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Analysis of residential water conservation practices in Cape Town, South Africa

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Summary:

Drought severity is expected to increase in South Africa in the coming years, given the deteriorating effects exerted by climate change on rainfall patterns and global temperature and evaporation. One common mitigation strategy adopted by households is to promote water demand management initiatives to reduce water consumption volume and complement the existing water supply management approaches being implemented by suppliers. This paper contributes to the discussion on adaptation strategies by investigating the determinants of adopting water-saving technologies through empirical evidence from urban Cape Town, South Africa. We estimate the attribute levels and household characteristics that influence the adoption of several water-saving technologies, including greywater reuse technology, rainwater collection systems, installment of dual-flush cisterns, and water-efficient showerheads. We use a choice modelling framework to investigate heterogeneity among households based on their preferences for individual or groups of characteristics embedded in each water-saving technology. A pilot survey (n=72) was first conducted using an orthogonal design method in order to obtain precise parameter priors for the D-efficient design framework used in our main survey (n=303) estimation. Random Parameter Logit (RPL) is compared with the Nested Logit (NL) model to estimate marginal willingness to pay (MWTP) for the adoption of water-saving technology. Our results show that households are sensitive to the reliability, lifespan, and quantity of water saved by the technologies when explaining the attributes that determine adoption. Alongside other policy interventions, our results also show that initiatives that support the installation of technologies with fewer complexities are favourable in predicting positive household response to adoption.

Analysis of residential water conservation practices in Cape Town, South Africa

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Abstract - Drought severity is expected to increase in South Africa in the coming years, given the deteriorating effects exerted by climate change on rainfall patterns and global temperature and evaporation. One common mitigation strategy adopted by households is to promote water demand management initiatives to reduce water consumption volume and complement the existing water supply management approaches being implemented by suppliers. This paper contributes to the discussion on adaptation strategies by investigating the determinants of adopting water-saving technologies through empirical evidence from urban Cape Town, South Africa. We estimate the attribute levels and household characteristics that influence the adoption of several water-saving technologies, including greywater reuse technology, rainwater collection systems, installment of dual-flush cisterns, and water-efficient showerheads. We use a choice modelling framework to investigate heterogeneity among households based on their preferences for individual or groups of characteristics embedded in each water-saving technology. A pilot survey (n=72) was first conducted using an orthogonal design method in order to obtain precise parameter priors for the D-efficient design framework used in our main survey (n=303) estimation. Random Parameter Logit (RPL) is compared with the Nested Logit (NL) model to estimate marginal willingness to pay (MWTP) for the adoption of water-saving technology. Our results show that households are sensitive to the reliability, lifespan, and quantity of water saved by the technologies when explaining the attributes that determine adoption. Alongside other policy interventions, our results also show that initiatives that support the installation of technologies with fewer complexities are favourable in predicting positive household response to adoption.

Keywords: water conservation, water economics, discrete choice modeling, South Africa

JEL Classification O33; Q25; Q55; Q58; D04

1 Introduction

Water management approaches that advocate for sustainability in water use have often been focused on using extreme measures such as tariff changes and implementation of strict water restriction programmes on residential water demand (Enqvist & Ziervogel, 2019). However, despite these measures, many empirical evidence has shown that an efficient water pricing

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structure is difficult to implement, especially in countries with severe water scarcity. In many instances, relatively high water prices are paid by poorer households compared to higher-income users who often pay low water prices relative to their consumption patterns (De Oliver, 1999). Also, implementation of strict water restriction programmes are often limited by political will (Cooper et. al., 2011; Stoutenborough & Vedlitz, 2014), and they are difficult to enforce, particularly in countries where institutions have limited capacity to monitor the policies adopted to support water use efficiency (Sisser et al., 2016). Studies showed that heavy-handed restrictions are unlikely to persist over time when drought severity decreases and consumption habits resume back to normality (Knickenmeyer & Taxin, 2018; Meissner *et. al.,* 2018). Therefore, promoting sustainable water resources management approaches that address water scarcity requires adopting and implementing more stable and long-term driven strategies that offset the limitations associated with drastic water pricing and restriction programmes. Efficient demand management measures may also focus on effective non-price strategies such as adopting water-saving technologies within households. For instance, an earlier study by Gilg & Barr (2006) showed that water demand management can be better understood by investigating the factors that drive water-saving within households. A more recent study conducted by Fielding *et. al*., (2012) further iterates the need to understand the determinants of the adoption of water-saving technologies. Yet, no consensus has emerged regarding understanding the factors that drive water-saving technologies in urban households.

Adopting water-saving technologies is an effective and sustainable non-price demand management measure that can reduce water scarcity (Fuenfschilling & Truffer, 2016; Ward *et al.*, 2012). A growing literature on urban water management reveals the importance of water-saving technologies in reducing overall water demand (Booysen, Visser, & Burger, 2019; Wu, Zhang, & Gao, 2018). This is achieved by analyzing the factors that drive the adoption of water-saving technologies by urban dwellers in South Africa. We target double flush toilets, low-flow showerheads, rainwater collection, and greywater treatment technologies. A typical South African middle-income household of four spends 25% of their water use in flushing the toilet, 25% on garden and outdoor activities, 24% on bathing or showering, 13% on laundry, 11% in the kitchen, and 2% on other activities (Price, Ross, Rabe, & Mander, 2009). Adopting double flush technology is expected to reduce as much as 75% water use in flushing (Murwirapachena & Dikgang, 2019). Greywater constitutes about 50% of the total wastewater generated within a household and its reuse may lead to significant reductions in household water demand (Carden *et al.*, 2007; Roesner *et al*., 2006).

This paper investigates the factors that drive the adoption of water-saving technologies in Cape Town. We use a choice modelling framework that compares various utility functions associated with different alternatives that represent payoffs associated with adopting water-saving technologies.

2 Brief Related Literature

The literature has identified several factors that drive household water demand and consumption patterns. These factors include household socio-demographic characteristics (Aitken *et al.*, 1994; Gregory & Di Leo, 2003), behavioural change towards water usage (Gregory & Di Leo, 2003; Richter & Stamminger, 2012), attitudes and values towards water conservation practices (Syme *et al.*, 2004; Willis *et al.*, 2011), water restrictions programmes (De Oliver, 1999; Kenney, Klein, & Clark, 2004) and pricing of water (Kenney *et al.*, 2008; Renwick & Archibald, 1998). Nauges & Whittington (2010) provide a comprehensive overview of the factors that influence residential water demand in the developing world.

Very few studies looked at the behavioural responses associated with the adoption of water-saving technologies by urban dwellers. This is because most of the water consumption occurs in the agricultural sector, and water-saving is mainly expected to take place at farm level. However, the growing urbanization in urban cities is not only expected to increase the volume of water use for drinking and residential consumption purposes but also water use in agriculture and manufacturing production for a growing population. More people will require more food and more manufacturing products, which will require more inputs used in the production process, including water. Despite this, few studies have looked at the determinants of adoption of residential water-saving technologies (Campbell, Johnson, & Larson, 2004; Millock & Nauges, 2010; Renwick & Archibald, 1998; Thiam, Dinar, & Ntuli, 2020). Campbell *et al*. (2004) looked at the impacts of price and non-price water demand-side management on the adoption of water-saving equipment in Arizona, USA. They collected data from 19,000 households over six years and found that changes in water pricing spur adoption of water-conservation measures. Millock & Nauges (2010) studied the factors that drive adoption of Waterwise washing machines, low-volume flush toilets, restrictor taps in water supply and rainwater collector tanks in 10 OECD countries in Europe. They found that household size, water price and whether households own property positively influence the adoption of water-saving technologies. Thiam *et al.* (2020) and Renwick & Archibald (1998) investigated the factors that drive the adoption of water-saving technologies in residential households in South Africa and California, respectively. Their results found that household size, income and education positively influence the adoption of water-saving technologies. This present paper contributes to the discussion on urban water management by investigating the factors that drive the adoption of water-saving technologies through empirical evidence from South Africa. We build on Thiam *et al.* (2020) and Campbell *et al.* (2004) and look at the behavioural responses associated with adoption of water-saving technologies in residential households. This research provides an improved understanding of the challenges associated with the adoption of water-saving behaviours in urban areas that experience water scarcity.

3 Theory and Methods

3.1 The Choice Experiment Method and the Econometric Model

Developed from the random utility theory, choice experiments assume that individuals are rational decision-makers who choose the most preferred (utility-maximising) option when faced with various possible set of options (McFadden, 1973; Howard, 1977). According to McFadden (1973), these rational individuals make choices based on the characteristics of the good, along with a random component. The random component could emerge from the uniqueness in the individuals' preferences, or due to researchers having in-complete information about the individual observed (Ben-Akiva & Lerman, 1985). Where a household head i's utility, U, of a water-saving technology j is assumed to consist of a deterministic and a stochastic element:

$$U_{ij} = V_{ij}\left(x_j, z_j, t\right) + e_{ij} \tag{1}$$

Where V depends on the characteristics of the technology x_j, individual specific characteristics z_j, and the price t and e_{ij} is the unobserved random component that is IID extreme value type 1[2] and consists of factors affecting the choice but are not observable to the researcher

[2] Historically, EV1 distribution has been referred to by a number of names, including Weibull, Gumbel and double-exponential.

(Louviere et al., 2000). The theory states that an individual will choose an alternative k from a finite set of alternatives C, given the indirect utility of k is greater than the indirect utility of any other alternative, j. This means that

$$U_{ik} > U_{ij} \implies V_{ik} + e_{ik} > V_{ij} + e_{ij} \quad \forall\, j \neq k; j, k \in C\,) \tag{2}$$

The probability that an individual chooses alternative k is the same as the probability that the utility of alternative k is greater than the utility of any other alternative of the choice set (Adamowicz, 2004). In our case, the utility definition of the choice-task among five alternatives, one of which is the status quo option, is

$$U_{kin} \begin{cases} V\big(ASC, x_{kin,} \beta_i\,, \varepsilon_i\,\big) + e_{kin}, & \text{if } k = 1; \\ V\big(ASC, x_{kin,} \beta_i\,, \varepsilon_i\,\big) + e_{kin}, & \text{if } k = 2; \\ V\big(ASC, x_{kin,} \beta_i\,, \varepsilon_i\,\big) + e_{kin}, & \text{if } k = 3; \\ V\big(ASC, x_{kin,} \beta_i\,, \varepsilon_i\,\big) + e_{kin}, & \text{if } k = 4; \\ e_{kin}, & \text{if } k = \text{status quo} \end{cases} \tag{3}$$

where i denotes the individual, k the alternative, and n the choice-occasion. V_{kin}, the indirect utility is a function of a vector of variables explaining choice x_{kin} and chosen vectors of individual-specific parameters, β_i . β_i is assumed to take on a multivariate normal distribution where the off-diagonal elements of the covariance matrix are zero. ε_i is an error component associated with the two non-status quo choices and is assumed to be normally distributed white noise, $\varepsilon_i \sim N\,(0, \sigma^2)$. This error component reflects that there may be additional variance related to the four non-status quo alternatives, because it is cognitively more demanding for respondents to evaluate four complex alternatives in each choice set as opposed to the status quo (Beharry-Borg et. al., 2009; Hensher et al., 2015; Morse-Jones et al., 2012). Lastly, e_{kin}, is a random error term that is iid extreme value type 1.

In order to calculate the choice probability for a given choice-occasion n, we use a random we use a random parameter logit model (RPL) and assume that individuals seek to maximise utility. Conditional on the individual-specific parameters, β_i, and error components, ε_i , the probability that respondent i chooses a specific alternative k in choice-task n (of the sequence n = 1, . . . , N) from the five alternatives (j = 1, . . . , J) is logit:

$$\Pr(kin|\ \beta_i, \varepsilon_i\ ) = \frac{\exp(\beta_i' X_{kin} + \varepsilon_i)}{\sum_j^J \exp\left(\beta_i' X_{jin} + \varepsilon_i\right)} \tag{3}$$

If we assume independence over choice-tasks made by the same individual, the joint probability of an individual making a sequence of choices is the product of the, in our case, ten probabilities. The probability of choice unconditional on the error component is obtained by integrating over the error-component space. Following this, the marginal probability of choice can be derived from integrating over the distribution functions for the random $\beta\_$ parameters (Beharry-Borg et al., 2009; Train et al., 1987). Following the above, the probability of choosing alternative k becomes:

$$\Pr(kin) = \int \left(\prod_{n=1}^{N} \left[\frac{\exp(\beta_i' X_{kin} + \varepsilon_i)}{\sum_j^J \exp(\beta_i' X_{jin} + \varepsilon_i)} \right] \right) f(\beta) d \tag{4}$$

Where $f(\beta)$ represents the distribution function for β, with mean b and variance W. The model is not sensitive to the independence of irrelevant alternatives (IIA) condition and, furthermore, it allows for individual-specific β estimates based on specified distributions (Train et al., 1998). This means that the model utilises the information that each respondent has answered several choice sets, by making taste parameters constant over choices within individuals but not between individuals. Including this information is likely to enhance the explanatory power of the model. Even though the integral in (4) does not have a closed-form, the choice probability in the RPL model can be estimated through simulation. The unknown parameters θ, such as the mean and variance of the random coefficient distribution, can be estimated by maximizing the simulated log-likelihood function. For a given mean and variance of a random coefficient distribution, the simulated probability $\breve{P}_{kin}$ is strictly positive and twice differentiable with respective to the unknown parameters θ. Therefore, the simulated log-likelihood function log-likelihood is:

$$LogL(\theta) = \sum_{i=1}^{I} \sum_{k=1}^{J} d_{kin} \ln \breve{P}_{kin} \tag{5}$$

Where d_{kin}=1 if individual i chooses alternative k and zero otherwise. Each individual is assumed to make choices independently and only make the choice once. The value of estimates that maximizes the SLL is called the maximum simulated likelihood (MSL) estimate.

