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Day Zero Effect: Adoption of water-saving equipment in Cape Town, South Africa

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Summary:

In many urban settings around the world, the severity of water scarcity has induced changes in household behaviors, leading to reduction in the volume of water demanded. One of the most widely used strategies is adoption of water-saving equipment that collects, stores and eventually treats wastewater from various sources within the household. This paper investigates the factors that drive adoption of water-saving equipment in Cape Town, South Africa, following the catastrophic "Day Zero" water crisis in 2018. The paper uses a disaggregated technology diffusion model to determine the attribute levels and socioeconomic characteristics that influence adoption of water-saving equipment in urban communities in South Africa. Data collected from a sample of 465 representative households in Cape Town are used in a choice modeling framework. Latent class analysis (LCA) is compared with both multinomial logit and conditional logit models to estimate marginal willingness to pay (MWTP) for adoption of water-saving equipment. The LCA revealed three household classes with distinct preferences, suggesting divergence in adoption of water-saving equipment.

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Day Zero Effect: Adoption of water-saving equipment in Cape Town, South Africa

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Abstract

In many urban settings around the world, the severity of water scarcity has induced changes in household behaviors, leading to reduction in the volume of water demanded. One of the most widely used strategies is adoption of water-saving equipment that collects, stores and eventually treats wastewater from various sources within the household. This paper investigates the factors that drive adoption of water-saving equipment in Cape Town, South Africa, following the catastrophic "Day Zero" water crisis in 2018. The paper uses a disaggregated technology diffusion model to determine the attribute levels and socioeconomic characteristics that influence adoption of water-saving equipment in urban communities in South Africa. Data collected from a sample of 465 representative households in Cape Town are used in a choice modeling framework. Latent class analysis (LCA) is compared with both multinomial logit and conditional logit models to estimate marginal willingness to pay (MWTP) for adoption of water-saving equipment. The LCA revealed three household classes with distinct preferences, suggesting divergence in adoption of water-saving equipment. [165 words]

Keywords: greywater technology, choice experiment, latent class analysis, technology diffusion, technology adoption, water scarcity, Cape Town, South Africa
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1. Introduction

Water scarcity is one of the biggest threats that can negatively affect not only economic development, but also environmental and human-health quality worldwide. These negative impacts are more severe for developing countries that face limited financial, technical, and regulatory capacities to allow mitigation of the water scarcity. Limited rainfall combined with mismanagement of available water resources and poor water supply infrastructures have led to disastrous situations that left many people – mainly the poor in the developing world – with limited access to water. Recent estimates by the World Health Organization (WHO) suggest that 2.1 billion people worldwide lack access to clean water services (WHO 2017).

Addressing water scarcity requires a combination of supply and demand management measures that not only promote technological change to support widespread adoption of water-efficient equipment, but also changes in behavior that contribute to water conservation. In the residential sector, examples of such technological changes could include adoption of low-flow showerheads, low-flow toilets, water-saving devices in taps, toilets and showers, greywater collection systems, and in-house greywater treatment technologies. Whereas examples of behavioral change could include turning off running water while brushing teeth, turning off the shower when soaping up, using dishwashers and washing machines when loads are full, and capturing water in buckets while showering.

Yet, no consensus has emerged when it comes to understanding the factors that drive adoption of water-saving technologies in urban households, especially in the developing world. The few examples that exist in the literature are focused on industrialized countries (Fuenfschilling and Truffer 2016; Ward et al. 2012), and have mainly highlighted the institutional conditions and governance structures that support sustainable transition to water-saving technologies in the urban sector. In developing countries, most of the existing studies have examined the economic, social, and sanitary problems associated with the lack of access to water services

(Fuente et al. 2016; Whittington and Hanemann 2009; Banerjee and Morella 2011; Jeuland et al. 2011; Cook et al. 2016), as well as the implications associated with a change in water tariff on access to water by poor households (Nauges and Whittington 2010; Banerjee et al. 2010; Whittington et al. 2015; Wang et al. 2005)[2].

