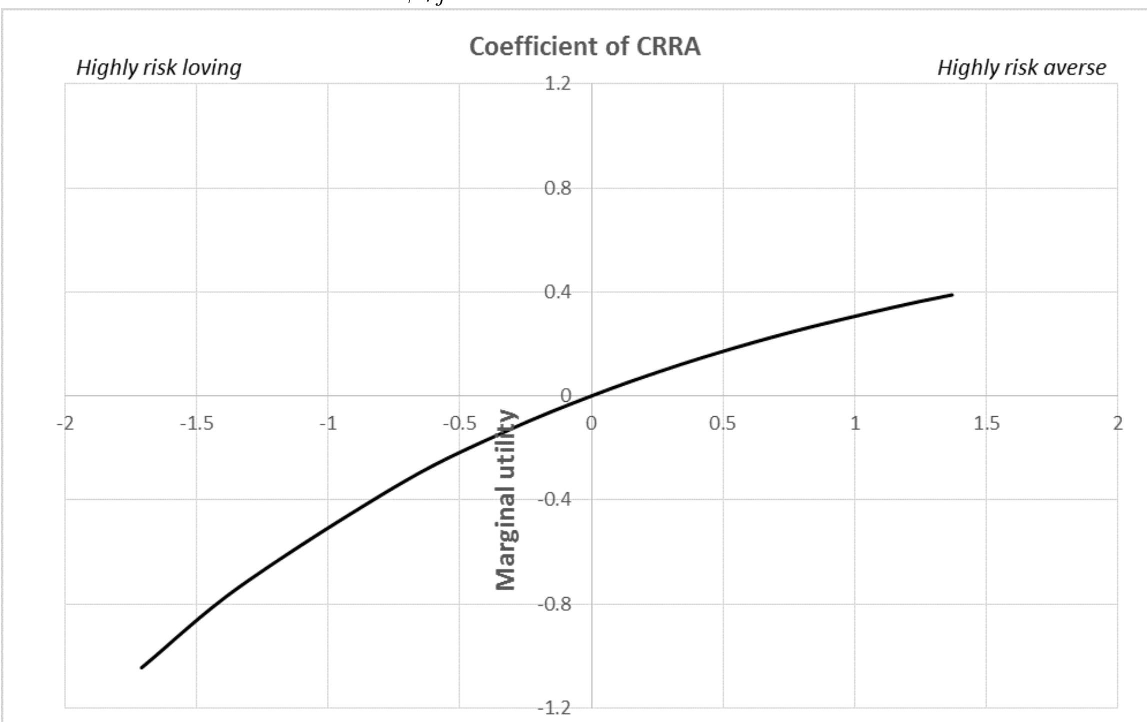


Figure 2: Marginal utility of switching from source k to source j where source j is considered safer than source k and $\beta_{rj} < 0$.



Whether a particular intrinsic attribute that is common to a subset of sources is considered risky by participants, and thus given a significant weight in determining their choice of a new water source, is an empirical question that we seek to answer using the data described in the next section. To address this question we assign a subset h of sources with the risky intrinsic attribute the dummy variable $X_{r,h} = 2$. In line with the illustration above, we reject the null hypothesis that participants did not consider a particular type of risk in their choice of water source when $\beta_{r,h} \neq 0$.

We test three hypotheses using three different groupings of water supply sources: we assess the riskiness of each source individually as well as for a subset of sources that are subject to supply risk and another subset that is subject to technology risk. The first hypothesis tests whether the utility for any water supply source depends on risk. Empirically, we must set one source as the reference level. In our setting we test each water source relative to the omitted categorical variable 'new dam', which implies further development of Australia's conventional water supply source. Source j is considered less risky relative to new dam if $\beta_{r,j} < 0$ and riskier than new dam if $\beta_{r,j} > 0$. The second hypothesis is that supply risk is an important intrinsic attribute for the three weather-dependent sources: new dam, stormwater harvesting and interbasin transfer pipeline. To test if supply risk is an important intrinsic attribute we test the null against a one-sided alternative hypothesis that $\beta_{r,supply} > 0$ when $X_{r,supply} = 2$ for weather-dependent sources. The third 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 assign $X_{r,tech} = 2$ to recycled water and harvested stormwater and test whether water technology risk matters to households by defining the null hypothesis $\beta_{r,tech} = 0$ against the alternative that $\beta_{r,tech} > 0$. Our second and third hypotheses relate directly to the literature that identifies supply risk and the deployment of new technologies as the primary risks related to public water that concern the Australian public.[6] The objective of our study is to test whether these concerns affect householders' preferences for new sources of water supply in a fundamental way, and therefore, whether policy makers should focus their attention on these risks when discussing new water infrastructure investments in the public domain.

