Achieving sustainable water management: Perspective from residential household farming in South Africa

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Abstract

Home gardening is extremely important for resource-poor households that have limited access to production inputs. However, in South Africa, attempts to implement home garden programmes often fail to improve food security of the poor due to water scarcity. However, the choice of water for use in urban households is usually limited to piped water supply from the municipality. 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. We use a choice modelling framework to investigate heterogeneity among farming households based on their preferences for individual or groups of characteristics embedded in each 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: Residential household farming, piped water, urban agriculture, choice experiment, Africa.

JEL code: Q12, Q25, Q31, Q50, L95

1. Introduction

Home gardens and backyard farm systems are an integral part of local food systems and the agricultural landscape of developing countries and have endured the test of time. However, cities in sub-Saharan Africa, like many parts of the developing world, face increasing water shortages. The availability of water resources to residential households is often affected by several bottlenecks including climate change and strategies of regulatory water agencies. The impact of climate change has made it increasingly challenging for households, especially in arid and semi-arid urban regions. In these regions, increased water scarcity implies limited access to water resources for indoor and outdoor uses. Notwithstanding this limitation, the benefits of home gardening include enhancement of food and nutritional security, improvement of health (as plants are an important source of medicine for humans and livestock), uplifting the socioeconomic status of household, contribution to income generation, improved livelihoods, and household economic welfare (Baiyegunhi, 2015; Galhena et al., 2013).

In this paper, we investigate water-saving technologies as an effective and sustainable demand management measure that can reduce the impact of water scarcity and increase household access to water for both indoor and outdoor uses. Our investigation is achieved by analysing the factors that drive the adoption of water-saving technologies by urban dwellers in Cape Town, South Africa. In the context of this study, Cape Town is an important case study because it is an extremely water-scarce city with a rapidly growing population of over 4 million people. Its dry climate and relatively high per capita water consumption has placed the city at risk of water scarcity for many years. In early 2018, after three concurrent winters of low rainfall the city almost ran out of drinking water. This is detrimental because water access has a significant implication on socioeconomic development and environmental sustainability. Even though dam levels returned to normal as rainfall improved in late 2019 (Burls et al., 2019; Simpson et al., 2020), evidence suggests the drought was not an isolated event and possibly recurrence (Luker & Harris 2019; Pascale et al., 2020).

A growing literature on urban water management reveals the importance of water-saving technologies in reducing overall water demand (Booysen et al., 2019; Fielding et al., 2012). In this study, we target four water-saving technologies, namely: i) greywater reuse ii) rainwater collection iii) efficient showerheads, and iv) dual flush cistern. 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 technologies water-saving technologies is expected to significantly reduce both indoor and outdoor water use within a household (Murwirapachena & Dikgang, 2019). Greywater constitutes about 50% of the total wastewater generated within a household and its reuse inside the house and for outdoor may lead to significant reductions in household water demand (Carden et al., 2007; Roesner et al., 2006). Rainwater harvesting is defined as the concentration, collection and storage of rainwater for use immediately or at a later time. The harvested rainwater is commonly used for toilet flushing, laundry and irrigation. This technology can contribute to more efficient use of water resources and greatly increase agricultural productivity, improve food security, and alleviate poverty.

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 representing payoffs associated with water-saving technologies. We use stated or discrete choice experiments (DCE) to explore the preferences of households for the characteristics of mutually exclusive alternatives and investigate the factors that drive the choice of an alternative. We also examine the effects of stated choice (SC) experimental design methods on households' choice for the water-saving technology alternatives. Our results provide important insights for understanding the conditions that would precipitate rapid and wide uptake of water-saving technology among farming households in cities and thereby make better use of limited water resources.

2. Brief Related Literature

Over the past decade, a growing body of literature recognises the importance of household farming as a relevant phenomenon able to interconnect a range of environmental, economic, and social issues in urban areas (Campisano et al., 2017; Dalla Marta et al., 2018; Hamilton et al., 2014; Pulighe et al., 2020; Zezza and Tasciotti, 2010). Some studies highlight household behaviour and water end-use as determinants of the volume of water demand. Usually, these studies highlight two types of activities based on place of dominant use: Indoor and outdoor use (Brennan et al., 2007; Kiesau, 2020; Manouseli et al., 2019; Mansur and Olmstead, 2012). They report that households with significant water need for outdoor activities demand more water than those whose water use is mainly limited indoor (Domene and Saurí, 2006; Syme et al., 2004).

Research in economic analysis and modelling urban water conservation methods for household farming efficiency is quite rare. The majority of available studies are focused on backyard farming in rural areas. For instance, Baiyegunhi (2015), evaluated the determinants of farmers' decisions to adopt rainwater harvesting technology in rural Msinga, KwaZulu-Natal Province, South Africa, using a binary logistic regression model based on a household survey of 180 rural home gardeners. The result of the logistic regression model showed that gender, age, education, income, social capital, contact with extension agent and perception/attitude towards rainwater harvesting technology are statistically significant in explaining farmers' adoption to adopt the technology. In an urban context, Amos et al. (2018) investigate the potential of using roof harvested rainwater to support household agriculture. The study shows the general lack of adoption and initiatives to utilise harvested rainwater in urban agriculture, given the reality of drought in developing countries. The paper further found that there is a considerable potential to supply water to urban agriculture using customised roof rainwater harvesting system designs. In another study, Pratt et al. (2019) performed irrigation evaluations for 24 urban and household small farms in Cache Valley, Utah. The paper explores case studies and identifies trends among gross irrigation depth and field variables including field size, irrigation method, application uniformity, and scheduling practices. Results show a great degree of heterogeneity in irrigation methods, equipment used, and management practices. Campisano et al. (2017) conducted a critical review of the state of the art of application of rainwater harvesting systems to clarify some key aspects that may determine their successful implementation. They find out that economic constraints and local regulations strongly influence the degree of implementation of rainwater harvesting systems and technology selection.