A number of policy instruments have been suggested for the residential sector to address water scarcity. Instruments range from applying sound water pricing that accounts for scarcity of the resource (Dinar et al. 2015; Diakité et al. 2009; Howitt et al. 2002; Howe 2007; Huang et al. 2010) to implementation water restriction programs (Kenney et al. 2004; Howe and Goemans 2002) that limit the authorized volume of water use per day. Additional instruments emphasize the need to raise awareness through education and capacity building in order to make users more cautious about the economic, sanitary, and environmental consequences associated with water scarcity. However, another type of non-price demand management approach that has not been fully investigated is adoption of water-saving equipment within residential households. The very few examples encountered in the literature are from developed countries where public authorities provide incentive schemes to encourage adoption of water-saving equipment. Such incentives include low-flow toilet rebate programs, and free distribution of plumbing retrofit kits offered by the local water agencies in California to mitigate the various droughts encountered in the region (LADWP 2015). Other examples are current rebates programs offered to households willing to adopt water-saving equipment in Canada and Australia (Statistics Canada 2009; Australian Bureau of Statistics 2006). We are not aware of any study

[2] A different stream of literature estimates water demand in the developing world (Fercovic et al. 2019; Nauges and Whittington 2010; Jimenez et al. 2017; Ojeda de la Cruz et al. 2017), or willingness to pay to access tap-water (Whittington et al. 2002; North and Griffin 1993; Nauges et al. 2009; Lauria et al. 1997) or household preferences for municipal water services (Vasquez et al. 2011). These are, however, not linked to the purpose of our present study. We focus on the introduction of wastewater treatment and water conservation measures in the residential sector of a developing country. Most studies about the water conservation measures are focused on the agriculture sector (Schoengold and Zilberman 2007; Winters et al. 2004; Bontemps and Couture 2002; Honlonkou 2004; Speelman et al. 2010). That is mainly because agriculture captures the bulk of water consumption.

that explains the factors that drive adoption of water-saving equipment by households in developing countries. This is despite the fact that some developing countries experience severe water scarcity.

The purpose of this paper is to investigate the factors that drive adoption of water-saving equipment within urban households in the city Cape Town, South Africa. The city recently experienced one of its worse drought seasons[3] over the past four decades. Limited rainfall put tremendous pressure on water allocation decisions and placed many households in difficult situations that require a strict reshaping of water consumption behaviors. We construct a theoretical model that builds on disaggregated technology diffusion framework, which identifies the diffusion path of a water-saving technology within households. The model is tested using choice modeling, where results from latent class analysis (LCA) are compared with estimates from both multinomial and conditional logit models. The results of our analysis show that key technological attributes (lifespan of the technology and its ease of use by the purchaser, the bad smell and likelihood to generate waterborne diseases) can influence household adoption decisions. Beyond its academic contribution, our work offers policy relevance in guiding public policy decisions that attempt to improve water use efficiency within the residential sector in urban settings in the developing world. Despite the fact that Cape Town is a relatively well-developed city yet with a high level of inequality, [4] this work can provide insights to many cities that experience water scarcity. We show that a combination of technological and targeted socioeconomic policies that support education and information

[3] The drought was taking place during the writing of this paper. Although the rainfall pattern has improved, the country is still under drought-management programs. For example, the city of Cape Town has implemented a level 6B water restriction program that limits the volume of water allowed for consumption to 50 liters per person, per day. This new measure was implemented to avoid the city's Day Zero – when the city completely runs out of water in its reservoir and no water is coming out of the taps.

[4] By inequality, we mean that a large disparity in wealth is observed between different classes in the city. The city is made up of rich residential areas and poor informal settlements. More than half of the informal dwellings in the city are found in the Khayelitsha/Mitchells Plain district (134 493 dwellings) in 2017.

dissemination about the features of the selected technologies can help enhance adoption of greywater technology in urban areas.

The paper is structured as follows: Section 2 provides an exhaustive review of the existing literature. The methodology of this paper is presented in section 3. Section 4 describes the different stages undertaken to design the choice of experiments and the data used. The results and discussions are presented in section 5. Section 6 concludes the paper and provides key policy implications.

2. Related literature

The importance of public policy in fostering adoption of more efficient technologies in various water-consuming sectors has been widely studied in the economic literature (Katz and Shapiro 1986; Nelson 1982; Koundouri et al. 2006; Dinar and Zilberman 1991; Hall and Khan 2003; Dosi 1982; Edquist 2004; Kerr and Newell 2003; Millock et al. 2012). Existing studies range from the energy (Jaffe and Stavins 1994; Jaffe et al. 2003; Li and Just 2018; haq and Weiss 2018; Versteeg et al. 2017), to the agricultural (Koundouri et al. 2006; Zilberman et al. 2013; Emerick et al. 2016; Sunding and Zilberman. 2001; Schoengold and Zilberman. 2007; Winters et al. 2004; Bontemps and Couture. 2002; Honlonkou. 2004; Speelman et al. 2010) and health sectors (Hyysalo 2010; Drummond et al. 2013; Faulkner 2009; Buxton and Chambers 2011; Dishman 2012). Usually, analysis of technology diffusion highlights two major factors as main drivers of adoption of more efficient, superior technologies: technology-push and demand-pull (Nelson 1982; Edler and Yeow 2016; Ghisetti 2017; Dosi 1982). Demand-pull assumes that technology diffusion remains mainly driven by the demand that emanates from consumers. Producers innovate and create a market that supplies those technologies, which match consumers' demands and trigger a technology push.