4 Survey Design and Data

4.1 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.[7]

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 [*reference removed to preserve anonymity*]. The second DCE given to participants elicited water source preferences and is the focus of this article.[8] The survey ended with a set of demographic and water-relevant questions.

[6]For example, Dolnicar et al. (2014) show that broadly defined concerns about the safety and security/sustainability of water comprise 7 of the top 10 attributes of public water supplies. The list of desirable attributes, along with the percentage of respondents listing that attribute, can be found in Table 3 in Dolnicar et al. (2014).

[7]By 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.

[8]While there are possibilities of order effects from the two DCEs we do not believe it will affect our central hypothesis about intrinsic risk attributes. Some respondents were incentivized for the first DCE, whereas others were not. When comparing the responses of these treatment groups to the second DCE, 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.

The survey was developed after a series of focus group meetings with researchers from different disciplines in the [research center name removed to preserve anonymity] in which appropriate attributes and levels were discussed.[9] 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.

4.1.1 Incentivized risk experiment

Before commencing the DCE a randomly selected subset of 167 respondents participated in a fully incentivized risk experiment involving choices over monetary lotteries, designed to allow risk attitudes to be estimated.[10] Experiments involving risk 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). Furthermore, by fully incentivizing the risk task we address concerns of hypothetical bias in the elicitation of risk attitudes (Holt and Laury, 2002; Lee

[9] The [*research center name removed to preserve anonymity*] is an Australian research organization, which is funded by the federal government.

[10] Risk elicitation was a component of a randomized field experiment linked to the first DCE in the survey that is unrelated to the DCE over new water sources. As a result, the risk task was not rolled out over the entire sample.

Table 2: Risk preference task questions, difference in expected values and coefficient of CRRA.

Option A	Option B	$\text{EV}_\text{A} - \text{EV}_\text{B}$	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	$1.37 < \gamma_i$

and Hwang, 2016). Full instructions and explanatory examples shown to participants are given in Appendix A.3. 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 2, which show the potential earnings and probabilities for each of the two lotteries. The third column of Table 2 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 2 is a choice between receiving \$12.00 with certainty (option A) and \$23.10 with certainty (option B) and acts as a control question.[11] 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 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

[11] A 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.

Figure 3: Example representation of the risk task to respondents.

for his second, lottery A for his third and lottery B thereafter, his estimated γ_i value lies between $-1.71 < \gamma_i < -0.15$.[12] 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 3.

4.1.2 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.4):

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

[12]This statement is made in accordance with the order of questions in Table 2, rather than referring to the particular random order in which the questions were displayed to the participant.

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 DCE participants received a brief explanation about the different water sources and attributes. This explanation did not mention risk to ensure that the respondents' preferences over intrinsic risk attributes can be estimated without potential framing confounds. Throughout the choice task the participants could refer to the summary information sheet, which is reproduced in Figure A.2 of Appendix A.4. Each participant was then given a sequence of ten separate questions, presented in a graphical format. Figure 4 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).[13] As shown in Figure 4, 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 4); 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

[13]While 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 the choice set.

Figure 4: Example of image shown to participants for a water supply source choice.

allowed use and cost approximately the same number of times. New dam and desalination were only assigned the allowed use category of potable as this reflects the water quality most commonly supplied by these sources.

The purpose of the survey is to determine community preferences over alternative future water supply augmentations, conditional on a new water supply source being developed. Accordingly, this survey represents a forced choice, DCE 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).[14] 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

[14]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).

4.2 Descriptive statistics

The demographics, flood risk perception and flood insurance ownership of the full sample of 981 participants are recorded in Table 3.[15] The second to last column of Table 3 shows the same data for the subsample of 137 respondents for whom we have observed risk attitudes.[16] The rightmost column of Table 3 shows p-values, using the non-parametric Mann-Whitney test, comparing the distribution of each variable 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.

4.2.1 Risk preference summary statistics

Table 4 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 2 as the order of lotteries.[17] 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 4, 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

[15] Flood risk perceptions and owning flood insurance are used to impute risk preferences as described in the Appendix.

[16] Thirty of the 167 who were given the risk task were excluded, as explained in Section 4.2.1.