To derive the mathematical form of the NL model, we consider a two-level NL structure[3] in which the total choice sets are partitioned in m nonoverlapping subsets (nests) $B_1, \ldots, B_m$. The utility of alternative k in nest B_m is still $U_{ij} = V_{ij} + e_{ij}$, again with V_{ij} the observed part of the utility. The NL model is obtained by assuming that the vector of disturbances has a cumulative distribution of a GEV type distribution:

$$exp\left(-\sum_{m=1}^{m}\left(\sum_{k\in B_m} e^{-\varepsilon ij/\lambda_m}\right)^{\lambda_m}\right) \qquad (6)$$

The parameter λ_m is a measure of the degree of independence in the random part of the utility among the alternatives in the nest m. The distribution for the unobserved components proceed the choice probability for alternative j in nest B_m:

$$P_{ij} = \frac{e^{V_{ij}/\lambda_m}\left(\sum_{k\in B_m} e^{V_{ik}/\lambda_m}\right)^{\lambda_m - 1}}{\sum_{l=1}^{m}\left(\sum_{k\in B_l} e^{V_{ik}/\lambda_l}\right)^{\lambda_l}} \qquad (7)$$

If $m = l$, meaning two alternatives are in the same nest, the factors in parentheses cancel each other out and it shows that IIA holds. Train (2003) shows that some other form of IIA holds across nests, such as independence from irrelevant nests (IIN). Therefore, in a NL model, IIA holds for alternatives within each nest and IIN holds over alternatives in different nests. The observed component of the utility function can be distinct in two parts: $U_{ij} = W_{im} + Y_{ij} + e_{ij}$. Here W_{im} is the part that is constant for all alternatives within a nest. This variable depends only on variables that describe next m, therefore they differ over the nests but not over the alternatives within a nest. Y_{ij} is simply define as $V_{ij} - W_{im}$ and depends on variables that describe alternative j, so they vary over alternatives within next m. The probability that an alternative is chosen ca be written as the product of the probability that a certain nest is chosen multiplied with the probability that an alternative within that nest is chosen:

$$P_{ij} = P_{ij\backslash B_m} \cdot P_{iB_m} \qquad (8)$$

The conditional probability $P_{ij\backslash B_m}$ can be given as:

[3] The extension of a two-level NL structure to three-level or four-level ones can be done with the same methodology used in this paper.

$$P_{ij\backslash B_m} = \frac{e^{Y_{ij}/\lambda_m}}{\sum_{k\in B_m} e^{Y_{ik}/\lambda_m}} \tag{9}$$

and

$$P_{iB_m} = \frac{e^{W_{im}+\lambda_m J_{im}}}{\sum_{l=1}^{m} e^{W_{il}+\lambda_l J_{il}}} \tag{10}$$

Where

$$J_{im} = \ln \sum_{k\in B_m} e^{Y_{ij}/\lambda_m} \tag{11}$$

These expressions are derived from the choice probabilities stated earlier. Train (2003) gives the derivation by algebraic rearrangement. It is customary to refer to the marginal probability as the upper model and to the conditional probability as the lower model. The quantity J_{im} links the lower and upper model by transferring information from the lower model to the upper model (Ben-Akiva and Lerman, 1985). This term is the logarithm of the denominator of the lower model, which means that $\lambda_m J_{im}$ is the expected utility that the decision maker obtains from the choice among the alternatives in nest B_m.

The parameter of the NL can be estimated by standard maximum likelihood techniques:

$$L = \prod_{i=1}^{I} \prod_{j\in B_m} \left(P_{ij\backslash B_m} P_{iB_m}\right)^{y_{ij}} \tag{12}$$

Thus, the log likelihood becomes:

$$\log L = \sum_{i=1}^{I} \sum_{j\in B_m} y_{ij} \ln P_{ij\backslash B_m} + \sum_{i=1}^{I} \sum_{m\in M} y_{im} \ln P_{iB_m} \tag{13}$$

We estimate the marginal effects of each attribute in order for the results to be of more policy relevance. Additionally, understanding the marginal effects allows us to test for variations in welfare measures by examining the marginal willingness to pay (MWTP) estimates. MWTP estimates show the marginal rate of substitution (MRS) between each attribute and the monetary attribute; this is an important output of choice models, as it gives average estimates of what respondents are prepared to pay for or against each attribute (Hensher *et al.*, 2015). Equation (14) below shows the expression of the MWTP.

$$WTP_X = \frac{\Delta X}{\Delta C} = -\frac{\frac{\delta U_{ij}}{\delta X_j}}{\frac{\delta U_{ij}}{\delta C_i}} = -\frac{\beta_j}{\mu} = MWTP \tag{14}$$

3.2 Introduction to Discrete Choice Experiment

The experimental design's quality drives the precision and statistical significance of parameter estimates when performing an empirical analysis. This is because there exists a relationship between the statistical properties of stated choice experiments and the econometric models used to estimate the experimental data (Butkeviciute, 2017). There are different choice experiment design types that have been adopted by researchers, including full factorial, fractional factorial, orthogonal and efficient designs (Gao et al., 2010; Kløjgaard et al., 2012; Ryan et al., 2008; Street et al., 2019). The designs primarily differ in the assumptions imposed, specifically on the type of correlation structure between attributes in the design matrix.

In this paper we focus on the orthogonal and D-efficient designs. The orthogonality property has often been considered the traditional and state-of-practice approach. A design is said to be orthogonal "*if it satisfies attribute level balance and all parameters are independently estimable*."[4] Orthogonal designs are generated by imposing the property of orthogonality on the attributes contained in the columns of the design matrix (J. M. Rose & Bliemer, 2009). On the other hand, efficient designs are derived based on the statistical properties of discrete choice models. Efficiency based designs reduce the sample size requirement needed to obtain robust parameter estimates. More specifically, D-efficient designs have been mostly relied on by researchers because it aims to minimize the standard errors of the parameters at design stages and improve the quality of the results obtained when estimating parameter values. (Alpízar et al., 2001; Bliemer et al., 2010; Dardanoni & Guerriero, 2021; Lai & Yue, 2020; Rose & Bliemer, 2009). However, efficient designs are only efficient if prior parameters are known. If incorrect prior parameters are used, efficient designs become inefficient (Bliemer et al., 2010). To address this problem, the literature recommends drawing prior parameters from i) the literature ii) pilot study iii) focus groups or iv) expert judgement (Rose, 2012). The

[4] Ngene Manual, p. 64, ChoiceMetrics, 2012

experiment designs discussed in this paper are applied using the Ngene[5] software in the context of the pilot and final survey designs.

3.3 Design of the choice experiment

In this study, the water-saving technologies we considered are i) greywater reuse ii) rainwater collection iii) efficient showerheads, and iv) dual flush cistern. Greywater constitutes about 50% (about 68litres/capital/day) of the total wastewater generated within a household in Cape Town (Carden *et al., 2007;* Roesner *et al., 2006)*. An integrated domestic rainwater harvesting involves collecting, storing, and channeling rainwater to the toilet for flushing and gardening irrigation outlets instead of using potable water. Replacing a 12L cistern with a 3L dual cistern saves about 75% of water (Jansen & Schulz, 2006; Murwirapachena & Dikgang, 2019; Zaied, 2018) in SA households.

Table 1 shows the selected attributes of each water-saving technology, and it describes their associated levels. Previous studies highlight "Reliability of Access" as one of the major factors that influence the adoption of water-saving technologies (Kaur & Rampersad, 2018; Zaunbrecher, Kowalewski & Ziefle, 2014). Households are more willing to adopt new technology that is perceived to be reliable when water can be accessed immediately it is needed. In our case, this refers to how dependable and reliable water supply from a given technology is. It considers the unpredictable nature of rainfall and the predictable availability of wastewater and cistern water within the household. The two levels of this attribute are: Reliable Access and Unreliable Access. The second attribute is "Perceived Health Risk". The level of health risk associated with a technology could largely influence its adoption rate. This risk can be present in the form of a foul smell, degree of water contamination and the possibility of diseases and infection to the household. This attribute has two levels: Health risk and No health risk. The third attribute identified in this study is the "Complexity of technology". This refers to the ease of use of a given technology and the expertise involved in installing and operating it. The ease of use of technology could have a huge influence on respondent's adoption rate (Makki & Mosly, 2020; Sharma, Begbie, & Gardner, 2015). The two levels of the attribute are; easy (when no extra training is required before usage of the technology) and

[5] Ngene is a comprehensive software for designing choice experiments. It is designed to be the single source of stated choice experimental designs (ChoiceMetrics, 2012).

hard (when very sophisticated and intensive training is needed before installation of the technology). The fourth attribute is the "Ease of Maintenance", this differs from the above third attribute mainly because maintenance and services are done post technology installation. The relevance of this attribute can be distinguished based on the needed frequency of maintenance of technology that will ensure optimal performance, as well as the expertise required for such maintenance. It also captures both the ease of acquisition of the maintenance skills and the intensity of training needed to service the technology after installation. The identified attribute levels are: Difficult and Easy. Investing in water-efficient technologies is expected to reduce the household's monthly water bill by reducing the quantity of water demanded from the municipality. Thus, the fifth attribute considered in this study is "Water Quantity Saved". The average urban household of 5 people uses 640 liters of water per day in South Africa (COCT, 2013). Technologies that reduce the quantity of water used for specific household activities, store rainwater and make wastewater available for reuse will ultimately reduce the total quantity of water demanded by this household. The attribute levels are; above 25% (when technology saves up to 25% of average household water demand) and below 25% (when technology saves less than 25% of average household demand. The sixth attribute identified is the "Costs of Technology", which can also influence adoption decisions within households. The adoption of technologies with high cost of purchase and installation could be limited in low-income households (Kaur & Rampersad, 2018). Four levels of costs were examined for this attribute. Finally, previous studies report the "lifespan of a technology" as an important factor that influences technology adoption (Heinz, 2013; Peek et al., 2016). In choosing water-saving technologies, a household is more willing to adopt technologies that have a longer lifespan. The two levels of the attribute are "less than 5 years" and "more than 10 years". There are 256 possible combinations of the attributes and their levels as shown in Table 1, with six attributes varying across two levels each and one attribute varying across four levels (2^6X 4^1).

Table 1: Definition of Attributes and their Level

Attributes	Definition	Levels of attributes
Reliability of Access	This indicates how dependable and reliable water supply from the technology is.	Reliable Access: Water can be accessed from selected technology every time it is needed.
		Unreliable Access: Access to water from technology may be seasonal.
Perceived Health Risk	This refers to the households' perception of possible health-related risks, discomfort or stress associated with the use of a technology	High risk: Selected technology uses chemicals products in water treatment and may emit foul smells.
		No health risk: No chemical products are used in technology and there is no emission of foul smell.
Complexity of Technology	This refers to the ease of use of technology and the expertise involved in the installation and day-to-day operation. It focuses on whether technology can be operated with no prior training or not.	Hard: When high-level expertise and training is needed for the installation and operation of the technology.
		Easy: When technology can be operated with no prior training.
Ease of Maintenance	This captures whether intensive training is needed for the maintenance or servicing of technology to ensure optimal performance. It also captures the frequency at which maintenance or servicing is needed.	Difficult: When intensive training is needed for the maintenance of technology and maintenance is required at least once a month.
		Easy: When maintenance is easy and rarely necessary
Water Quantity Saved	This refers to the percentage of water saved in a household after technology adoption.	Above 25%: If technology saves more than 25% of the average water demand of household before installation.
		Below 25%: If the presence of technology does not reduce household water demand by up to 25%.
Costs of Technology	Cost of purchasing and installing the technology	R5,000; R10,000; R15,000; R20,000
Lifespan of the technology	This refers to the average number of years the technology can be used optimally without the need for replacement.	Less than 5 years
		More than 10 years

4 Survey Design and Data Collection

4.1 Pilot and Main Survey Design

The pilot survey's aim is not to obtain precise parameter estimates for the D-efficient design. Instead, the goal is to roughly estimate the weight individuals place on water-saving technologies' different attributes. To minimize bias and elicit the weight households place on the attributes that form of prior values required to generate the final design of the survey, an orthogonal design of 36 alternative profiles made up of six blocks was created using Ngene from the full set of possible combinations. The number of alternatives is informed by the literature review and is based on the frequently used number of blocks and choice sets for a design similar to the one being considered in this paper. The software produced a design with one status quo and four non-status quo alternatives per choice set, and six choice sets arranged in six survey blocks/cards. The status quo represents the household's current situation, i.e., what they are doing now, whether they have a technology installed or not. Each respondent was randomly assigned six choice sets which had been prepopulated in six different questionnaire versions. In addition, each pilot survey questionnaire also included sections on socioeconomic characteristics of households. We carried out the pilot survey in November 2020 and obtained responses from 72 households. Each respondent evaluated 5 alternatives throughout 6 survey questions which generated 1040 observations in total. The main survey design generation process took place over many days to allow Ngene to evaluate as many potential designs as possible and locate the smallest comparable D-error for the final questionnaire.

The prior parameter estimates from the pilot orthogonal survey were then used to construct the main survey. After allowing Ngene to run the D-efficient design syntax, we manually saved designs with the lowest D_b-errors. A design of eight distinct choice sets was evaluated using Ngene, from the full set of all possible combinations. Like the pilot design, the software also produced a design with one status quo and four non-status quo alternatives per choice set. In addition to the section on households' socioeconomic characteristics, the questionnaire also recorded information on household water consumption and water-saving strategies adopted within households. The final survey instrument was administered to 303 households within the City of Cape Town.

5 Results

Table 2 shows the descriptive statistics of the respondents for both the pilot and main surveys. During data inputting for the pilot survey, data was captured such that each individual household head was entered 30 times to include the choices they made for five options and six different choice sets. In the main survey data was captured such that each individual was entered 40 times to include the choices they made for five options and eight different choice sets. Responders averaged 54 years old in the pilot and 50 years of age in the main survey. The average household size is 5 in the pilot survey while it is 4 in the main survey. The gender of the household heads showed minor differences in both surveys, from 82% male respondents in the pilot survey to 83% in the main survey. More results of our main survey showed that 66% of the respondents are employed and about 16% of the respondents have total yearly household income of above one million Rand. The average tap water consumption per month is 6262L while the mean monthly water bill is R367.

Table 2: Descriptive Statistics

	Mean (Std. Dev.)	
Variables	Pilot Survey (n=72)	Main Survey (n=303)
Age (Years)	54.24 (9.61)	49.66 (15.61)
Gender (1 =male, 0 = female)	0.82 (0.39)	0.83 (0.37)
Household Size	4.58 (3.27)	3.70 (1.47)
Number of employed household member	2.15 (1.39)	1.83 (1.32)
Educational Level (1=Primary education, 2=Secondary school, 3=Some technical certificate/diploma, 4=Bachelor’s degree, 5=Honor’s degree, 6=Professional/Master’s degree, 7=Doctorate degree)	4.22 (1.69)	3.55 (1.53)
Total Annual Household Income (1=R50,000 or below, 2=R50,001 to R100,000, 3=R100,000 to R150,000 4=R150,000 to R200,000 5=200,000 to R350,000 6=R350,000 to R500,000 7=R500,000 to R750,000 8=R750,000 to R1,000,000 9=R1,000,000 to R2,000,000 10=Above R2,000,000)	7.86 (2.71)	5.41 (2.92)

5.1 Parameter Priors

The pilot coefficient estimates were estimated using Stata and used in the main survey design as parameter priors. These priors are outlined in Table 3 along with the assumed standard deviations. The population standard deviations of the respective attributes included in the design were approximated using the values of the coefficient estimates' standard errors. In our model, each parameter prior $\widetilde{\boldsymbol{\beta}}_t$ is assumed to follow a normal distribution with mean $\boldsymbol{\mu_t}$ and standard deviation $\boldsymbol{\sigma_t}$. The population standard deviation Table 3 have been approximated using the standard errors of the mean coefficient estimates from the pilot study (Greene, 2008). In order to obtain a rough approximation of the population standard deviation $\boldsymbol{\sigma}$ we use the relationship between sample size, the standard error of the parameter estimate and the population standard deviation $S.E._{\bar{X}} = \frac{\sigma}{\sqrt{n}}$[6]. This method was followed instead of randomly assigning values to the standard deviations.