However, it is important to highlight that such clear-cut distinction between demand-pull and technology-push hardly reflects the reality of technology diffusion. This has been highlighted in Roger (2003) as well as in Hall and Khan (2003), who argued that many technologies are disseminated because the right combination of market, governmental and institutional policies have been provided, which create incentives for consumers and producers to adopt such new technologies. With regard to water-conserving technology in urban setting, as indicated earlier, the literature about the factors that drive adoption of water-saving equipment in developing countries is very limited. Most of the existing studies are focused on the developed countries where access to data is much easier.

For instance, Renwick and Archibald (1998) developed a theoretical framework that helps us understand the extent to which water demand side management (DSM) policies might affect residential demand for different classes in Southern California. The theoretical model is tested by using a two-stage least square (2SLS) estimation procedure in a natural experiment and data collected from 119 single-family dwelling in Santa Barbara and Goleta, California. The findings show that adoption of water-efficient garden-irrigation technologies has a positive and significant effect on reducing water consumption. The authors argue that policies that aim at promoting water conservation measures positively influence probability of adoption of water-efficient equipment. Campbell et al. (2004) investigate the impacts of various policies (both price and non-price water demand side management) on promoting water-saving behaviors and adoption of water-saving equipment in Arizona. Data collected from 19,000 households over six years were used in a multivariate regression analysis. The results show that even a small increase in water pricing leads to adoption of water conservation measures. Their findings confirm that even an imposition of non-price policy (rules, increased awareness, and providing engineering technologies) may equally lead to a decrease in water consumption and adoption of more water-efficient equipment. Geller, Erickson and Buttram (1983) show the positive and significant impact of non-price DSM on reduction in water consumption. The results highlight the importance of supporting educational, behavioral, and technological changes within households for promoting water-use efficiency. Naugues and Whittington (2010) provide a comprehensive overview of the factors that influence water demand in the developing world. The study highlights the need for a better understanding of the characteristics of water consumers in these underdeveloped countries. The improved understanding is expected to encourage a better design and implementation of efficient water conservation measures. Three classifications of water consumers are identified in their paper: households with incomes ranging between US $150 and $400 per month that can afford municipal piped-water services; households in slums with income levels below US $150 per month; and households in the rural areas in Sub-Saharan Africa and South East Asia with income levels less than US $30 per month. The authors highlight the need to find appropriate and targeted policy mechanisms that not only foster an increase in water access but also favor sustainable water consumption. Using data collected from urban households in the city of Granada in Spain, Perez-Urdiales et al. (2016) evaluate the extent to which water tariff structures influence water consumption. Their findings show the need to carefully choose the type of instruments used to induce reduction in water consumption. The authors argue that a combination of price and non-price mechanisms might help reduce water consumption and promote water use efficiency. Millock et al. (2012) develop a theoretical framework that studies the impacts of non-price tax policy on adoption of monitoring technology to control stock of externality. Although their study was not referring specifically to household water consumption, the underlying theoretical framework provides good insight that helps quantify the factors that drive adoption of environmentally sound technologies. Renwick and Green (2000) evaluate the impacts of various DSMs on urban water resource management in eight water agencies in California, serving 7.1 million people. Their targeted policy instruments were water allocations, use restrictions, and public education. The results suggest that targeted policies were effective in inducing water use efficiency in the sample areas. However, the magnitude of these changes may be different depending on the seasons in which the households experience policy interventions. For instance, responses to a price change was 25% higher in summer, reflecting outdoor water consumption associated with high temperature. Grafton et al. (2011) show the extent to which implementation of various pricing schemes may affect water consumption in 10 OECD countries. Their results show that price and non-price mechanisms influence household adoption of water-saving technologies and change in behaviors. Millock and Nauges (2010) investigate the factors that drive adoption of four different types of water-saving technologies: waterwise washing machine, low-volume flush toilets, restrictor taps in water supply, and rainwater collector tanks in 10 OECD countries. Their results show that adoption of water-saving equipment remains strongly driven by key factors, such as household size, ownership of the property, water pricing, as well as degree of sensitivity towards environmental values. Olmstead and Stavins (2009) compare price and nonprice approaches to urban water conservation. The paper shows the relative merits of market-based and prescriptive approaches to water conservation. The results show that using price to manage water demand is more cost effective than implementing nonprice conservation measures. However, their paper highlights the importance of including key important factors (equity and distributional consideration, political consideration, and the costs of monitoring and enforcement) in designing any water-demand management options, especially when it comes to adoption of water-saving technologies. **Table A.1** in the appendix presents a more exhaustive list of previous studies that investigated the impacts of socioeconomic and attributional features on adoption of water conservation practices.