[17] Answering lottery B for the first question of Table 2 is considered one switch.

Table 3: 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	
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 4: 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

population in the USA.

To utilize the estimated coefficients of CRRA in the modeling approach of this article, we allocate the midpoint of the estimated range for γ_i to each participant (see Andersen et al., 2006; Liu, 2013, and 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.[18]

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.[19] The 137 participants for whom risk attitude is observed are a random subsample of the full 981 participants, as already shown in Table 3. The mean and standard deviation of the observed coefficient of CRRA are 0.10 and 0.88 respectively. This shows that people are on average risk averse, as found in similar field experiments (Anderson and Mellor, 2008; Harrison et al., 2007; Dave et al., 2010).

5 Empirical Specification

This article 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 among participants, by incorporating both fixed and random coefficients.

To simplify notation we group all coefficients into a single vector $\boldsymbol{\beta}$, and all variables

[18] An 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).

[19] The 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 source j at time t into a single $\boldsymbol{X}_{jt}$. 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 $\boldsymbol{\beta}_i$

$$\begin{aligned}
\Pr(Y_{it} = j) &= \Pr(U_{ijt} > U_{ikt}) \quad \forall j \neq k && \text{(6a)} \\
&= \Pr(\boldsymbol{\beta}_i \boldsymbol{X}_{jt} + \epsilon_{ijt} > \boldsymbol{\beta}_i \boldsymbol{X}_{kt} + \epsilon_{ikt}) \quad \forall j \neq k && \text{(6b)} \\
&= \Pr(\epsilon_{ikt} - \epsilon_{ijt} < \boldsymbol{\beta}_i \boldsymbol{X}_{jt} - \boldsymbol{\beta}_i \boldsymbol{X}_{kt}) \quad \forall j \neq k. && \text{(6c)}
\end{aligned}$$

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 (6c). The mixed logit model allows for individual heterogeneity in $\boldsymbol{\beta}$ in the following way:

$$\Pr(Y_t = j) = \int \frac{\exp(\boldsymbol{\beta} \boldsymbol{X}_{jt})}{\sum_{k \in J} \exp(\boldsymbol{\beta} \boldsymbol{X}_{kt})} f(\boldsymbol{\beta} | \boldsymbol{\theta}) d\boldsymbol{\beta}. \tag{7}$$

Here, $\boldsymbol{\theta}$ is a vector of distributional parameters, such as the mean and variance, estimated using numerical simulation of maximum likelihood. Estimating the model requires the specification of 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).

6 Results

The base model in the first column of Table 5, is based on equation (3) and is the mixed logit estimation of the explicit, extrinsic attributes presented in the DCE. It is estimated on a subsample of 860 people using maximum simulated likelihood with 400 Halton draws; this number of draws is used to ensure stability of estimates for this dataset and model specification (Hensher and Greene, 2003; Train, 2009).[20] 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) of Table 5 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 random coefficient is cost. The mean is negative and statistically significant, as expected. Using a symmetric triangular distribution, we find that sensitivity to cost is low 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. Thus, preferences for new water source are highly heterogeneous. The spread of the cost coefficient is also significant, indicating a range of cost sensitivities among respondents.

[20] The subsample of 860 is used so that it the same subsample as all models in Table 5, which arises as a result of the imputation process. This is explained in detail in Appendix A.2.