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 in Cape Town households (Carden *et al., 2007;* Roesner *et al., 2006)*. An integrated domestic rainwater harvesting involves collecting, storing, and channelling rainwater to the toilet for flushing and gardening irrigation outlets instead of potable water. Replacing a 12L cistern with a 3L dual cistern saves about 75% of water (Jansen and Schulz, 2006; Murwirapachena and 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 and Mosly, 2020; Sharma et al., 2015). The two levels of the attribute are; easy (when no extra training is required before usage of the technology) and 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 and 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. Theory and Methods

The analysis of data derived from the discrete choice experiment is grounded in Lancaster's attribute theory of value and consumer choice (Lancaster, 1966), and has an econometric basis in random utility theory (McFadden, 1974). Where a household head i's utility, U, of a water-saving technology j out of a set of available alternatives k, is assumed to consist of a deterministic and a stochastic element:

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

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. Assuming that the error components are distributed independently and identically (IID) following a type 1 extreme value distribution (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

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

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:

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

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 maximising 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 maximises the SLL is called the maximum simulated likelihood (MSL) estimate.

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.

$$WTP_X = \frac{\Delta X}{\Delta C} = -\frac{\frac{\delta U_{ij}}{\delta X_j}}{\frac{\delta U_{ij}}{\delta C_i}} = -\frac{\beta_j}{\mu} = MWTP \qquad (6)$$

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[1].

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 RPL 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 3, only four attributes in the base RPL model are significant. Access to technology and lifespan of the

[1] 1 South African Rand = 17 US Dollars

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 the quantity of water they save are important determinants technology adoption within households. The interactions of the Income and water quantity saved, income and health risk and Waterbill and Reliability of technology all show statistical significance in the RPL model. Table 3 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.

Table 3: Random Parameter Logit

	Base RPL		RPL Interaction		
Attributes	Coefficient (SE)	$\|z-stat\|$	Coefficient (SE)	$\|z-stat\|$	Coefficient (SE)
Reliability of Access	-0.293** (0.135)	-2.16	0.369 (0.406)	0.91	-0.285*** (0.065)
Perceived Health Risk	-0.048 (0.079)	-0.60	0.188 (0.326)	0.58	0.056 (0.056)
Comp. of Technology	0.089 (0.059)	1.51	-0.496* (0.297)	-1.67	0.137*** (0.051)
Ease of Maintenance	-0.063 (0.067)	-0.95	-0.474 (0.331)	-1.43	0.116** (0.057)
Water Quantity Saved	0.090* (0.054)	1.68	0.466 (0.290)	1.60	0.169*** (0.050)
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)
Lifespan of technology	0.128** (0.064)	2.00	-0.130 (0.297)	-0.44	0.157*** (0.051)
Income × Reliability			-0.035 (0.028)	-1.26	
Income × Health Risk			0.038* (0.023)	1.67	
Income × Complexity			0.009 (0.021)	0.41	
Income × Maintenance			-0.007 (0.023)	-0.29	
Income × quantity			-0.038*	-1.84	

		(0.021)		
Income × Cost		1.30e-06 (3.05e-06)	0.43	
Income × lifespan		0.027 (0.021)	1.31	
Waterbill × Reliability		-0.001** (3.18e-04)	-1.99	
Waterbill × Health Risk		4.0e-04 (2.57e-04)	1.55	
Waterbill × Complexity		-4.56e-05 (2.28e-04)	-0.20	
Waterbill × Maintenance		1.05e-04 (2.64e-04)	0.40	
Waterbill × quantity		-1.72e-04 (2.26e-04)	-0.76	
Waterbill × Cost		3.37e-08 (3.44e-08)	0.98	
Waterbill × Lifespan		2.55e-04 (2.31e-04)	1.10	
Log-likelihood	-3724.419	-3661.766		-3773.157
Nr. Obs.	12,120	12,120		12,120
Nr. Respondents	303	303		303
AIC	7470.837	7429.533		7560.315
BIC	7534.562	7736.571		7600.867

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

The marginal willingness to pay (MWTP) result in Table 4 shows attributes that are valuable for households to invest in water-saving technologies. When we consider the MWTP across base models, we observe that the RPL base model have the high MWTP for complexity of technology, quantity of water saved, and lifespan of technology. While the RPL 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 4: Average Household marginal willingness to pay

	Base RPL			RPL interaction			
Attributes	Average Household MWTP	95% Conf. Interval		Average Household MWTP	95% Conf. Interval		Average Household MWTP
Reliability of Access	-11277.49	-26059.77	3504.79	-12612.98	-70599.73	45373.77	-5556.72
Health Risk	-1838.19	-7962.31	4285.93	-6436.62	-34247.02	21373.78	1097.90
Comp. of Technology	3413.38	-745.42	7572.19	16978.12	-29885.73	63841.98	2665.17
Ease of Maintenance	-2442.28	-8281.89	3397.34	16234.22	-31961.54	64429.97	2256.15
Water Quantity Saved	3487.2598	-1662.81	8637.33	-15944.98	-61534.19	29644.24	3300.03
Lifespan of technology	4941.89	-973.87	10857.65	4464.85	-19464.43	28394.14	3071.38

6. Conclusion and Policy Implication

This paper has investigated the factors driving the adoption of four water-saving technologies among farming households by using econometric models that account for 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.

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