Table 3: Main survey parameter priors

Attribute $\boldsymbol{t}$	Assumed Priors $\widetilde{\boldsymbol{\beta}}_t \sim \boldsymbol{N}(\boldsymbol{\mu_t}, \boldsymbol{\sigma_t})$
Reliability of access	$\boldsymbol{N}$(0.38, 1.10)
Perceived Health Risk	$\boldsymbol{N}$(0.57, 1.10)
Complexity of Technology	$\boldsymbol{N}$(-0.12, 1.02)
Ease of Maintenance	$\boldsymbol{N}$(0.90, (1.02)
Water Quantity Saved	$\boldsymbol{N}$(-0.61, 1.10)
Cost of Technology	$\boldsymbol{N}$(-8e4, 1e4)
Lifespan of Technology	$\boldsymbol{N}$(-0.17, 1.10)

5.2 RPL and Nested Logit Model

To test all attributes for presence of preference heterogeneity, RPL model assumes that all the variable coefficients are distributed randomly following a normal distribution. In the RPL model estimation, not all the attributes were found to be significant. As shown in Table 4, only four attributes in the base RPL model are significant. Access to technology and lifespan of the technology shows statistical significance at 5% while the cost of the technology is significant at 1%. The estimates show that the cost of water-saving technologies, their access, lifespan, and

[6] This method does not present a precise and unbiased estimate of the population standard deviation but helps us to avoid assigning random prior values using of sample size of 72 in the pilot study.

the quantity of water they save are important determinants technology adoption within households. The interactions of the Age and Health Risk, Gender and Reliability, Household income and Health Risk, Income and water quantity saved, Household size and Lifespan, Education and Lifespan and Waterbill and Reliability of technology all show statistical significance in the RPL model. Table 4 also includes columns for z-statistics which indicate the relative explanatory power of the various attributes in respondents' choice of water-saving technology. Under the base RPL model the attributes with the largest z-values are the quantity of water saved and lifespan of technology.

The nest structure of our nested logit model is shown in figure. We generated a categorical variable that identifies the first-level set of alternatives based on the cost implication of our five choice alternatives: (i) High-Cost technologies, (ii) Minimal cost technologies and (iii) no cost alternative. Figure 1 shows the nesting structure in which rainwater collection and greywater treatment technologies are more similar to each other than they are to water-efficient showerhead and double-flush toilet. The base NL results in table 4 shows that all attributes are statistically significant except the perceived health risk associated with water-saving technologies. The z-values of the NL interactions and RPL interactions show very similar results to each other.

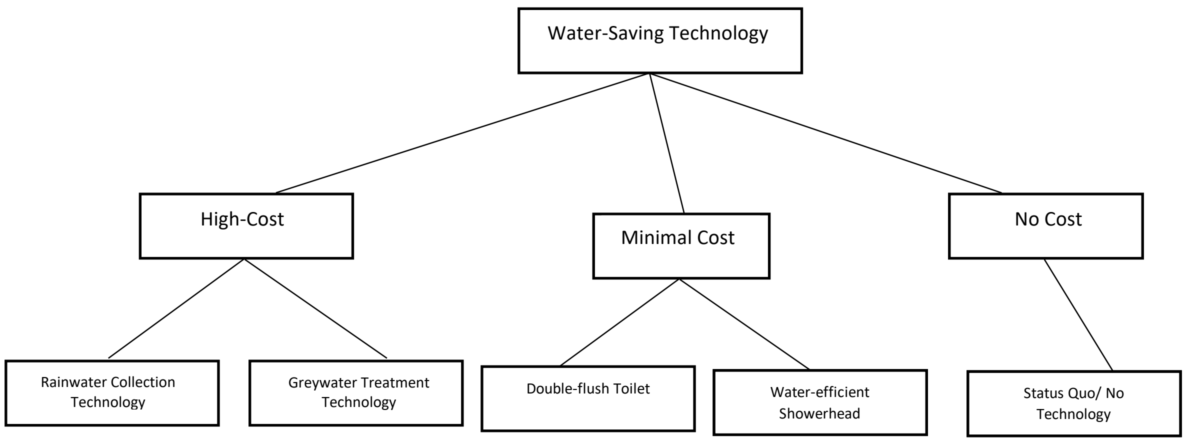

Figure 1: Two-Level Nest Structure

Table 4: Random Parameter Logit and Nested Logit Model

	Base RPL		RPL Interaction		Base NL		NL Interaction	
Attributes	Coefficient (SE)	$\|z-stat\|$	Coefficient (SE)	$\|z-stat\|$	Coefficient (SE)	$\|z-stat\|$	Coefficient (SE)	$\|z-stat\|$
Reliability of Access	-0.293** (0.135)	-2.16	0.369 (0.406)	0.91	-0.285*** (0.065)	-4.37	0.324 (0.370)	0.87
Perceived Health Risk	-0.048 (0.079)	-0.60	0.188 (0.326)	0.58	0.056 (0.056)	1.00	0.269 (0.319)	0.84
Comp. of Technology	0.089 (0.059)	1.51	-0.496* (0.297)	-1.67	0.137*** (0.051)	2.70	-0.357 (0.289)	-1.24
Ease of Maintenance	-0.063 (0.067)	-0.95	-0.474 (0.331)	-1.43	0.116** (0.057)	2.04	-0.274 (0.323)	-0.85
Water Quantity Saved	0.090* (0.054)	1.68	0.466 (0.290)	1.60	0.169*** (0.050)	3.38	0.494* (0.285)	1.74
Costs of Technology	-2.59e-05*** (8.81e-06)	-2.95	2.92e-5 (4.33e-5)	0.67	-5.13e-05*** (7.51e-06)	-6.83	6.32e-06 (4.24e-05)	0.15
Lifespan of technology	0.128** (0.064)	2.00	-0.130 (0.297)	-0.44	0.157*** (0.051)	3.07	-0.092 (0.296)	-0.31
Age × Reliability			0.004 (0.005)	0.91			0.004 (0.004)	0.86
Age × Health Risk			-0.012*** (0.004)	-2.99			-0.011*** (0.004)	-2.99
Age × Complexity			0.003 (0.004)	0.71			0.003 (0.003)	0.78
Age × Maintenance			0.001 (0.004)	0.30			0.001 (0.004)	0.21
Age × quantity			0.002	0.44			0.002	0.51

	(0.004)			(0.003)	
Age × Cost	--6.16e-07 (5.19e-07)	-1.19		--5.82e-07 (5.11e-07)	-1.14
Age × Lifespan	-0.003 (0.004)	-0.74		-0.002 (0.004)	-0.67
Gender × Reliability	-0.486*** (0.180)	-2.70		-0.436** (0.172)	-2.53
Gender × Health Risk	-0.096 (0.154)	-0.63		-0.092 (0.152)	-0.61
Gender × Complexity	0.142 (0.144)	0.99		0.115 (0.141)	0.81
Gender × Maintenance	-0.023 (0.157)	-0.14		-0.005 (0.154)	-0.03
Gender × quantity	-0.042 (0.140)	-0.30		-0.032 (0.137)	-0.23
Gender × Cost	1.22e-05 (2.04e-05)	0.60		8.57e-06 (2.01e-05)	0.43
Gender × lifespan	0.150 (0.142)	1.05		0.130 (0.143)	0.91
Income × Reliability	-0.035 (0.028)	-1.26		-0.030 (0.026)	-1.13
Income × Health Risk	0.038* (0.023)	1.67		0.038* (0.023)	1.69
Income × Complexity	0.009 (0.021)	0.41		0.005 (0.021)	0.23
Income × Maintenance	-0.007 (0.023)	-0.29		-0.005 (0.023)	-0.22
Income × quantity	-0.038* (0.021)	-1.84		-0.037* (0.020)	-1.80

Income × Cost	1.30e-06 (3.05e-06)	0.43	1.07e-06 (3.00e-06)	0.36
Income × lifespan	0.027 (0.021)	1.31	0.025 (0.021)	1.20
Household size × Reliability	0.006 (0.047)	0.12	-0.004 (0.045)	-0.08
Household size × Health Risk	-0.039 (0.039)	-0.98	-0.037 (0.039)	-0.95
Household size × Complexity	0.036 (0.036)	1.01	0.037 (0.035)	1.05
Household size × Maintenance	0.078* (0.040)	1.94	0.073* (0.039)	1.85
Household size × quantity	0.021 (0.035)	0.60	0.024 (0.035)	0.70
Household size × Cost	-6.51e-06 (5.27e-06)	-1.23	-5.80e-06 (5.19e-06)	-1.12
Household size × Lifespan	-0.069* (0.036)	-1.94	-0.067* (0.036)	-1.87
Education × Reliability	-0.019 (0.052)	-0.37	-0.013 (0.049)	-0.26
Education × Health Risk	0.058 (0.043)	1.36	0.061 (0.042)	1.45
Education × Complexity	0.051 (0.039)	1.30	0.040 (0.038)	1.05
Education × Maintenance	0.021 (0.044)	0.48	0.018 (0.043)	0.42
Education × quantity	-0.061 (0.039)	-1.58	-0.057 (0.038)	-1.50
Education × Cost	-8.51e-06 (5.79e-06)	-1.47	-9.09e-06 (5.70e-06)	-1.60

Education × lifespan		0.079** (0.039)	2.03		0.081** (0.039)	2.08
Waterbill × Reliability		-0.001** (3.18e-04)	-1.99		-0.001* (3.03e-04)	-1.90
Waterbill × Health Risk		4.0e-04 (2.57e-04)	1.55		4.07e04 (2,55e-04)	1.60
Waterbill × Complexity		-4.56e-05 (2.28e-04)	-0.20		-9.0e-05 (2.25e-04)	-0.40
Waterbill × Maintenance		1.05e-04 (2.64e-04)	0.40		1.35e-04 (2.59e-04)	0.52
Waterbill × quantity		-1.72e-04 (2.26e-04)	-0.76		-1.77e-04 (2.22e-04)	-0.80
Waterbill × Cost		3.37e-08 (3.44e-08)	0.98		2.92e-08 (3.38e-08)	0.87
Waterbill × Lifespan		2.55e-04 (2.31e-04)	1.10		2.34e-04 (2.31e-04)	1.01
Log-likelihood	-3724.419	-3661.766		-3773.157	-3712.321	
Nr. Obs.	12,120	12,120		12,120	12,120	
Nr. Respondents	303	303		303	303	
AIC	7470.837	7429.533		7560.315	7522.643	
BIC	7534.562	7736.571		7600.867	7806.508	

Notes: Robust standard errors presented in parentheses. ***, **, *, next to coefficients represents statistical significance at the 1%, 5%, and 10% respectively.

In addition to the RPL and NL models, we also estimated both a multinomial logit (ML) model and a conditional logit (CL) model. All attributes in the base ML showed statistical significance and the ML with interaction also reported similar results like the RPL model. In the base CL model only the perceived health risk associated with water-saving technologies was not statistically significant. However, the CL model with interactions also showed similar results with all other three models.

The marginal willingness to pay (MWTP) result in Table 5 shows attributes that are valuable for households to invest in water-saving technologies. When we consider the MWTP across base models, we observe that both the RPL and NL base models have the high MWTP for complexity of technology, quantity of water saved, and lifespan of technology. While the RPL and NL with interactions shows the highest MWTP for complexity of the technology, ease of maintenance and lifespan of the technology. This result indicates that both complexity of water-saving technologies and the lifespan of technologies are major determinants for adoption of technologies and are important attributes to households since they have high MWTP across all four models. In making their choice of water-saving technologies, households prefer technologies that can be easily operated and last for a long time after installation.

Table 5: Average Household marginal willingness to pay (Base RPL, RPL Interaction, Base Nlogit, Nlogit Interaction)

	Base RPL			RPL interaction			Base NL			Nlogit Interaction		
Attributes	Average Household MWTP	95% Conf. Interval		Average Household MWTP	95% Conf. Interval		Average Household MWTP	95% Conf. Interval		Average Household MWTP	95% Conf. Interval	
Reliability of Access	-11277.49	-26059.77	3504.79	-12612.98	-70599.73	45373.77	-5556.72	-9278.71	-1834.72	-51215.79	-804107.52	701675.93
Health Risk	-1838.19	-7962.31	4285.93	-6436.62	-34247.02	21373.78	1097.90	-1090.06	3285.87	-42629.86	-606991.59	521731.87
Comp. of Technology	3413.38	-745.42	7572.19	16978.12	-29885.73	63841.98	2665.17	828.73	4501.62	56597.20	-664858.7	778053.1
Ease of Maintenance	-2442.28	-8281.89	3397.34	16234.22	-31961.54	64429.97	2256.15	66.02	4446.29	43373.13	-525671.59	612417.85
Water Quantity Saved	3487.2598	-1662.81	8637.33	-15944.98	-61534.19	29644.24	3300.03	994.04	5606.02	-78245.42	-1093855.5	937364.68
Lifespan of technology	4941.89	-973.87	10857.65	4464.85	-19464.43	28394.14	3071.38	963.51	5179.26	14603.83	-193129.97	222337.63

6 Conclusion and Policy Implication

This paper has investigated the factors driving the adoption of four water-saving technologies by using econometric models that account for residential household heterogeneity in Cape Town, South Africa. A CE study of seven attributes, which were identified as relevant for household water-saving decisions, was applied. In our pilot survey estimation, an orthogonal design estimate was administered to 72 respondents in other to generate parameter priors that were then used in our D-efficient design estimation for 303 respondents. An in-depth understanding of households' preference for water-saving technology is of interest since it provides the foundation for urban water management, which will ultimately impact cities' sustainable environmental policy goals.

The results show that households are sensitive to the reliability, lifespan and quantity of water saved by the technology when explaining the attributes that determine adoption. We also found that respondents have strong preference for the technologies with least cost of purchase. Policy interventions should support initiatives that attempt to encourage better water-saving technologies that consider cost, longevity and increased water saving capacity. The implication of this is that investment in research and development should be promoted around such technologies. Alongside these technical interventions, our results also show the initiatives that support installation of technologies with less complexities are favourable in predicting positive household response to adoption. Finally, costs may also hinder adoption of water-saving technology. Policy interventions should be articulated around possible financial support that could assist poor households in acquiring such technology.