Table 5: Mixed logit regression results

	Base	All with risk	Supply Risk	Technology Risk
	(1)	(2)	(3)	(4)
Fixed Coefficients & Means				
Fixed Coefficients				
Non-potable outdoor	0.0265	0.0259	0.0259	0.0259
	(0.0470)	(0.0511)	(0.0496)	(0.0481)
Non-potable indoor	-0.1452^{***}	-0.1471^{***}	-0.1471^{***}	-0.1455^{***}
	(0.0514)	(0.0504)	(0.0531)	(0.0498)
$\beta_{r,desalination}$		-1.2484^{***}		
		(0.4682)		
$\beta_{r,recycled}$		-0.7858		
		(0.6179)		
$\beta_{r,groundwater}$		-0.2815		
		(0.4957)		
$\beta_{r,stormwater}$		-0.3155		
		(0.5083)		
$\beta_{r,pipeline}$		-0.1122		
		(0.4029)		
$\beta_{r,supply}$			0.7115^{*}	
			(0.3847)	
$\beta_{r,tech}$				-0.3891
				(0.4581)
Random Coefficients				
Desalination	-0.7724^{***}	0.4811	-0.0546	-0.7746^{***}
	(0.0879)	(0.4661)	(0.4014)	(0.1021)
Recycled	-1.6845^{***}	-0.8863	-0.9622^{**}	-1.2903^{***}
	(0.1109)	(0.6392)	(0.3995)	(0.4823)
Groundwater	-2.5589^{***}	-2.2713^{***}	-1.8375^{***}	-2.5616^{***}
	(0.1207)	(0.5202)	(0.4047)	(0.1331)
Stormwater	-0.9977^{***}	-0.6797	-0.9998^{***}	-0.6053
	(0.0788)	(0.5250)	(0.0845)	(0.4747)
Pipeline	-2.2565^{***}	-2.1380^{***}	-2.2534^{***}	-2.2554^{***}
	(0.0980)	(0.4220)	(0.0992)	(0.1074)
Cost	-0.1118^{***}	-0.1073	-0.1086	-0.1138
	(0.0425)	(0.0884)	(0.0927)	(0.0912)
Standard Deviation or Spread				
Standard Deviation				
Desalination	2.1183^{***}	2.0891^{***}	2.0923^{***}	2.1244^{***}
	(0.0961)	(0.1020)	(0.1025)	(0.1068)
Recycled	2.2761^{***}	2.2566^{***}	2.2593^{***}	2.2716^{***}
	(0.1083)	(0.1192)	(0.1205)	(0.1223)
Groundwater	1.6403^{***}	1.6369^{***}	1.6346^{***}	1.6458^{***}
	(0.1013)	(0.1381)	(0.1276)	(0.1334)
Stormwater	1.6482^{***}	1.6492^{***}	1.6516^{***}	1.6520^{***}
	(0.0729)	(0.0926)	(0.0940)	(0.0877)
Pipeline	1.3142^{***}	1.3089^{***}	1.3092^{***}	1.3118^{***}
	(0.0910)	(0.1409)	(0.1321)	(0.1306)
Spread				
Cost	0.2639^{***}	0.2522^{***}	0.2549^{**}	0.2701^{**}
	(0.0981)	(0.0946)	(0.1005)	(0.1058)
AIC	23795.0	23790.4	23787.7	23794.2
BIC	23893.8	23924.5	23893.6	23900.1
Observations	8600	8600	8600	8600
Individuals	860	860	860	860

Note: Standard errors clustered at the respondent level are in parentheses. CRRA data is imputed for 723 individuals for models (2) to (4), 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. Allowed use variables are relative to potable, water source variables are relative to new dam. All models are estimated using 400 Halton draws.

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

6.1 Incorporating preferences for intrinsically risky attributes

The three hypotheses regarding source specific risk, supply risk and technology risk are tested subsequently in models (2)-(4). In order to utilize as many individuals in the sample as possible, we use imputed risk preference data. 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 approach 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 favorably 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; these details include Table A.2, which estimates the models in 5 using just individuals with observed risk preferences. The results are very similar overall, but yield slightly lower levels of statistical significance for the coefficients due to the smaller sample size.

Bootstrapping of standard errors is undertaken in all models (2) to (4) of Table 5 in order to account for the uncertainty from the imputation stage. We use the Shao and Sitter (1996) method for bootstrapping, as it is robust to imputation method. It requires the full imputation procedure to be completed for each bootstrap replication. 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 among the survey participants, this split bootstrap sampling process does not impact the validity of the estimated standard errors.

In model (2) of Table 5 we test the first hypothesis of whether the utility for any water supply source depends on risk. Thus, we estimate the model from equation (4) with a vector of risk dummies $\boldsymbol{X}_r$, such that each source j except new dam has a unique $\beta_{r,j}$.

We conduct a two-sided test on each $\beta_{r,j}$; further we note that if $\beta_{r,j} < 0$ the source is considered safe relative to new dam, and risky if $\beta_{r,j} > 0$.

We find that only $\beta_{r,desalination}$ is individually, statistically significant and different from zero (at the 1% level). Thus, only the intrinsic risk profile of desalination is found to be significantly different from that of a new dam. Specifically, the negative sign on $\beta_{r,desalination}$ indicates that augmenting the water supply with desalinated water is considered less risky than sourcing additional water from a new dam. This result is intuitive in light of the frequent water shortages that are imposed in Australia as a result of the reservoirs' vulnerability to droughts. Desalination, on the other hand, is seen as the most robust, drought-resistant supply source. Ranking all sources by the size of their $\beta_{r,j}$ coefficient and ignoring statistical significance for the moment reveals that desalination is perceived to be the least risky source, followed by recycled, stormwater, groundwater, pipeline and finally new dam.