Our paper contributes to the current discussion on factors that drive adoption of water-saving technologies by using empirical evidence from a developing country. Rapid population growth and rural-to-urban migration observed in the developing countries, combined with poor quality of water supply infrastructures and weak regulatory capacity have led to situations in which urban dwellers may find it more appropriate to respond to water-demand management measures that reduce volume of water consumption within the household, especially through adoption of water-saving equipment.

The city of Cape Town faced a water-crisis situation that was brought on by three consecutive years of insignificant rainfall. In January 2018, Cape Town city officials announced that the reservoir serving 4 million people was three months away from running out of municipal water. That water crisis was coined "Day Zero." City inhabitants were requested to drastically cut their water consumption in order to reduce the risk of having no running water from their taps. Was that a sufficient "threat" to induce changes in the behavior of household water consumption, including adoption of water-conserving technologies?

The underlying hypothesis of this paper is that adoption of water-saving technologies may help households reduce the volume of water consumption, allowing the city of Cape Town to meet its water budget. The selected water-saving method referred to throughout the paper is greywater technology. Greywater is usually consists of wastewater coming from baths, showers, kitchen sinks, and washing machines. It contains lower concentrations of microbial contents and chemical characteristics than sewage water (Roesner et al. 2006). Previous studies show that usage and treatment of greywater by households and communities allow not only a reduced demand for freshwater, but it also saves in public expenditures by centralized wastewater treatment plants (Gross et al. 2005; Jefferson et al. 1999; Wiltshire 2005; Morel and Diener 2006; Carden et al. 2007). This paper targets two widely used greywater technologies: stand-alone greywater tank (*technology 1*), and a sophisticated and integrated system of greywater that is connected to the toilet, and can be used to flush the toilet instead of using potable water (*technology 2*). Both technologies are used to collect, store, and treat greywater from various sources within the household (bath, kitchen, washing machines, showers, etc.). The difference between the two is as follows: technology 1 is not connected to the plumbing structure that is linked to the toilet, whereas technology 2 is. Therefore, with technology 1, the collected greywater is treated and transported to the end-use point, whereas technology 2 only treats the greywater and returns it to the system. Treatment consists of a combination of anaerobic and aerobic processes with disinfection options that eliminate esthetic, health, and other problems that are caused by organic matter, pathogens, and solids, and they meet reuse standards. These technologies are currently being manufactured in Cape Town, South Africa.

3. Methodology

3.1. Theoretical model of diffusion of water-saving technology

The proposed methodological framework builds on the disaggregate technology diffusion literature to account for consumer heterogeneity impacts on adoption of a new technology. We introduce a simple theoretical model that explains the diffusion process of water-saving technology within urban households. Our theoretical approach builds on Bass (1969) but extends it by introducing assumptions that allow us to capture the characteristics of different types of urban households. Let's assume that adoption of greywater equipment within a household is a function of innovation (p > 0) and imitation (q > 0). Equation (1) shows the probability of diffusion P_t of the new technology, when p and q are exogenous:

$$P_t = p - \frac{q}{M} B(\ldots), \qquad (1)$$

p and q represent the parameters that capture the desire of certain individuals to innovate and to imitate, respectively. Innovation refers to the desire that some households have to install and experience (innovate) new water-efficient technologies in their homes. Whereas imitation refers to those households that have installed such technology only after having observed that their neighbors have previously adopted water-saving technologies. The latter type of household is supposed to imitate the former one. Arrow (1962) refers to this classification as the first mover and the follower, respectively. M is a parameter that captures the potential market share of the technology and $B(\ldots)$ is the cumulative number of people that are willing to adopt the technology. If we define *f(t)* as the likelihood of purchase at time t, with $F(t)=\int_{t=0}^{T} f(\tau)\,d\tau$ and F(0)= 0, Equation (1), the probability of adoption, can be transformed into Equation (2), following Srinivasan and Mason (1986) .