7 Reference

Adamowicz, W. L. (2004). What’s it worth? An examination of historical trends and future directions in environmental valuation. *Australian Journal of Agricultural and Resource Economics*, *48*(3), 419–443. https://doi.org/10.1111/j.1467-8489.2004.00258.x

Aitken, C. K., Mcmahon, T. A., Wearing, A. J., & Finlayson, B. L. (1994). Residential Water Use: Predicting and Reducing Consumption1. *Journal of Applied Social Psychology*, *24*(2), 136–158. https://doi.org/10.1111/j.1559-1816.1994.tb00562.x

Alpízar, F., Carlsson, F., & Martinsson, P. (2001). Using Choice Experiments for Non-Market Valuation Francisco Alpízar, Fredrik Carlsson 1 and Peter Martinsson. *Economic Issues*, *8*, 83–110.

Beharry-Borg, N., Hensher, D. A., & Scarpa, R. (2009). An analytical framework for joint vs separate decisions by couples in choice experiments: The case of coastal water quality in tobago. *Environmental and Resource Economics*, *43*(1), 95–117. https://doi.org/10.1007/s10640-009-9283-7

Ben-Akiva, M., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand*. Retrieved from https://books.google.com/books?hl=en&lr=&id=oLC6ZYPs9UoC&oi=fnd&pg=PR11&ots=nNise4fkGe&sig=gB217hA1f6FgNqvIYOSrez_uMcg

Bliemer, M., Rose, J. M., Bliemer, M., & Rose, J. (2010). Construction of experimental designs for mixed logit models allowing for correlation across choice observations. *Transportation Research Part B: Methodological*, *44*(6), 720–734. Retrieved from https://econpapers.repec.org/RePEc:eee:transb:v:44:y:2010:i:6:p:720-734

Booysen, M. J., Visser, M., & Burger, R. (2019). Temporal case study of household behavioural response to Cape Town's "Day Zero" using smart meter data. *Water Research*, *149*, 414–420. https://doi.org/10.1016/j.watres.2018.11.035

Butkeviciute, D. (2017). *Consumer Preferences & Loyalty Discounts: The Case of UK Grocery Retail* (University of London). Retrieved from http://openaccess.city.ac.uk/19171/http://openaccess.city.ac.uk/

Campbell, H. E., Johnson, R. M., & Larson, E. H. (2004). Prices, Devices, People, or Rules: The Relative Effectiveness of Policy Instruments in Water Conservation1. *Review of Policy Research*, *21*(5), 637–662. https://doi.org/10.1111/j.1541-1338.2004.00099.x

Carden, K., Armitage, N., Sichone, O., & Winter, K. (2007). The use and disposal of greywater in the non-sewered areas of South Africa: Part 2 - Greywater management options.

Water SA, *33*(4), 433–441. https://doi.org/10.4314/wsa.v33i4.52936

COCT. (2013). *City of Cape Town Smart Office Toolkit – Water Cheat Sheet*. Retrieved from https://www.capetown.gov.za/Document-centre#k=smart office toolkit

Cooper, B., Burton, M., & Crase, L. (2011). Urban water restrictions: Attitudes and avoidance. *Water Resources Research*, *47*(12), 1–13. https://doi.org/10.1029/2010WR010226

Dardanoni, V., & Guerriero, C. (2021). Young people' s willingness to pay for environmental protection. *Ecological Economics*, *179*, 106853. https://doi.org/10.1016/j.ecolecon.2020.106853

De Oliver, M. (1999). Attitudes and inaction: A case study of the manifest demographics of urban water conservation. *Environment and Behavior*, *31*(3), 372–394. https://doi.org/10.1177/00139169921972155

Enqvist, J. P., & Ziervogel, G. (2019). Water governance and justice in Cape Town: An overview. *Wiley Interdisciplinary Reviews: Water*, *6*(4), e1354. https://doi.org/10.1002/wat2.1354

Fielding, K. S., Russell, S., Spinks, A., & Mankad, A. (2012). Determinants of household water conservation: The role of demographic, infrastructure, behavior, and psychosocial variables. *Water Resources Research*, *48*(10). https://doi.org/10.1029/2012WR012398

Fuenfschilling, L., & Truffer, B. (2016). The interplay of institutions, actors and technologies in socio-technical systems - An analysis of transformations in the Australian urban water sector. *Technological Forecasting and Social Change*, *103*, 298–312. https://doi.org/10.1016/j.techfore.2015.11.023

Gao, Z., House, L. O., & Yu, X. (2010). Using choice experiments to estimate consumer valuation: the role of experimental design and attribute information loads. *Agricultural Economics*, *41*(6), 555–565. https://doi.org/10.1111/j.1574-0862.2010.00470.x

Gilg, A., & Barr, S. (2006). Behavioural attitudes towards water saving? Evidence from a study of environmental actions. *Ecological Economics*, *57*(3), 400–414. https://doi.org/10.1016/j.ecolecon.2005.04.010

Greene, W. H. (2008). *Econometric Analysis* (6th Edition). Retrieved from http://www.sciepub.com/reference/179239

Gregory, G. D., & Di Leo, M. (2003). Repeated Behavior and Environmental Psychology: The Role of Personal Involvement and Habit Formation in Explaining Water Consumption. *Journal of Applied Social Psychology*, *33*(6), 1261–1296. https://doi.org/10.1111/j.1559-1816.2003.tb01949.x

Heinz, M. S. (2013). Exploring predictors of technology adoption among older adults (Iowa State University, Digital Repository). https://doi.org/10.31274/etd-180810-3401

Hensher, D. A., Rose, J. M., & Greene, W. (2015). Applied choice analysis. In *Cambridge University Press: UK*. Cambridge University Press.

Howard, J. (1977). *Consumer behavior: Application of theory*. Retrieved from https://pdfs.semanticscholar.org/abf6/c3c55c2800743c52f9a6c462e043618857fe.pdf

Jansen, A., & Schulz, C. (2006). Water demand and the urban poor: A study of the factors influencing water consumption among households in Cape Town, South Africa. *South African Journal of Economics*, *74*(3), 593–609. https://doi.org/10.1111/j.1813-6982.2006.00084.x

Kaur, K., & Rampersad, G. (2018). Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. *Journal of Engineering and Technology Management - JET-M*, *48*, 87–96. https://doi.org/10.1016/j.jengtecman.2018.04.006

Kenney, D. S., Goemans, C., Klein, R., Lowrey, J., & Reidy, K. (2008). Residential water demand management: Lessons from Aurora, Colorado. *Journal of the American Water Resources Association*, *44*(1), 192–207. https://doi.org/10.1111/j.1752-1688.2007.00147.x

Kenney, D. S., Klein, R. A., & Clark, M. P. (2004). Use and effectiveness of municipal water restrictions during drought in Colorado. *Journal of the American Water Resources Association*, *40*(1), 77–87. https://doi.org/10.1111/j.1752-1688.2004.tb01011.x

Kløjgaard, M. E., Bech, M., & Søgaard, R. (2012). Designing a stated choice experiment: The value of a qualitative process. *Journal of Choice Modelling*, *5*(2), 1–18.

https://doi.org/10.1016/S1755-5345(13)70050-2

Knickenmeyer, E., & Taxin, A. (2018). Water use climbs in California enclaves as drought returns.

Lai, Y., & Yue, C. (2020). Consumer Willingness to pay for Organic and Animal Welfare Product Attributes: Do Experimental Results Align with Market Data? *Journal of Agricultural and Resource Economics*, 43. Retrieved from https://papers.ssrn.com/abstract=3588016

Louviere, J. J., Hensher, D. A., Swait, J. D., & Adamowicz, W. (2000). Stated Choice Methods. In *Stated Choice Methods*. https://doi.org/10.1017/cbo9780511753831

Makki, A. A., & Mosly, I. (2020). Factors Affecting Public Willingness to Adopt Renewable Energy Technologies: An Exploratory Analysis. *Sustainability*, *12*(3), 845. https://doi.org/10.3390/su12030845

McFadden, D. (1972). Conditional logit analysis of qualitative choice behavior. In *WORKING PAPER INSTITUTE OF URBAN AND REGIONAL* (No. 10).

Meissner, R., Steyn, M., Moyo, E., Shadung, J., & Jacobs-Mata, I. (2018). South African local government perceptions of the state of water security. *Environmental Science & Policy*, *87*, 112–127.

Millock, K., & Nauges, C. (2010). Household adoption of water-efficient equipment: The role of socio-economic factors, environmental attitudes and policy. *Environmental and Resource Economics*, *46*(4), 539–565. https://doi.org/10.1007/s10640-010-9360-y

Morse-Jones, S., Bateman, I. J., Kontoleon, A., Ferrini, S., Burgess, N. D., & Turner, R. K. (2012). Stated preferences for tropical wildlife conservation amongst distant beneficiaries: Charisma, endemism, scope and substitution effects. *Ecological Economics*, *78*, 9–18. https://doi.org/10.1016/j.ecolecon.2011.11.002

Murwirapachena, G., & Dikgang, J. (2019). *The effects of presentation formats in choice experiments | Economic Research Southern Africa*. Retrieved from https://www.econrsa.org/publications/working-papers/effects-presentation-formats-choice-experiments

Nauges, C., & Whittington, D. (2010). Estimation of water demand in developing countries: An overview. *The World Bank Research Observer*, *25*(2), 263–294. https://doi.org/10.1093/WBRO.25.ISSUE_2;WEBSITE:WEBSITE:WB-SITE;JOURNAL:JOURNAL:WBRO;ARTICLE:ARTICLE:10.1093

Peek, S. T. M., Luijkx, K. G., Rijnaard, M. D., Nieboer, M. E., van der Voort, C. S., Aarts, S., … Wouters, E. J. M. (2016). Older Adults' Reasons for Using Technology while Aging in Place. *Gerontology*, *62*(2), 226–237. https://doi.org/10.1159/000430949

Price, G., Ross, D., Rabe, M., & Mander, N. D. (2009). *Thekwini Water Conservation Guideline*. Retrieved from https://www.researchgate.net/publication/281293020_eThekwini_Water_Conservation_Guideline

Renwick, M. E., & Archibald, S. O. (1998). Demand side management policies for residential water use: who bears the conservation burden? *Land Economics*, *74*(3), 343–359. https://doi.org/10.2307/3147117

Richter, C. P., & Stamminger, R. (2012). Water Consumption in the Kitchen - A Case Study in Four European Countries. *Water Resources Management*, *26*(6), 1639–1649. https://doi.org/10.1007/s11269-012-9976-5

Roesner, L. A., Qian, Y., Stromberger, M., Klein, S., Criswell, M., & Alkhatib, R. (2006). Long-term Effects of Landscape Irrigation Using Household Graywater: Literature Review and Synthesis. In *aciscience.com*. Retrieved from http://www.aciscience.com/docs/SDA-WERF Graywater Lit Review.pdf

Rose, J. (2012). *Workshop on experimental designs* .

Rose, J. M., & Bliemer, Mi. C. J. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews*, *29*(5), 587–617. https://doi.org/10.1080/01441640902827623

Ryan, M., Gerard, K., Watson, V., Street, D. J., & Burgess, L. (2008). *Practical Issues in*

Conducting a Discrete Choice Experiment. https://doi.org/10.1007/978-1-4020-5753-3_3

Sharma, A. K., Begbie, D., & Gardner, T. (2015). Rainwater Tank Systems for Urban Water Supply: Design, Yield, Energy, Health Risks, Economics and Social Perceptions. In *Water Intelligence Online* (Vol. 14). https://doi.org/10.2166/9781780405360

Sisser, J. M., Nelson, K. C., Larson, K. L., Ogden, L. A., Polsky, C., & Chowdhury, R. R. (2016). Lawn enforcement: How municipal policies and neighborhood norms influence homeowner residential landscape management. *Landscape and Urban Planning*, *150*, 16–25. https://doi.org/10.1016/j.landurbplan.2016.02.011

Stoutenborough, J. W., & Vedlitz, A. (2014). Public attitudes toward water management and drought in the United States. *Water Resources Management*, *28*(3), 697–714. https://doi.org/10.1007/s11269-013-0509-7

Street, D. J., Viney, R., Street, D. J., & Viney, R. (2019). Design of Discrete Choice Experiments. In *Oxford Research Encyclopedia of Economics and Finance*. https://doi.org/10.1093/acrefore/9780190625979.013.91

Syme, G. J., Shao, Q., Po, M., & Campbell, E. (2004). Predicting and understanding home garden water use. *Landscape and Urban Planning*, *68*(1), 121–128. https://doi.org/10.1016/j.landurbplan.2003.08.002

Thiam, D., Dinar, A., & Ntuli, H. (2020). *Day Zero Effect: Adoption of water-saving equipment in Cape Town, South Africa*. Retrieved from https://www.researchgate.net/publication/339935988_Day_Zero_Effect_Adoption_of_water-saving_equipment_in_Cape_Town_South_Africa

Train, KE, Ben-Akiva, M., & Atherton, T. (1989). Consumption patterns and self-selecting tariffs. *The Review of Economics and Statistics*, *71*(1), 62–73. Retrieved from https://www.jstor.org/stable/1928052?casa_token=b4x74feLglwAAAAA:fxCv8Jpr5dMHF_PdJZoGYFuOFWxvSU1TAPiajH_02i70uZY1Pwbcof3foOI8tFKe2gKF36cHXqEqbYn24--o_iqJOCpCf8TV8q3TqUCkQg48_pdLltQe

Train, Kenneth. (2003). *Discrete Choice Methods with Simulation*. Retrieved from https://econpapers.repec.org/RePEc:oet:tbooks:emetr2

Train, Kenneth, McFadden, D., & Ben-Akiva, M. (1987). The Demand for Local Telephone Service: A Fully Discrete Model of Residential Calling Patterns and Service Choices. *The RAND Journal of Economics*, *18*(1), 109–123. https://doi.org/10.1111/j.0741-6261.2007.00115.x

Ward, S., Barr, S., Butler, D., & Memon, F. A. (2012). Rainwater harvesting in the UK: Socio-technical theory and practice. *Technological Forecasting and Social Change*, *79*(7), 1354–1361. https://doi.org/10.1016/j.techfore.2012.04.001

Willis, R. M., Stewart, R. A., Panuwatwanich, K., Williams, P. R., & Hollingsworth, A. L. (2011). Quantifying the influence of environmental and water conservation attitudes on household end use water consumption. *Journal of Environmental Management*, *92*(8), 1996–2009. https://doi.org/10.1016/j.jenvman.2011.03.023

Wu, F., Zhang, Q., & Gao, X. (2018, April 1). Does water-saving technology reduce water use in economic systems? A rebound effect in zhangye city in the heihe river basin, China. *Water Policy*, Vol. 20, pp. 355–368. https://doi.org/10.2166/wp.2017.003

Zaied, R. A. (2018). Development of water saving toilet-flushing mechanisms. *Applied Water Science*, *8*(2), 1–10. https://doi.org/10.1007/s13201-018-0696-8

Zaunbrecher, B. S., Kowalewski, S., & Ziefle, M. (2014). The willingness to adopt technologies: A cross-sectional study on the influence of technical self-efficacy on acceptance. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *8512 LNCS*(PART 3), 764–775. https://doi.org/10.1007/978-3-319-07227-2_73

Analysis of residential water conservation practices in Cape Town, South Africa

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Abstract - Drought severity is expected to increase in South Africa in the coming years, given the deteriorating effects exerted by climate change on rainfall patterns and global temperature and evaporation. One common mitigation strategy adopted by households is to promote water demand management initiatives to reduce water consumption volume and complement the existing water supply management approaches being implemented by suppliers. This paper contributes to the discussion on adaptation strategies by investigating the determinants of adopting water-saving technologies through empirical evidence from urban Cape Town, South Africa. We estimate the attribute levels and household characteristics that influence the adoption of several water-saving technologies, including greywater reuse technology, rainwater collection systems, installment of dual-flush cisterns, and water-efficient showerheads. We use a choice modelling framework to investigate heterogeneity among households based on their preferences for individual or groups of characteristics embedded in each water-saving technology. A pilot survey (n=72) was first conducted using an orthogonal design method in order to obtain precise parameter priors for the D-efficient design framework used in our main survey (n=303) estimation. Random Parameter Logit (RPL) is compared with the Nested Logit (NL) model to estimate marginal willingness to pay (MWTP) for the adoption of water-saving technology. Our results show that households are sensitive to the reliability, lifespan, and quantity of water saved by the technologies when explaining the attributes that determine adoption. Alongside other policy interventions, our results also show that initiatives that support the installation of technologies with fewer complexities are favourable in predicting positive household response to adoption.