Following from equation (5), both the ASCs and the $\beta_{r,j}$ coefficients must be taken into account when comparing preferences for sources in model (2), and for any model with intrinsic risk. In the base model, the only relevant coefficients for comparing preferences, *ceteris paribus*, are the ASCs. As an example, the difference in model (2) relative to model (1) can be observed for the ASC for desalination. This coefficient goes from negative and statistically significant in in the base model, to positive and insignificant in model (2). However, taking into account $\beta_{r,desalination}$ and risk preferences, overall new dam is still preferred to desalination at the mean in model (2) as in model (1). The difference is that the results for model (2) can be used to determine how risk aversion affects the preferences for desalination relative to new dam.

6.1.1 Supply risk preferences

In model (3) of Table 5 we test the second hypothesis that supply risk is an important intrinsic attribute. We assign the three weather-dependent sources (new dams, stormwater harvesting and interbasin-transfer pipeline) the risk variable $X_{r,supply} = 2$ and formally test the null that $\beta_{r,supply} = 0$ against the alternative that $\beta_{r,supply} > 0$. Using a one-sided test, we reject the null hypothesis in favor of the alternative hypothesis at the 5% level. Furthermore, the model fit improves over the base model (1) and over model (2) using both AIC and BIC criteria. Combining this result with the estimated β_r coefficients in model (2) that ranked new dam, pipeline and stormwater respectively as first, second and fourth riskiest sources, we conclude that supply risk is an important driver of preferences for weather-dependent sources. While the results from model (2) suggest that it is the supply risk of new dam relative to desalination that is a major driver behind the supply risk coefficient, it is important to model supply risk as a single joint coefficient to test whether supply risk is an overall driver of preferences. Similar to the interpretation of individual source risk, the marginal utility from supply risk must be taken into account in addition to the ASCs when comparing preferences for sources in model (3).

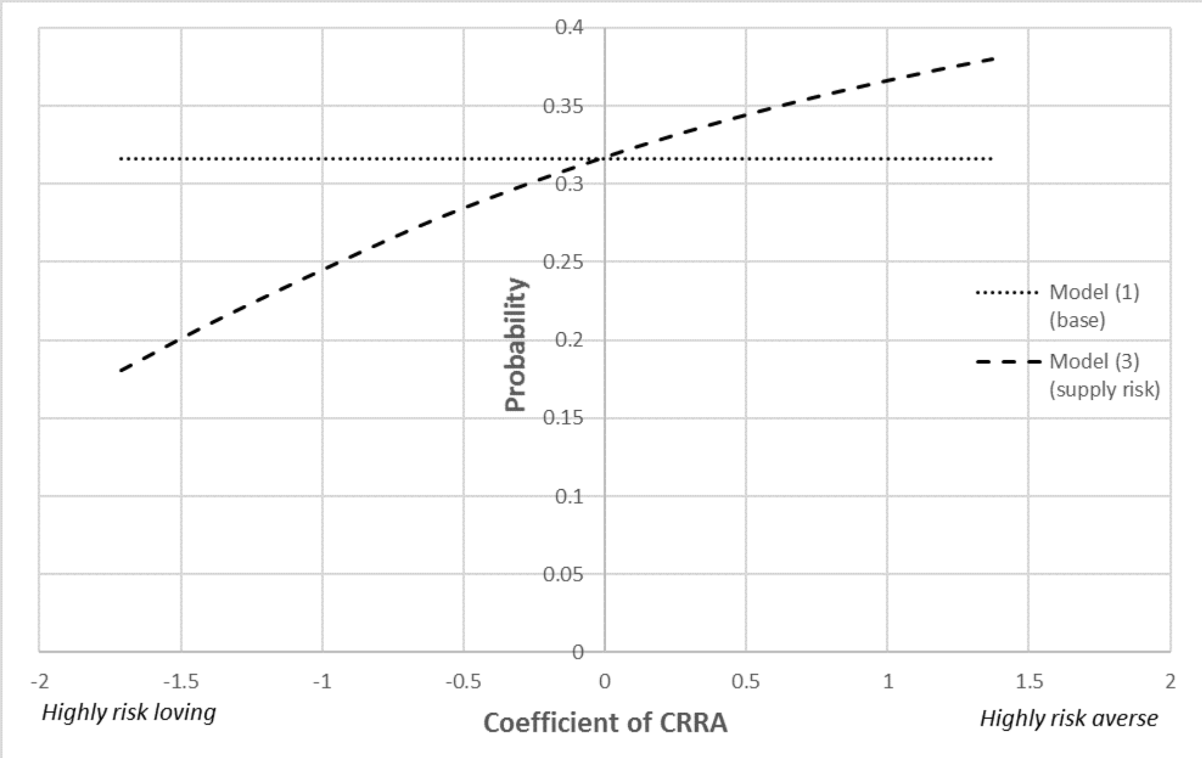
Accounting for supply risk has important consequences for the probability with which a specific source is preferred over another. For example, model (3) predicts a risk loving individual is 34% more likely to choose new dam compared with a risk averse individual. This result is reversed for desalination, where a risk loving individual is 52% less likely to choose it compared with a risk averse individual. Figure 5 shows the probability of choosing desalination over new dam as predicted by models (1) and (3). As can be seen, the probability predicted by the base model in Table 5 does not vary by risk preferences. In contrast, in model (3) the probability of choosing desalination over new dam more than doubles from a highly risk loving to a highly risk averse individual.[21]

6.1.2 New technology risk preferences

The third hypothesis concerning the importance of technology risk in driving preferences is tested in model (4). Here we assign $X_{r,tech} = 2$ to the new and unfamiliar technologies (recycled and stormwater) and formally test the null hypothesis that $\beta_{r,tech} = 0$ against the alternative that $\beta_{r,tech} > 0$. The estimated coefficient of $\beta_{r,tech}$ for new technology risk is negative and statistically insignificant, thus indicating that the null hypothesis cannot

[21] All the values in this paragraph and Figure 5 are calculated *ceteris paribus*, assuming ASCs at their means and all sources are of high quality and cost $2.40 per kiloliter. Risk preferences used are at the extreme CRRA values of -1.71 and 1.37.

Figure 5: Probability of choosing desalination over new dam by level of risk aversion for the base model (1) and when accounting for supply risk (model 3).



be rejected. We therefore conclude that new technology risk is not an important driver of preferences over additional sources of municipal water. Furthermore, using the AIC and BIC criteria, the model incorporating technology risk does not fit the data as well as the model with supply risk.

7 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 article 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. Some recent studies that allow risk to vary explicitly find that risk matters for preferences. However, what truly drives decisions is risk perceptions, which may or may not be related to the defined risk levels in a DCE. Moreover, if existing perceptions about an attribute are well-established the attribute cannot plausibly be 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 identify which, and to what extent, intrinsic attributes drive preferences. This approach can be generalized to account for other experimentally-elicited preferences such conditional cooperation and trust.

We utilize a fully incentivized risk experiment to accurately elicit risk attitudes of respondents. We leverage this information on risk attitudes to model the intrinsic risk perceptions and preferences over new water supply sources in a setting where the public knowledge about water source risk is high. Indeed, the respondents in our sample frequently experience water restrictions imposed by water shortages and are subjected to 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 no evidence that technology risk is an important consideration when choosing alternative sources of municipal water supply. In contrast our results suggest that water supply risk is an important driver of preferences and that including this type of intrinsic risk improves model fit. These findings are important for water managers who want to utilize green infrastructure for water management but are concerned about the public perception of alternative supply sources.

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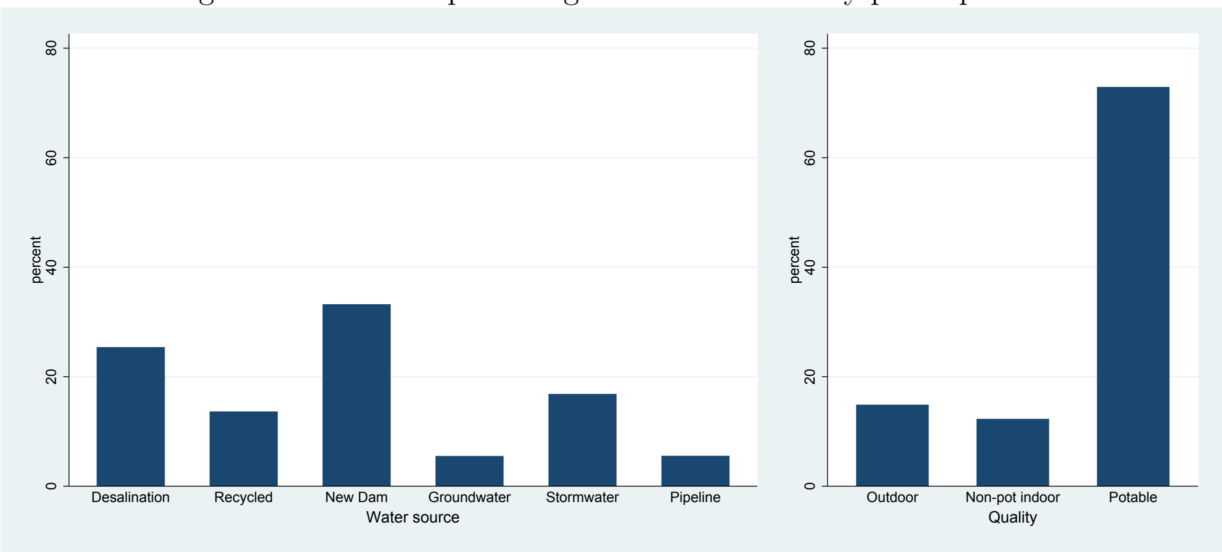
A Appendix