Keywords: water conservation, water economics, discrete choice modeling, South Africa

JEL Classification O33; Q25; Q55; Q58; D04

1 Introduction

Water management approaches that advocate for sustainability in water use have often been focused on using extreme measures such as tariff changes and implementation of strict water restriction programmes on residential water demand (Enqvist & Ziervogel, 2019). However, despite these measures, many empirical evidence has shown that an efficient water pricing

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structure is difficult to implement, especially in countries with severe water scarcity. In many instances, relatively high water prices are paid by poorer households compared to higher-income users who often pay low water prices relative to their consumption patterns (De Oliver, 1999). Also, implementation of strict water restriction programmes are often limited by political will (Cooper et. al., 2011; Stoutenborough & Vedlitz, 2014), and they are difficult to enforce, particularly in countries where institutions have limited capacity to monitor the policies adopted to support water use efficiency (Sisser et al., 2016). Studies showed that heavy-handed restrictions are unlikely to persist over time when drought severity decreases and consumption habits resume back to normality (Knickenmeyer & Taxin, 2018; Meissner *et. al.,* 2018). Therefore, promoting sustainable water resources management approaches that address water scarcity requires adopting and implementing more stable and long-term driven strategies that offset the limitations associated with drastic water pricing and restriction programmes. Efficient demand management measures may also focus on effective non-price strategies such as adopting water-saving technologies within households. For instance, an earlier study by Gilg & Barr (2006) showed that water demand management can be better understood by investigating the factors that drive water-saving within households. A more recent study conducted by Fielding *et. al*., (2012) further iterates the need to understand the determinants of the adoption of water-saving technologies. Yet, no consensus has emerged regarding understanding the factors that drive water-saving technologies in urban households.

Adopting water-saving technologies is an effective and sustainable non-price demand management measure that can reduce water scarcity (Fuenfschilling & Truffer, 2016; Ward *et al.*, 2012). A growing literature on urban water management reveals the importance of water-saving technologies in reducing overall water demand (Booysen, Visser, & Burger, 2019; Wu, Zhang, & Gao, 2018). This is achieved by analyzing the factors that drive the adoption of water-saving technologies by urban dwellers in South Africa. We target double flush toilets, low-flow showerheads, rainwater collection, and greywater treatment technologies. A typical South African middle-income household of four spends 25% of their water use in flushing the toilet, 25% on garden and outdoor activities, 24% on bathing or showering, 13% on laundry, 11% in the kitchen, and 2% on other activities (Price, Ross, Rabe, & Mander, 2009). Adopting double flush technology is expected to reduce as much as 75% water use in flushing (Murwirapachena & Dikgang, 2019). Greywater constitutes about 50% of the total wastewater generated within a household and its reuse may lead to significant reductions in household water demand (Carden *et al.*, 2007; Roesner *et al*., 2006).

This paper investigates the factors that drive the adoption of water-saving technologies in Cape Town. We use a choice modelling framework that compares various utility functions associated with different alternatives that represent payoffs associated with adopting water-saving technologies.

2 Brief Related Literature

The literature has identified several factors that drive household water demand and consumption patterns. These factors include household socio-demographic characteristics (Aitken *et al.*, 1994; Gregory & Di Leo, 2003), behavioural change towards water usage (Gregory & Di Leo, 2003; Richter & Stamminger, 2012), attitudes and values towards water conservation practices (Syme *et al.*, 2004; Willis *et al.*, 2011), water restrictions programmes (De Oliver, 1999; Kenney, Klein, & Clark, 2004) and pricing of water (Kenney *et al.*, 2008; Renwick & Archibald, 1998). Nauges & Whittington (2010) provide a comprehensive overview of the factors that influence residential water demand in the developing world.

Very few studies looked at the behavioural responses associated with the adoption of water-saving technologies by urban dwellers. This is because most of the water consumption occurs in the agricultural sector, and water-saving is mainly expected to take place at farm level. However, the growing urbanization in urban cities is not only expected to increase the volume of water use for drinking and residential consumption purposes but also water use in agriculture and manufacturing production for a growing population. More people will require more food and more manufacturing products, which will require more inputs used in the production process, including water. Despite this, few studies have looked at the determinants of adoption of residential water-saving technologies (Campbell, Johnson, & Larson, 2004; Millock & Nauges, 2010; Renwick & Archibald, 1998; Thiam, Dinar, & Ntuli, 2020). Campbell *et al*. (2004) looked at the impacts of price and non-price water demand-side management on the adoption of water-saving equipment in Arizona, USA. They collected data from 19,000 households over six years and found that changes in water pricing spur adoption of water-conservation measures. Millock & Nauges (2010) studied the factors that drive adoption of Waterwise washing machines, low-volume flush toilets, restrictor taps in water supply and rainwater collector tanks in 10 OECD countries in Europe. They found that household size, water price and whether households own property positively influence the adoption of water-saving technologies. Thiam *et al.* (2020) and Renwick & Archibald (1998) investigated the factors that drive the adoption of water-saving technologies in residential households in South Africa and California, respectively. Their results found that household size, income and education positively influence the adoption of water-saving technologies. This present paper contributes to the discussion on urban water management by investigating the factors that drive the adoption of water-saving technologies through empirical evidence from South Africa. We build on Thiam *et al.* (2020) and Campbell *et al.* (2004) and look at the behavioural responses associated with adoption of water-saving technologies in residential households. This research provides an improved understanding of the challenges associated with the adoption of water-saving behaviours in urban areas that experience water scarcity.

3 Theory and Methods

3.1 The Choice Experiment Method and the Econometric Model

Developed from the random utility theory, choice experiments assume that individuals are rational decision-makers who choose the most preferred (utility-maximising) option when faced with various possible set of options (McFadden, 1973; Howard, 1977). According to McFadden (1973), these rational individuals make choices based on the characteristics of the good, along with a random component. The random component could emerge from the uniqueness in the individuals' preferences, or due to researchers having in-complete information about the individual observed (Ben-Akiva & Lerman, 1985). Where a household head i's utility, U, of a water-saving technology j is assumed to consist of a deterministic and a stochastic element:

$$U_{ij} = V_{ij}(x_j, z_j, t) + e_{ij} \quad (1)$$

Where V depends on the characteristics of the technology x_j, individual specific characteristics z_j, and the price t and e_{ij} is the unobserved random component that is IID extreme value type 1[2] and consists of factors affecting the choice but are not observable to the researcher

[2] Historically, EV1 distribution has been referred to by a number of names, including Weibull, Gumbel and double-exponential.

(Louviere et al., 2000). The theory states that an individual will choose an alternative k from a finite set of alternatives C, given the indirect utility of k is greater than the indirect utility of any other alternative, j. This means that

$$U_{ik} > U_{ij} \implies V_{ik} + e_{ik} > V_{ij} + e_{ij} \quad \forall j \neq k; j, k \in C) \qquad (2)$$

The probability that an individual chooses alternative k is the same as the probability that the utility of alternative k is greater than the utility of any other alternative of the choice set (Adamowicz, 2004). In our case, the utility definition of the choice-task among five alternatives, one of which is the status quo option, is

$$U_{kin} \begin{cases} V\left(ASC, x_{kin,} \beta_i , \varepsilon_i \right) + e_{kin}, & \text{if } k = 1; \\ V\left(ASC, x_{kin,} \beta_i , \varepsilon_i \right) + e_{kin}, & \text{if } k = 2; \\ V\left(ASC, x_{kin,} \beta_i , \varepsilon_i \right) + e_{kin}, & \text{if } k = 3; \\ V\left(ASC, x_{kin,} \beta_i , \varepsilon_i \right) + e_{kin}, & \text{if } k = 4; \\ e_{kin}, & \text{if } k = \text{status quo} \end{cases} \qquad (3)$$

where i denotes the individual, k the alternative, and n the choice-occasion. V_{kin}, the indirect utility is a function of a vector of variables explaining choice x_{kin} and chosen vectors of individual-specific parameters, β_i . β_i is assumed to take on a multivariate normal distribution where the off-diagonal elements of the covariance matrix are zero. ε_i is an error component associated with the two non-status quo choices and is assumed to be normally distributed white noise, $\varepsilon_i \sim N\,(0, \sigma^2)$. This error component reflects that there may be additional variance related to the four non-status quo alternatives, because it is cognitively more demanding for respondents to evaluate four complex alternatives in each choice set as opposed to the status quo (Beharry-Borg et. al., 2009; Hensher et al., 2015; Morse-Jones et al., 2012). Lastly, e_{kin}, is a random error term that is iid extreme value type 1.

In order to calculate the choice probability for a given choice-occasion n, we use a random we use a random parameter logit model (RPL) and assume that individuals seek to maximise utility. Conditional on the individual-specific parameters, β_i, and error components, ε_i , the probability that respondent i chooses a specific alternative k in choice-task n (of the sequence n = 1, . . . , N) from the five alternatives (j = 1, . . . , J) is logit:

$$\Pr(kin|\, \beta_i, \varepsilon_i\,) = \frac{\exp(\beta_i' X_{kin} + \varepsilon_i)}{\sum_j^J \exp\left(\beta_i' X_{jin} + \varepsilon_i\right)} \qquad (3)$$

If we assume independence over choice-tasks made by the same individual, the joint probability of an individual making a sequence of choices is the product of the, in our case, ten probabilities. The probability of choice unconditional on the error component is obtained by integrating over the error-component space. Following this, the marginal probability of choice can be derived from integrating over the distribution functions for the random $\beta\_$ parameters (Beharry-Borg et al., 2009; Train et al., 1987). Following the above, the probability of choosing alternative k becomes:

$$\Pr(kin) = \int \left(\prod_{n=1}^{N} \left[\frac{\exp(\beta_i' X_{kin} + \varepsilon_i)}{\sum_j^J \exp(\beta_i' X_{jin} + \varepsilon_i)} \right] \right) f(\beta) d \qquad (4)$$

Where $f(\beta)$ represents the distribution function for β, with mean b and variance W. The model is not sensitive to the independence of irrelevant alternatives (IIA) condition and, furthermore, it allows for individual-specific β estimates based on specified distributions (Train et al., 1998). This means that the model utilises the information that each respondent has answered several choice sets, by making taste parameters constant over choices within individuals but not between individuals. Including this information is likely to enhance the explanatory power of the model. Even though the integral in (4) does not have a closed-form, the choice probability in the RPL model can be estimated through simulation. The unknown parameters θ, such as the mean and variance of the random coefficient distribution, can be estimated by maximizing the simulated log-likelihood function. For a given mean and variance of a random coefficient distribution, the simulated probability $\breve{P}_{kin}$ is strictly positive and twice differentiable with respective to the unknown parameters θ. Therefore, the simulated log-likelihood function log-likelihood is:

$$LogL(\theta) = \sum_{i=1}^{I} \sum_{k=1}^{J} d_{kin} \ln \breve{P}_{kin} \qquad (5)$$

Where d_{kin}=1 if individual i chooses alternative k and zero otherwise. Each individual is assumed to make choices independently and only make the choice once. The value of estimates that maximizes the SLL is called the maximum simulated likelihood (MSL) estimate.

To derive the mathematical form of the NL model, we consider a two-level NL structure[3] in which the total choice sets are partitioned in m nonoverlapping subsets (nests) $B_1, \ldots, B_m$. The utility of alternative k in nest B_m is still $U_{ij} = V_{ij} + e_{ij}$, again with V_{ij} the observed part of the utility. The NL model is obtained by assuming that the vector of disturbances has a cumulative distribution of a GEV type distribution:

$$exp\left(-\sum_{m=1}^{m}\left(\sum_{k\in B_m} e^{-\varepsilon ij/\lambda_m}\right)^{\lambda_m}\right) \qquad (6)$$

The parameter λ_m is a measure of the degree of independence in the random part of the utility among the alternatives in the nest m. The distribution for the unobserved components proceed the choice probability for alternative j in nest B_m:

$$P_{ij} = \frac{e^{V_{ij}/\lambda_m}\left(\sum_{k\in B_m} e^{V_{ik}/\lambda_m}\right)^{\lambda_m - 1}}{\sum_{l=1}^{m}\left(\sum_{k\in B_l} e^{V_{ik}/\lambda_l}\right)^{\lambda_l}} \qquad (7)$$

If $m = l$, meaning two alternatives are in the same nest, the factors in parentheses cancel each other out and it shows that IIA holds. Train (2003) shows that some other form of IIA holds across nests, such as independence from irrelevant nests (IIN). Therefore, in a NL model, IIA holds for alternatives within each nest and IIN holds over alternatives in different nests. The observed component of the utility function can be distinct in two parts: $U_{ij} = W_{im} + Y_{ij} + e_{ij}$. Here W_{im} is the part that is constant for all alternatives within a nest. This variable depends only on variables that describe next m, therefore they differ over the nests but not over the alternatives within a nest. Y_{ij} is simply define as $V_{ij} - W_{im}$ and depends on variables that describe alternative j, so they vary over alternatives within next m. The probability that an alternative is chosen ca be written as the product of the probability that a certain nest is chosen multiplied with the probability that an alternative within that nest is chosen:

$$P_{ij} = P_{ij\backslash B_m} \cdot P_{iB_m} \qquad (8)$$

The conditional probability $P_{ij\backslash B_m}$ can be given as:

[3] The extension of a two-level NL structure to three-level or four-level ones can be done with the same methodology used in this paper.

$$P_{ij\backslash B_m} = \frac{e^{Y_{ij}/\lambda_m}}{\sum_{k\in B_m} e^{Y_{ik}/\lambda_m}} \quad (9)$$

and

$$P_{iB_m} = \frac{e^{W_{im}+\lambda_m J_{im}}}{\sum_{l=1}^{m} e^{W_{il}+\lambda_l J_{il}}} \quad (10)$$

Where

$$J_{im} = \ln \sum_{k\in B_m} e^{Y_{ij}/\lambda_m} \quad (11)$$

These expressions are derived from the choice probabilities stated earlier. Train (2003) gives the derivation by algebraic rearrangement. It is customary to refer to the marginal probability as the upper model and to the conditional probability as the lower model. The quantity J_{im} links the lower and upper model by transferring information from the lower model to the upper model (Ben-Akiva and Lerman, 1985). This term is the logarithm of the denominator of the lower model, which means that $\lambda_m J_{im}$ is the expected utility that the decision maker obtains from the choice among the alternatives in nest B_m.