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 allowed use (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 allowed use. 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.[22] 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 3. 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.

We also include Table A.2 in this appendix to replicate Table 5, but estimated using just the 137 individuals for whom risk preferences are observed. The overall results between the two tables are similar, but with overall a lower level of statistical significance on the coefficients in Table A.2 as expected.

[22] 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 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.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.2: Mixed logit regression results - those with observed risk preference data only.

	Base	All with risk	Supply Risk	Technology Risk
	(1)	(2)	(3)	(4)
Fixed Coefficients & Means				
Fixed Coefficients				
Non-potable outdoor	-0.0587	-0.0587	-0.0583	-0.0587
	(0.1080)	(0.1081)	(0.1080)	(0.1080)
Non-potable indoor	-0.2602^{**}	-0.2599^{**}	-0.2595^{**}	-0.2601^{**}
	(0.1202)	(0.1203)	(0.1202)	(0.1201)
$\beta_{r,desalination}$		-0.9913^{**}		
		(0.4417)		
$\beta_{r,recycled}$		-0.1791		
		(0.4311)		
$\beta_{r,groundwater}$		0.3353		
		(0.4380)		
$\beta_{r,stormwater}$		-0.1140		
		(0.3410)		
$\beta_{r,pipeline}$		-0.1826		
		(0.3490)		
$\beta_{r,supply}$			0.2247	
			(0.2729)	
$\beta_{r,tech}$				-0.1209
				(0.2759)
Random Coefficients				
Desalination	-0.6763^{***}	0.3287	-0.4354	-0.6748^{***}
	(0.1781)	(0.4697)	(0.3400)	(0.1783)
Recycled	-1.3025^{***}	-1.1034^{**}	-1.0638^{***}	-1.1771^{***}
	(0.2077)	(0.5041)	(0.3551)	(0.3528)
Groundwater	-2.1674^{***}	-2.5231^{***}	-1.9428^{***}	-2.1664^{***}
	(0.2540)	(0.5479)	(0.3707)	(0.2538)
Stormwater	-0.7050^{***}	-0.5866	-0.7071^{***}	-0.5778^{*}
	(0.1558)	(0.3911)	(0.1558)	(0.3283)
Pipeline	-1.6346^{***}	-1.4344^{***}	-1.6346^{***}	-1.6342^{***}
	(0.1774)	(0.4089)	(0.1771)	(0.1774)
Cost	-0.1538	-0.1662	-0.1543	-0.1528
	(0.1108)	(0.1020)	(0.1107)	(0.1112)
Standard Deviation or Spread				
Standard Deviation				
Desalination	1.6336^{***}	1.5527^{***}	1.6085^{***}	1.6400^{***}
	(0.1987)	(0.1783)	(0.2009)	(0.1991)
Recycled	1.6001^{***}	1.6775^{***}	1.6101^{***}	1.5955^{***}
	(0.2123)	(0.2246)	(0.2144)	(0.2099)
Groundwater	1.2644^{***}	1.2648^{***}	1.2825^{***}	1.2624^{***}
	(0.2344)	(0.2343)	(0.2359)	(0.2339)
Stormwater	1.1651^{***}	1.1628^{***}	1.1648^{***}	1.1628^{***}
	(0.1433)	(0.1398)	(0.1428)	(0.1431)
Pipeline	0.7929^{***}	0.7856^{***}	0.7937^{***}	0.7921^{***}
	(0.1945)	(0.1942)	(0.1925)	(0.1942)
Spread				
Cost	0.2485	0.2828	0.2502	0.2462
	(0.2702)	(0.2349)	(0.2700)	(0.2719)
AIC	4128.2	4132.7	4129.5	4130.0
BIC	4201.3	4231.9	4207.8	4208.3
Observations	1370	1370	1370	1370
Individuals	137	137	137	137