The parameter of the NL can be estimated by standard maximum likelihood techniques:

$$L = \prod_{i=1}^{I} \prod_{j\in B_m} \left(P_{ij\backslash B_m} P_{iB_m}\right)^{y_{ij}} \quad (12)$$

Thus, the log likelihood becomes:

$$\log L = \sum_{i=1}^{I} \sum_{j\in B_m} y_{ij} \ln P_{ij\backslash B_m} + \sum_{i=1}^{I} \sum_{m\in M} y_{im} \ln P_{iB_m} \quad (13)$$

We estimate the marginal effects of each attribute in order for the results to be of more policy relevance. Additionally, understanding the marginal effects allows us to test for variations in welfare measures by examining the marginal willingness to pay (MWTP) estimates. MWTP estimates show the marginal rate of substitution (MRS) between each attribute and the monetary attribute; this is an important output of choice models, as it gives average estimates of what respondents are prepared to pay for or against each attribute (Hensher *et al.*, 2015). Equation (14) below shows the expression of the MWTP.

$$WTP_X = \frac{\Delta X}{\Delta C} = -\frac{\frac{\delta U_{ij}}{\delta X_j}}{\frac{\delta U_{ij}}{\delta C_i}} = -\frac{\beta_j}{\mu} = MWTP \quad (14)$$

3.2 Introduction to Discrete Choice Experiment

The experimental design's quality drives the precision and statistical significance of parameter estimates when performing an empirical analysis. This is because there exists a relationship between the statistical properties of stated choice experiments and the econometric models used to estimate the experimental data (Butkeviciute, 2017). There are different choice experiment design types that have been adopted by researchers, including full factorial, fractional factorial, orthogonal and efficient designs (Gao et al., 2010; Kløjgaard et al., 2012; Ryan et al., 2008; Street et al., 2019). The designs primarily differ in the assumptions imposed, specifically on the type of correlation structure between attributes in the design matrix.

In this paper we focus on the orthogonal and D-efficient designs. The orthogonality property has often been considered the traditional and state-of-practice approach. A design is said to be orthogonal "*if it satisfies attribute level balance and all parameters are independently estimable*."[4] Orthogonal designs are generated by imposing the property of orthogonality on the attributes contained in the columns of the design matrix (J. M. Rose & Bliemer, 2009). On the other hand, efficient designs are derived based on the statistical properties of discrete choice models. Efficiency based designs reduce the sample size requirement needed to obtain robust parameter estimates. More specifically, D-efficient designs have been mostly relied on by researchers because it aims to minimize the standard errors of the parameters at design stages and improve the quality of the results obtained when estimating parameter values. (Alpízar et al., 2001; Bliemer et al., 2010; Dardanoni & Guerriero, 2021; Lai & Yue, 2020; Rose & Bliemer, 2009). However, efficient designs are only efficient if prior parameters are known. If incorrect prior parameters are used, efficient designs become inefficient (Bliemer et al., 2010). To address this problem, the literature recommends drawing prior parameters from i) the literature ii) pilot study iii) focus groups or iv) expert judgement (Rose, 2012). The

[4] Ngene Manual, p. 64, ChoiceMetrics, 2012

experiment designs discussed in this paper are applied using the Ngene[5] software in the context of the pilot and final survey designs.

3.3 Design of the choice experiment

In this study, the water-saving technologies we considered are i) greywater reuse ii) rainwater collection iii) efficient showerheads, and iv) dual flush cistern. Greywater constitutes about 50% (about 68litres/capital/day) of the total wastewater generated within a household in Cape Town (Carden *et al., 2007;* Roesner *et al., 2006)*. An integrated domestic rainwater harvesting involves collecting, storing, and channeling rainwater to the toilet for flushing and gardening irrigation outlets instead of using potable water. Replacing a 12L cistern with a 3L dual cistern saves about 75% of water (Jansen & Schulz, 2006; Murwirapachena & Dikgang, 2019; Zaied, 2018) in SA households.

Table 1 shows the selected attributes of each water-saving technology, and it describes their associated levels. Previous studies highlight "Reliability of Access" as one of the major factors that influence the adoption of water-saving technologies (Kaur & Rampersad, 2018; Zaunbrecher, Kowalewski & Ziefle, 2014). Households are more willing to adopt new technology that is perceived to be reliable when water can be accessed immediately it is needed. In our case, this refers to how dependable and reliable water supply from a given technology is. It considers the unpredictable nature of rainfall and the predictable availability of wastewater and cistern water within the household. The two levels of this attribute are: Reliable Access and Unreliable Access. The second attribute is "Perceived Health Risk". The level of health risk associated with a technology could largely influence its adoption rate. This risk can be present in the form of a foul smell, degree of water contamination and the possibility of diseases and infection to the household. This attribute has two levels: Health risk and No health risk. The third attribute identified in this study is the "Complexity of technology". This refers to the ease of use of a given technology and the expertise involved in installing and operating it. The ease of use of technology could have a huge influence on respondent's adoption rate (Makki & Mosly, 2020; Sharma, Begbie, & Gardner, 2015). The two levels of the attribute are; easy (when no extra training is required before usage of the technology) and

[5] Ngene is a comprehensive software for designing choice experiments. It is designed to be the single source of stated choice experimental designs (ChoiceMetrics, 2012).

hard (when very sophisticated and intensive training is needed before installation of the technology). The fourth attribute is the "Ease of Maintenance", this differs from the above third attribute mainly because maintenance and services are done post technology installation. The relevance of this attribute can be distinguished based on the needed frequency of maintenance of technology that will ensure optimal performance, as well as the expertise required for such maintenance. It also captures both the ease of acquisition of the maintenance skills and the intensity of training needed to service the technology after installation. The identified attribute levels are: Difficult and Easy. Investing in water-efficient technologies is expected to reduce the household's monthly water bill by reducing the quantity of water demanded from the municipality. Thus, the fifth attribute considered in this study is "Water Quantity Saved". The average urban household of 5 people uses 640 liters of water per day in South Africa (COCT, 2013). Technologies that reduce the quantity of water used for specific household activities, store rainwater and make wastewater available for reuse will ultimately reduce the total quantity of water demanded by this household. The attribute levels are; above 25% (when technology saves up to 25% of average household water demand) and below 25% (when technology saves less than 25% of average household demand. The sixth attribute identified is the "Costs of Technology", which can also influence adoption decisions within households. The adoption of technologies with high cost of purchase and installation could be limited in low-income households (Kaur & Rampersad, 2018). Four levels of costs were examined for this attribute. Finally, previous studies report the "lifespan of a technology" as an important factor that influences technology adoption (Heinz, 2013; Peek et al., 2016). In choosing water-saving technologies, a household is more willing to adopt technologies that have a longer lifespan. The two levels of the attribute are "less than 5 years" and "more than 10 years". There are 256 possible combinations of the attributes and their levels as shown in Table 1, with six attributes varying across two levels each and one attribute varying across four levels (2^6X 4^1).

Table 1: Definition of Attributes and their Level

Attributes	Definition	Levels of attributes
Reliability of Access	This indicates how dependable and reliable water supply from the technology is.	Reliable Access: Water can be accessed from selected technology every time it is needed.
		Unreliable Access: Access to water from technology may be seasonal.
Perceived Health Risk	This refers to the households' perception of possible health-related risks, discomfort or stress associated with the use of a technology	High risk: Selected technology uses chemicals products in water treatment and may emit foul smells.
		No health risk: No chemical products are used in technology and there is no emission of foul smell.
Complexity of Technology	This refers to the ease of use of technology and the expertise involved in the installation and day-to-day operation. It focuses on whether technology can be operated with no prior training or not.	Hard: When high-level expertise and training is needed for the installation and operation of the technology.
		Easy: When technology can be operated with no prior training.
Ease of Maintenance	This captures whether intensive training is needed for the maintenance or servicing of technology to ensure optimal performance. It also captures the frequency at which maintenance or servicing is needed.	Difficult: When intensive training is needed for the maintenance of technology and maintenance is required at least once a month.
		Easy: When maintenance is easy and rarely necessary
Water Quantity Saved	This refers to the percentage of water saved in a household after technology adoption.	Above 25%: If technology saves more than 25% of the average water demand of household before installation.
		Below 25%: If the presence of technology does not reduce household water demand by up to 25%.
Costs of Technology	Cost of purchasing and installing the technology	R5,000; R10,000; R15,000; R20,000
Lifespan of the technology	This refers to the average number of years the technology can be used optimally without the need for replacement.	Less than 5 years
		More than 10 years

4 Survey Design and Data Collection

4.1 Pilot and Main Survey Design

The pilot survey's aim is not to obtain precise parameter estimates for the D-efficient design. Instead, the goal is to roughly estimate the weight individuals place on water-saving technologies' different attributes. To minimize bias and elicit the weight households place on the attributes that form of prior values required to generate the final design of the survey, an orthogonal design of 36 alternative profiles made up of six blocks was created using Ngene from the full set of possible combinations. The number of alternatives is informed by the literature review and is based on the frequently used number of blocks and choice sets for a design similar to the one being considered in this paper. The software produced a design with one status quo and four non-status quo alternatives per choice set, and six choice sets arranged in six survey blocks/cards. The status quo represents the household's current situation, i.e., what they are doing now, whether they have a technology installed or not. Each respondent was randomly assigned six choice sets which had been prepopulated in six different questionnaire versions. In addition, each pilot survey questionnaire also included sections on socioeconomic characteristics of households. We carried out the pilot survey in November 2020 and obtained responses from 72 households. Each respondent evaluated 5 alternatives throughout 6 survey questions which generated 1040 observations in total. The main survey design generation process took place over many days to allow Ngene to evaluate as many potential designs as possible and locate the smallest comparable D-error for the final questionnaire.

The prior parameter estimates from the pilot orthogonal survey were then used to construct the main survey. After allowing Ngene to run the D-efficient design syntax, we manually saved designs with the lowest D_b-errors. A design of eight distinct choice sets was evaluated using Ngene, from the full set of all possible combinations. Like the pilot design, the software also produced a design with one status quo and four non-status quo alternatives per choice set. In addition to the section on households' socioeconomic characteristics, the questionnaire also recorded information on household water consumption and water-saving strategies adopted within households. The final survey instrument was administered to 303 households within the City of Cape Town.

5 Results

Table 2 shows the descriptive statistics of the respondents for both the pilot and main surveys. During data inputting for the pilot survey, data was captured such that each individual household head was entered 30 times to include the choices they made for five options and six different choice sets. In the main survey data was captured such that each individual was entered 40 times to include the choices they made for five options and eight different choice sets. Responders averaged 54 years old in the pilot and 50 years of age in the main survey. The average household size is 5 in the pilot survey while it is 4 in the main survey. The gender of the household heads showed minor differences in both surveys, from 82% male respondents in the pilot survey to 83% in the main survey. More results of our main survey showed that 66% of the respondents are employed and about 16% of the respondents have total yearly household income of above one million Rand. The average tap water consumption per month is 6262L while the mean monthly water bill is R367.

Table 2: Descriptive Statistics

	Mean (Std. Dev.)	
Variables	**Pilot Survey (n=72)**	**Main Survey (n=303)**
Age (Years)	54.24 (9.61)	49.66 (15.61)
Gender (1 =male, 0 = female)	0.82 (0.39)	0.83 (0.37)
Household Size	4.58 (3.27)	3.70 (1.47)
Number of employed household member	2.15 (1.39)	1.83 (1.32)
Educational Level (1=Primary education, 2=Secondary school, 3=Some technical certificate/diploma, 4=Bachelor’s degree, 5=Honor’s degree, 6=Professional/Master’s degree, 7=Doctorate degree)	4.22 (1.69)	3.55 (1.53)
Total Annual Household Income (1=R50,000 or below, 2=R50,001 to R100,000, 3=R100,000 to R150,000 4=R150,000 to R200,000 5=200,000 to R350,000 6=R350,000 to R500,000 7=R500,000 to R750,000 8=R750,000 to R1,000,000 9=R1,000,000 to R2,000,000 10=Above R2,000,000)	7.86 (2.71)	5.41 (2.92)

5.1 Parameter Priors

The pilot coefficient estimates were estimated using Stata and used in the main survey design as parameter priors. These priors are outlined in Table 3 along with the assumed standard deviations. The population standard deviations of the respective attributes included in the design were approximated using the values of the coefficient estimates' standard errors. In our model, each parameter prior $\widetilde{\boldsymbol{\beta}}_{\boldsymbol{t}}$ is assumed to follow a normal distribution with mean $\boldsymbol{\mu}_{\boldsymbol{t}}$ and standard deviation $\boldsymbol{\sigma}_{\boldsymbol{t}}$. The population standard deviation Table 3 have been approximated using the standard errors of the mean coefficient estimates from the pilot study (Greene, 2008). In order to obtain a rough approximation of the population standard deviation $\boldsymbol{\sigma}$ we use the relationship between sample size, the standard error of the parameter estimate and the population standard deviation $S.E._{\bar{X}} = \frac{\sigma}{\sqrt{n}}$[6]. This method was followed instead of randomly assigning values to the standard deviations.

Table 3: Main survey parameter priors

Attribute $\boldsymbol{t}$	Assumed Priors $\widetilde{\boldsymbol{\beta}}_{\boldsymbol{t}} \sim \boldsymbol{N}(\boldsymbol{\mu}_{\boldsymbol{t}}, \boldsymbol{\sigma}_{\boldsymbol{t}})$
Reliability of access	$\boldsymbol{N}$(0.38, 1.10)
Perceived Health Risk	$\boldsymbol{N}$(0.57, 1.10)
Complexity of Technology	$\boldsymbol{N}$(-0.12, 1.02)
Ease of Maintenance	$\boldsymbol{N}$(0.90, (1.02)
Water Quantity Saved	$\boldsymbol{N}$(-0.61, 1.10)
Cost of Technology	$\boldsymbol{N}$(-8e4, 1e4)
Lifespan of Technology	$\boldsymbol{N}$(-0.17, 1.10)

5.2 RPL and Nested Logit Model

To test all attributes for presence of preference heterogeneity, RPL model assumes that all the variable coefficients are distributed randomly following a normal distribution. In the RPL model estimation, not all the attributes were found to be significant. As shown in Table 4, only four attributes in the base RPL model are significant. Access to technology and lifespan of the technology shows statistical significance at 5% while the cost of the technology is significant at 1%. The estimates show that the cost of water-saving technologies, their access, lifespan, and

[6] This method does not present a precise and unbiased estimate of the population standard deviation but helps us to avoid assigning random prior values using of sample size of 72 in the pilot study.

the quantity of water they save are important determinants technology adoption within households. The interactions of the Age and Health Risk, Gender and Reliability, Household income and Health Risk, Income and water quantity saved, Household size and Lifespan, Education and Lifespan and Waterbill and Reliability of technology all show statistical significance in the RPL model. Table 4 also includes columns for z-statistics which indicate the relative explanatory power of the various attributes in respondents' choice of water-saving technology. Under the base RPL model the attributes with the largest z-values are the quantity of water saved and lifespan of technology.

The nest structure of our nested logit model is shown in figure. We generated a categorical variable that identifies the first-level set of alternatives based on the cost implication of our five choice alternatives: (i) High-Cost technologies, (ii) Minimal cost technologies and (iii) no cost alternative. Figure 1 shows the nesting structure in which rainwater collection and greywater treatment technologies are more similar to each other than they are to water-efficient showerhead and double-flush toilet. The base NL results in table 4 shows that all attributes are statistically significant except the perceived health risk associated with water-saving technologies. The z-values of the NL interactions and RPL interactions show very similar results to each other.

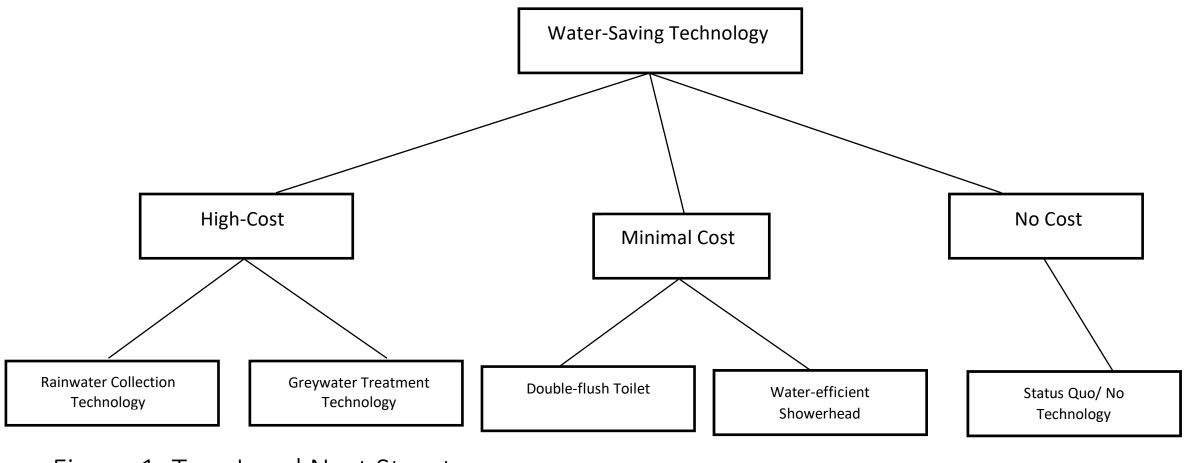

Figure 1: Two-Level Nest Structure

Table 4: Random Parameter Logit and Nested Logit Model

	Base RPL		RPL Interaction		Base NL		NL Interaction	
Attributes	Coefficient (SE)	$\|z - stat\|$	Coefficient (SE)	$\|z - stat\|$	Coefficient (SE)	$\|z - stat\|$	Coefficient (SE)	$\|z - stat\|$
Reliability of Access	-0.293** (0.135)	-2.16	0.369 (0.406)	0.91	-0.285*** (0.065)	-4.37	0.324 (0.370)	0.87
Perceived Health Risk	-0.048 (0.079)	-0.60	0.188 (0.326)	0.58	0.056 (0.056)	1.00	0.269 (0.319)	0.84
Comp. of Technology	0.089 (0.059)	1.51	-0.496* (0.297)	-1.67	0.137*** (0.051)	2.70	-0.357 (0.289)	-1.24
Ease of Maintenance	-0.063 (0.067)	-0.95	-0.474 (0.331)	-1.43	0.116** (0.057)	2.04	-0.274 (0.323)	-0.85
Water Quantity Saved	0.090* (0.054)	1.68	0.466 (0.290)	1.60	0.169*** (0.050)	3.38	0.494* (0.285)	1.74
Costs of Technology	-2.59e-05*** (8.81e-06)	-2.95	2.92e-5 (4.33e-5)	0.67	-5.13e-05*** (7.51e-06)	-6.83	6.32e-06 (4.24e-05)	0.15
Lifespan of technology	0.128** (0.064)	2.00	-0.130 (0.297)	-0.44	0.157*** (0.051)	3.07	-0.092 (0.296)	-0.31
Age × Reliability			0.004 (0.005)	0.91			0.004 (0.004)	0.86
Age × Health Risk			-0.012*** (0.004)	-2.99			-0.011*** (0.004)	-2.99
Age × Complexity			0.003 (0.004)	0.71			0.003 (0.003)	0.78
Age × Maintenance			0.001 (0.004)	0.30			0.001 (0.004)	0.21
Age × quantity			0.002	0.44			0.002	0.51

	(0.004)			(0.003)	
Age × Cost	--6.16e-07 (5.19e-07)	-1.19		--5.82e-07 (5.11e-07)	-1.14
Age × Lifespan	-0.003 (0.004)	-0.74		-0.002 (0.004)	-0.67
Gender × Reliability	-0.486*** (0.180)	-2.70		-0.436** (0.172)	-2.53
Gender × Health Risk	-0.096 (0.154)	-0.63		-0.092 (0.152)	-0.61
Gender × Complexity	0.142 (0.144)	0.99		0.115 (0.141)	0.81
Gender × Maintenance	-0.023 (0.157)	-0.14		-0.005 (0.154)	-0.03
Gender × quantity	-0.042 (0.140)	-0.30		-0.032 (0.137)	-0.23
Gender × Cost	1.22e-05 (2.04e-05)	0.60		8.57e-06 (2.01e-05)	0.43
Gender × lifespan	0.150 (0.142)	1.05		0.130 (0.143)	0.91
Income × Reliability	-0.035 (0.028)	-1.26		-0.030 (0.026)	-1.13
Income × Health Risk	0.038* (0.023)	1.67		0.038* (0.023)	1.69
Income × Complexity	0.009 (0.021)	0.41		0.005 (0.021)	0.23
Income × Maintenance	-0.007 (0.023)	-0.29		-0.005 (0.023)	-0.22
Income × quantity	-0.038* (0.021)	-1.84		-0.037* (0.020)	-1.80

Income × Cost	1.30e-06 (3.05e-06)	0.43		1.07e-06 (3.00e-06)	0.36
Income × lifespan	0.027 (0.021)	1.31		0.025 (0.021)	1.20
Household size × Reliability	0.006 (0.047)	0.12		-0.004 (0.045)	-0.08
Household size × Health Risk	-0.039 (0.039)	-0.98		-0.037 (0.039)	-0.95
Household size × Complexity	0.036 (0.036)	1.01		0.037 (0.035)	1.05
Household size × Maintenance	0.078* (0.040)	1.94		0.073* (0.039)	1.85
Household size × quantity	0.021 (0.035)	0.60		0.024 (0.035)	0.70
Household size × Cost	-6.51e-06 (5.27e-06)	-1.23		-5.80e-06 (5.19e-06)	-1.12
Household size × Lifespan	-0.069* (0.036)	-1.94		-0.067* (0.036)	-1.87
Education × Reliability	-0.019 (0.052)	-0.37		-0.013 (0.049)	-0.26
Education × Health Risk	0.058 (0.043)	1.36		0.061 (0.042)	1.45
Education × Complexity	0.051 (0.039)	1.30		0.040 (0.038)	1.05
Education × Maintenance	0.021 (0.044)	0.48		0.018 (0.043)	0.42
Education × quantity	-0.061 (0.039)	-1.58		-0.057 (0.038)	-1.50
Education × Cost	-8.51e-06 (5.79e-06)	-1.47		-9.09e-06 (5.70e-06)	-1.60

Education × lifespan		0.079**	2.03		0.081**	2.08
		(0.039)			(0.039)	
Waterbill × Reliability		-0.001**	-1.99		-0.001*	-1.90
		(3.18e-04)			(3.03e-04)	
Waterbill × Health Risk		4.0e-04	1.55		4.07e04	1.60
		(2.57e-04)			(2,55e-04)	
Waterbill × Complexity		-4.56e-05	-0.20		-9.0e-05	-0.40
		(2.28e-04)			(2.25e-04)	
Waterbill × Maintenance		1.05e-04	0.40		1.35e-04	0.52
		(2.64e-04)			(2.59e-04)	
Waterbill × quantity		-1.72e-04	-0.76		-1.77e-04	-0.80
		(2.26e-04)			(2.22e-04)	
Waterbill × Cost		3.37e-08	0.98		2.92e-08	0.87
		(3.44e-08)			(3.38e-08)	
Waterbill × Lifespan		2.55e-04	1.10		2.34e-04	1.01
		(2.31e-04)			(2.31e-04)	
Log-likelihood	-3724.419	-3661.766		-3773.157	-3712.321	
Nr. Obs.	12,120	12,120		12,120	12,120	
Nr. Respondents	303	303		303	303	
AIC	7470.837	7429.533		7560.315	7522.643	
BIC	7534.562	7736.571		7600.867	7806.508	

Notes: Robust standard errors presented in parentheses. ***, **, *, next to coefficients represents statistical significance at the 1%, 5%, and 10% respectively.

In addition to the RPL and NL models, we also estimated both a multinomial logit (ML) model and a conditional logit (CL) model. All attributes in the base ML showed statistical significance and the ML with interaction also reported similar results like the RPL model. In the base CL model only the perceived health risk associated with water-saving technologies was not statistically significant. However, the CL model with interactions also showed similar results with all other three models.

The marginal willingness to pay (MWTP) result in Table 5 shows attributes that are valuable for households to invest in water-saving technologies. When we consider the MWTP across base models, we observe that both the RPL and NL base models have the high MWTP for complexity of technology, quantity of water saved, and lifespan of technology. While the RPL and NL with interactions shows the highest MWTP for complexity of the technology, ease of maintenance and lifespan of the technology. This result indicates that both complexity of water-saving technologies and the lifespan of technologies are major determinants for adoption of technologies and are important attributes to households since they have high MWTP across all four models. In making their choice of water-saving technologies, households prefer technologies that can be easily operated and last for a long time after installation.

Table 5: Average Household marginal willingness to pay (Base RPL, RPL Interaction, Base Nlogit, Nlogit Interaction)

	Base RPL			RPL interaction			Base NL			Nlogit Interaction		
Attributes	Average Household MWTP	95% Conf. Interval		Average Household MWTP	95% Conf. Interval		Average Household MWTP	95% Conf. Interval		Average Household MWTP	95% Conf. Interval	
Reliability of Access	-11277.49	-26059.77	3504.79	-12612.98	-70599.73	45373.77	-5556.72	-9278.71	-1834.72	-51215.79	-804107.52	701675.93
Health Risk	-1838.19	-7962.31	4285.93	-6436.62	-34247.02	21373.78	1097.90	-1090.06	3285.87	-42629.86	-606991.59	521731.87
Comp. of Technology	3413.38	-745.42	7572.19	16978.12	-29885.73	63841.98	2665.17	828.73	4501.62	56597.20	-664858.7	778053.1
Ease of Maintenance	-2442.28	-8281.89	3397.34	16234.22	-31961.54	64429.97	2256.15	66.02	4446.29	43373.13	-525671.59	612417.85
Water Quantity Saved	3487.2598	-1662.81	8637.33	-15944.98	-61534.19	29644.24	3300.03	994.04	5606.02	-78245.42	-1093855.5	937364.68
Lifespan of technology	4941.89	-973.87	10857.65	4464.85	-19464.43	28394.14	3071.38	963.51	5179.26	14603.83	-193129.97	222337.63

6 Conclusion and Policy Implication

This paper has investigated the factors driving the adoption of four water-saving technologies by using econometric models that account for residential household heterogeneity in Cape Town, South Africa. A CE study of seven attributes, which were identified as relevant for household water-saving decisions, was applied. In our pilot survey estimation, an orthogonal design estimate was administered to 72 respondents in other to generate parameter priors that were then used in our D-efficient design estimation for 303 respondents. An in-depth understanding of households' preference for water-saving technology is of interest since it provides the foundation for urban water management, which will ultimately impact cities' sustainable environmental policy goals.

The results show that households are sensitive to the reliability, lifespan and quantity of water saved by the technology when explaining the attributes that determine adoption. We also found that respondents have strong preference for the technologies with least cost of purchase. Policy interventions should support initiatives that attempt to encourage better water-saving technologies that consider cost, longevity and increased water saving capacity. The implication of this is that investment in research and development should be promoted around such technologies. Alongside these technical interventions, our results also show the initiatives that support installation of technologies with less complexities are favourable in predicting positive household response to adoption. Finally, costs may also hinder adoption of water-saving technology. Policy interventions should be articulated around possible financial support that could assist poor households in acquiring such technology.

7 Reference

Adamowicz, W. L. (2004). What’s it worth? An examination of historical trends and future directions in environmental valuation. *Australian Journal of Agricultural and Resource Economics*, *48*(3), 419–443. https://doi.org/10.1111/j.1467-8489.2004.00258.x

Aitken, C. K., Mcmahon, T. A., Wearing, A. J., & Finlayson, B. L. (1994). Residential Water Use: Predicting and Reducing Consumption1. *Journal of Applied Social Psychology*, *24*(2), 136–158. https://doi.org/10.1111/j.1559-1816.1994.tb00562.x

Alpízar, F., Carlsson, F., & Martinsson, P. (2001). Using Choice Experiments for Non-Market Valuation Francisco Alpízar, Fredrik Carlsson 1 and Peter Martinsson. *Economic Issues*, *8*, 83–110.