Note: Standard errors clustered at the respondent level are in parentheses. The coefficient for cost follows a triangular distribution. All other random coefficients are normally distributed. Allowed use variables are relative to potable, water source variables are relative to new dam. All models are estimated using 500 Halton draws.

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

A.3 Instructions - incentivized risk task

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

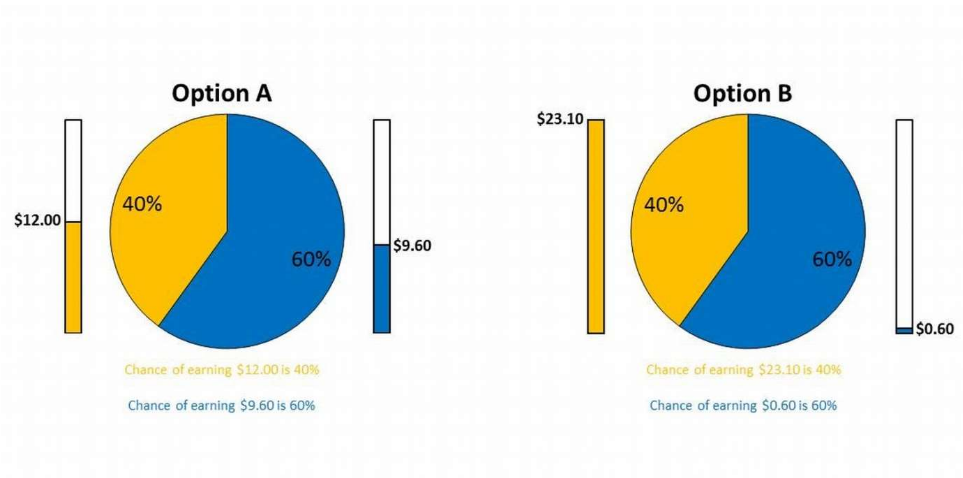
ACTIVITY 1

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.

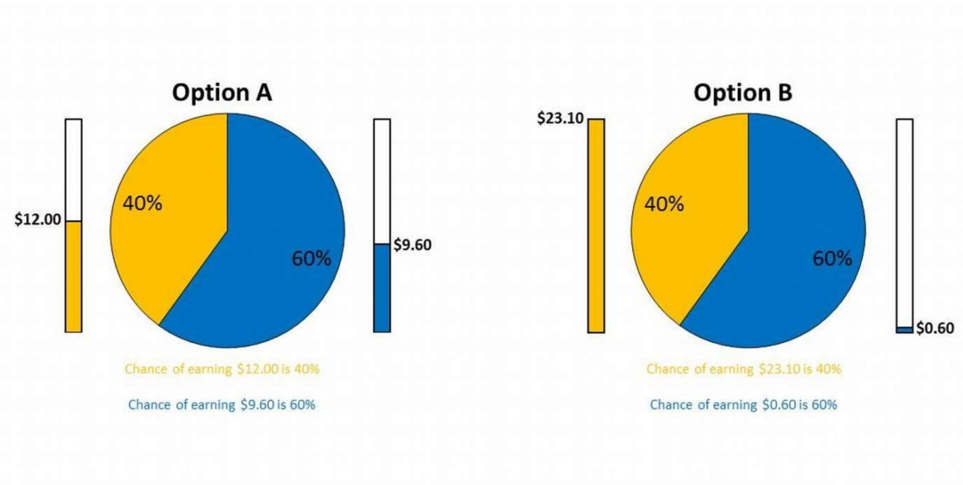
In short, this activity is trying to explore how you respond to risk.

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.

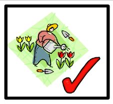
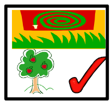
	Desalination	Recycled	New Dam	Groundwater	Stormwater	Pipeline
Allowed Use						
Price/Kl	$2.80	$1.60	$2.20	$2.80	$3.20	$1.60

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.2: 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).	**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)	
2) Technological solutions exist to bring water from any source up the highest (fit for drinking) standard.	**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