Beharry-Borg, N., Hensher, D. A., & Scarpa, R. (2009). An analytical framework for joint vs separate decisions by couples in choice experiments: The case of coastal water quality in tobago. *Environmental and Resource Economics*, *43*(1), 95–117. https://doi.org/10.1007/s10640-009-9283-7

Ben-Akiva, M., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand*. Retrieved from https://books.google.com/books?hl=en&lr=&id=oLC6ZYPs9UoC&oi=fnd&pg=PR11&ots=nNise4fkGe&sig=gB217hA1f6FgNqvIYOSrez_uMcg

Bliemer, M., Rose, J. M., Bliemer, M., & Rose, J. (2010). Construction of experimental designs for mixed logit models allowing for correlation across choice observations. *Transportation Research Part B: Methodological*, *44*(6), 720–734. Retrieved from https://econpapers.repec.org/RePEc:eee:transb:v:44:y:2010:i:6:p:720-734

Booysen, M. J., Visser, M., & Burger, R. (2019). Temporal case study of household behavioural response to Cape Town's "Day Zero" using smart meter data. *Water Research*, *149*, 414–420. https://doi.org/10.1016/j.watres.2018.11.035

Butkeviciute, D. (2017). *Consumer Preferences & Loyalty Discounts: The Case of UK Grocery Retail* (University of London). Retrieved from http://openaccess.city.ac.uk/19171/http://openaccess.city.ac.uk/

Campbell, H. E., Johnson, R. M., & Larson, E. H. (2004). Prices, Devices, People, or Rules: The Relative Effectiveness of Policy Instruments in Water Conservation1. *Review of Policy Research*, *21*(5), 637–662. https://doi.org/10.1111/j.1541-1338.2004.00099.x

Carden, K., Armitage, N., Sichone, O., & Winter, K. (2007). The use and disposal of greywater in the non-sewered areas of South Africa: Part 2 - Greywater management options.

Water SA, *33*(4), 433–441. https://doi.org/10.4314/wsa.v33i4.52936

COCT. (2013). *City of Cape Town Smart Office Toolkit – Water Cheat Sheet*. Retrieved from https://www.capetown.gov.za/Document-centre#k=smart office toolkit

Cooper, B., Burton, M., & Crase, L. (2011). Urban water restrictions: Attitudes and avoidance. *Water Resources Research*, *47*(12), 1–13. https://doi.org/10.1029/2010WR010226

Dardanoni, V., & Guerriero, C. (2021). Young people' s willingness to pay for environmental protection. *Ecological Economics*, *179*, 106853. https://doi.org/10.1016/j.ecolecon.2020.106853

De Oliver, M. (1999). Attitudes and inaction: A case study of the manifest demographics of urban water conservation. *Environment and Behavior*, *31*(3), 372–394. https://doi.org/10.1177/00139169921972155

Enqvist, J. P., & Ziervogel, G. (2019). Water governance and justice in Cape Town: An overview. *Wiley Interdisciplinary Reviews: Water*, *6*(4), e1354. https://doi.org/10.1002/wat2.1354

Fielding, K. S., Russell, S., Spinks, A., & Mankad, A. (2012). Determinants of household water conservation: The role of demographic, infrastructure, behavior, and psychosocial variables. *Water Resources Research*, *48*(10). https://doi.org/10.1029/2012WR012398

Fuenfschilling, L., & Truffer, B. (2016). The interplay of institutions, actors and technologies in socio-technical systems - An analysis of transformations in the Australian urban water sector. *Technological Forecasting and Social Change*, *103*, 298–312. https://doi.org/10.1016/j.techfore.2015.11.023

Gao, Z., House, L. O., & Yu, X. (2010). Using choice experiments to estimate consumer valuation: the role of experimental design and attribute information loads. *Agricultural Economics*, *41*(6), 555–565. https://doi.org/10.1111/j.1574-0862.2010.00470.x

Gilg, A., & Barr, S. (2006). Behavioural attitudes towards water saving? Evidence from a study of environmental actions. *Ecological Economics*, *57*(3), 400–414. https://doi.org/10.1016/j.ecolecon.2005.04.010

Greene, W. H. (2008). *Econometric Analysis* (6th Edition). Retrieved from http://www.sciepub.com/reference/179239

Gregory, G. D., & Di Leo, M. (2003). Repeated Behavior and Environmental Psychology: The Role of Personal Involvement and Habit Formation in Explaining Water Consumption. *Journal of Applied Social Psychology*, *33*(6), 1261–1296. https://doi.org/10.1111/j.1559-1816.2003.tb01949.x

Heinz, M. S. (2013). Exploring predictors of technology adoption among older adults (Iowa State University, Digital Repository). https://doi.org/10.31274/etd-180810-3401

Hensher, D. A., Rose, J. M., & Greene, W. (2015). Applied choice analysis. In *Cambridge University Press: UK*. Cambridge University Press.

Howard, J. (1977). *Consumer behavior: Application of theory*. Retrieved from https://pdfs.semanticscholar.org/abf6/c3c55c2800743c52f9a6c462e043618857fe.pdf

Jansen, A., & Schulz, C. (2006). Water demand and the urban poor: A study of the factors influencing water consumption among households in Cape Town, South Africa. *South African Journal of Economics*, *74*(3), 593–609. https://doi.org/10.1111/j.1813-6982.2006.00084.x

Kaur, K., & Rampersad, G. (2018). Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. *Journal of Engineering and Technology Management - JET-M*, *48*, 87–96. https://doi.org/10.1016/j.jengtecman.2018.04.006

Kenney, D. S., Goemans, C., Klein, R., Lowrey, J., & Reidy, K. (2008). Residential water demand management: Lessons from Aurora, Colorado. *Journal of the American Water Resources Association*, *44*(1), 192–207. https://doi.org/10.1111/j.1752-1688.2007.00147.x

Kenney, D. S., Klein, R. A., & Clark, M. P. (2004). Use and effectiveness of municipal water restrictions during drought in Colorado. *Journal of the American Water Resources Association*, *40*(1), 77–87. https://doi.org/10.1111/j.1752-1688.2004.tb01011.x

Kløjgaard, M. E., Bech, M., & Søgaard, R. (2012). Designing a stated choice experiment: The value of a qualitative process. *Journal of Choice Modelling*, *5*(2), 1–18.

https://doi.org/10.1016/S1755-5345(13)70050-2

Knickenmeyer, E., & Taxin, A. (2018). Water use climbs in California enclaves as drought returns.

Lai, Y., & Yue, C. (2020). Consumer Willingness to pay for Organic and Animal Welfare Product Attributes: Do Experimental Results Align with Market Data? *Journal of Agricultural and Resource Economics*, 43. Retrieved from https://papers.ssrn.com/abstract=3588016

Louviere, J. J., Hensher, D. A., Swait, J. D., & Adamowicz, W. (2000). Stated Choice Methods. In *Stated Choice Methods*. https://doi.org/10.1017/cbo9780511753831

Makki, A. A., & Mosly, I. (2020). Factors Affecting Public Willingness to Adopt Renewable Energy Technologies: An Exploratory Analysis. *Sustainability*, *12*(3), 845. https://doi.org/10.3390/su12030845

McFadden, D. (1972). Conditional logit analysis of qualitative choice behavior. In *WORKING PAPER INSTITUTE OF URBAN AND REGIONAL* (No. 10).

Meissner, R., Steyn, M., Moyo, E., Shadung, J., & Jacobs-Mata, I. (2018). South African local government perceptions of the state of water security. *Environmental Science & Policy*, *87*, 112–127.

Millock, K., & Nauges, C. (2010). Household adoption of water-efficient equipment: The role of socio-economic factors, environmental attitudes and policy. *Environmental and Resource Economics*, *46*(4), 539–565. https://doi.org/10.1007/s10640-010-9360-y

Morse-Jones, S., Bateman, I. J., Kontoleon, A., Ferrini, S., Burgess, N. D., & Turner, R. K. (2012). Stated preferences for tropical wildlife conservation amongst distant beneficiaries: Charisma, endemism, scope and substitution effects. *Ecological Economics*, *78*, 9–18. https://doi.org/10.1016/j.ecolecon.2011.11.002

Murwirapachena, G., & Dikgang, J. (2019). *The effects of presentation formats in choice experiments | Economic Research Southern Africa*. Retrieved from https://www.econrsa.org/publications/working-papers/effects-presentation-formats-choice-experiments

Nauges, C., & Whittington, D. (2010). Estimation of water demand in developing countries: An overview. *The World Bank Research Observer*, *25*(2), 263–294. https://doi.org/10.1093/WBRO.25.ISSUE_2;WEBSITE:WEBSITE:WB-SITE;JOURNAL:JOURNAL:WBRO;ARTICLE:ARTICLE:10.1093

Peek, S. T. M., Luijkx, K. G., Rijnaard, M. D., Nieboer, M. E., van der Voort, C. S., Aarts, S., … Wouters, E. J. M. (2016). Older Adults' Reasons for Using Technology while Aging in Place. *Gerontology*, *62*(2), 226–237. https://doi.org/10.1159/000430949

Price, G., Ross, D., Rabe, M., & Mander, N. D. (2009). *Thekwini Water Conservation Guideline*. Retrieved from https://www.researchgate.net/publication/281293020_eThekwini_Water_Conservation_Guideline

Renwick, M. E., & Archibald, S. O. (1998). Demand side management policies for residential water use: who bears the conservation burden? *Land Economics*, *74*(3), 343–359. https://doi.org/10.2307/3147117

Richter, C. P., & Stamminger, R. (2012). Water Consumption in the Kitchen - A Case Study in Four European Countries. *Water Resources Management*, *26*(6), 1639–1649. https://doi.org/10.1007/s11269-012-9976-5

Roesner, L. A., Qian, Y., Stromberger, M., Klein, S., Criswell, M., & Alkhatib, R. (2006). Long-term Effects of Landscape Irrigation Using Household Graywater: Literature Review and Synthesis. In *aciscience.com*. Retrieved from http://www.aciscience.com/docs/SDA-WERF Graywater Lit Review.pdf

Rose, J. (2012). *Workshop on experimental designs* .

Rose, J. M., & Bliemer, Mi. C. J. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews*, *29*(5), 587–617. https://doi.org/10.1080/01441640902827623

Ryan, M., Gerard, K., Watson, V., Street, D. J., & Burgess, L. (2008). *Practical Issues in*

Conducting a Discrete Choice Experiment. https://doi.org/10.1007/978-1-4020-5753-3_3

Sharma, A. K., Begbie, D., & Gardner, T. (2015). Rainwater Tank Systems for Urban Water Supply: Design, Yield, Energy, Health Risks, Economics and Social Perceptions. In *Water Intelligence Online* (Vol. 14). https://doi.org/10.2166/9781780405360

Sisser, J. M., Nelson, K. C., Larson, K. L., Ogden, L. A., Polsky, C., & Chowdhury, R. R. (2016). Lawn enforcement: How municipal policies and neighborhood norms influence homeowner residential landscape management. *Landscape and Urban Planning*, *150*, 16–25. https://doi.org/10.1016/j.landurbplan.2016.02.011

Stoutenborough, J. W., & Vedlitz, A. (2014). Public attitudes toward water management and drought in the United States. *Water Resources Management*, *28*(3), 697–714. https://doi.org/10.1007/s11269-013-0509-7

Street, D. J., Viney, R., Street, D. J., & Viney, R. (2019). Design of Discrete Choice Experiments. In *Oxford Research Encyclopedia of Economics and Finance*. https://doi.org/10.1093/acrefore/9780190625979.013.91

Syme, G. J., Shao, Q., Po, M., & Campbell, E. (2004). Predicting and understanding home garden water use. *Landscape and Urban Planning*, *68*(1), 121–128. https://doi.org/10.1016/j.landurbplan.2003.08.002

Thiam, D., Dinar, A., & Ntuli, H. (2020). *Day Zero Effect: Adoption of water-saving equipment in Cape Town, South Africa*. Retrieved from https://www.researchgate.net/publication/339935988_Day_Zero_Effect_Adoption_of_water-saving_equipment_in_Cape_Town_South_Africa

Train, KE, Ben-Akiva, M., & Atherton, T. (1989). Consumption patterns and self-selecting tariffs. *The Review of Economics and Statistics*, *71*(1), 62–73. Retrieved from https://www.jstor.org/stable/1928052?casa_token=b4x74feLglwAAAAA:fxCv8Jpr5dMHF_PdJZoGYFuOFWxvSU1TAPiajH_02i70uZY1Pwbcof3foOI8tFKe2gKF36cHXqEqbYn24--o_iqJOCpCf8TV8q3TqUCkQg48_pdLltQe

Train, Kenneth. (2003). *Discrete Choice Methods with Simulation*. Retrieved from https://econpapers.repec.org/RePEc:oet:tbooks:emetr2

Train, Kenneth, McFadden, D., & Ben-Akiva, M. (1987). The Demand for Local Telephone Service: A Fully Discrete Model of Residential Calling Patterns and Service Choices. *The RAND Journal of Economics*, *18*(1), 109–123. https://doi.org/10.1111/j.0741-6261.2007.00115.x

Ward, S., Barr, S., Butler, D., & Memon, F. A. (2012). Rainwater harvesting in the UK: Socio-technical theory and practice. *Technological Forecasting and Social Change*, *79*(7), 1354–1361. https://doi.org/10.1016/j.techfore.2012.04.001

Willis, R. M., Stewart, R. A., Panuwatwanich, K., Williams, P. R., & Hollingsworth, A. L. (2011). Quantifying the influence of environmental and water conservation attitudes on household end use water consumption. *Journal of Environmental Management*, *92*(8), 1996–2009. https://doi.org/10.1016/j.jenvman.2011.03.023

Wu, F., Zhang, Q., & Gao, X. (2018, April 1). Does water-saving technology reduce water use in economic systems? A rebound effect in zhangye city in the heihe river basin, China. *Water Policy*, Vol. 20, pp. 355–368. https://doi.org/10.2166/wp.2017.003

Zaied, R. A. (2018). Development of water saving toilet-flushing mechanisms. *Applied Water Science*, *8*(2), 1–10. https://doi.org/10.1007/s13201-018-0696-8

Zaunbrecher, B. S., Kowalewski, S., & Ziefle, M. (2014). The willingness to adopt technologies: A cross-sectional study on the influence of technical self-efficacy on acceptance. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *8512 LNCS*(PART 3), 764–775. https://doi.org/10.1007/978-3-319-07227-2_73