$$P_t = \frac{f(t)}{1-F(t)} = p + \frac{q}{M}F(t). \qquad (2)$$

In the early Bass (1969) model, the cumulative function $B(\ldots)$ has been considered linear, despite the fact that diffusion of new technology hardly takes place in an environment that is stable, linear, and unchanging. Mansfield (1985), for instance, argued that diffusion of a technology is driven by a combination of factors, such as risk profile of the adopters, their level of income, and the institutional settings in which they operate. We follow Mansfield (1985) and argue that elements such as risk profile might also affect the extent to which a technology gets diffused within a society. When a new innovation is introduced, it has been shown that rate of adoption might differ between not only rich and poor households (Khan and Ravikumar 2002), but also between potential adopters with different risk profiles (Foster and Rosenzweig 2010). We account for the risk profile of the potential adopters and assume a cumulative function that includes a parameter μ that captures that risk profile. Individuals are risk-neutral when $(\mu=1)$, and risk-averse when $(\mu=0)$. Therefore, assuming that $B(\ )=M\left(1+\frac{1}{\mu}\right)F(t)$ and taking into account Equation (2), we determine the likelihood of purchase of greywater technology at time t. This likelihood is represented in Equation (3):

$$f(t)=\left[p+q\left(1+\frac{1}{\mu}\right)F(t)\right]\left[1-F(t)\right] \quad (3)$$

with $f(t)=\frac{d}{dt}F(t)$. (4)

Finally, let's assume the existence of a state variable $s(t)=Mf(t)$ that captures the evolution of sales of the new technology. Transformation of Equations (1-3) leads to Equations (5) and (6):

$$P_t=\frac{s(t)}{B(t)\left[M-\frac{\mu}{\mu+1}\right]}=p+\frac{q}{M}B(t) \quad (5)$$

$$s(t)=p\left(M-\frac{\mu}{\mu+1}\right)B(t)+\frac{1}{1+\mu}qB^2(t) \quad (6)$$

The intuition behind (5) and (6) is straightforward. The evolution of sales of water-saving technology is a function of the risk profile, the innovation and imitation coefficients and the cumulative function, B. It is important to highlight that the dynamics of B(t) satisfied Ricacati principle.[5] Successful diffusion of the technology must account for these features to ensure that consumers adopt the proposed technology. Therefore given Equation (6), if one assumes a solution B (t), the standard transformation property provided in Hille (1969) shows that $B(t)+\frac{1}{\alpha}$ remains another linear and independent solution of the same Riccati equation, where $B(t)$ satisfies the linear ordinary differential equation below:

$$\Delta(\alpha)+\left[2B(t)+\phi\right]\alpha+1. \quad (7)$$

[5] The FOC remains non-linear (i.e. quadratic).

Therefore any given solution of the Riccati equation presented in Equation (7) is a Liouvillian solution, which is by using the boundaries solutions. Figures 1 and 2 below show the evolution in the sales of the technology, under different scenarios of risk attitudes (μ) and market shares (M). In Figure 1 sales in technology (in percentage) vary as a function of the risk profile of the households μ, which represents the X-axis. One can observe that higher risks with regards to certain attributes of the technology reduce probability of adoption. For instance, a decrease in the distribution in adoption is observed, as sensitivity towards risks increase. Three curves (Red: $\mu = 0.03$; Yellow: $\mu = 0.09$; Green: $\mu = 0.15$) are portrayed to capture various sale percentages, according to different risk-profiles. Two effects can be identified: a scale effect that influences the magnitude of the sales reached, and a distributional effect that changes the repartition in terms of access to the technology. On the other hand, the influence of market share M (x- axis in Figure 2) is determined by a combination of different factors – those associated with the technology (attributes), as well as those that are associated with the socioeconomic characteristics of the potential adopters. The empirical evidence below helps explain those factors.

3.2. Empirical strategy

The previous theoretical framework is used to construct a standard latent class discrete-choice model with covariates. Our model consists of (S) different behavioral classes that represent different groups within the population. Classes are determined based on two criteria: BIC and AIC. Regrouping potential adopters into different classes accounts for heterogeneity between responders, and to investigate the extent to which different parameters estimated across classes may be compared. Additionally, this can be very useful for policy intervention. Better knowledge about specific characteristics that shape household behavior helps tailor public interventions that attempt to promote widespread adoption of water-saving technologies.

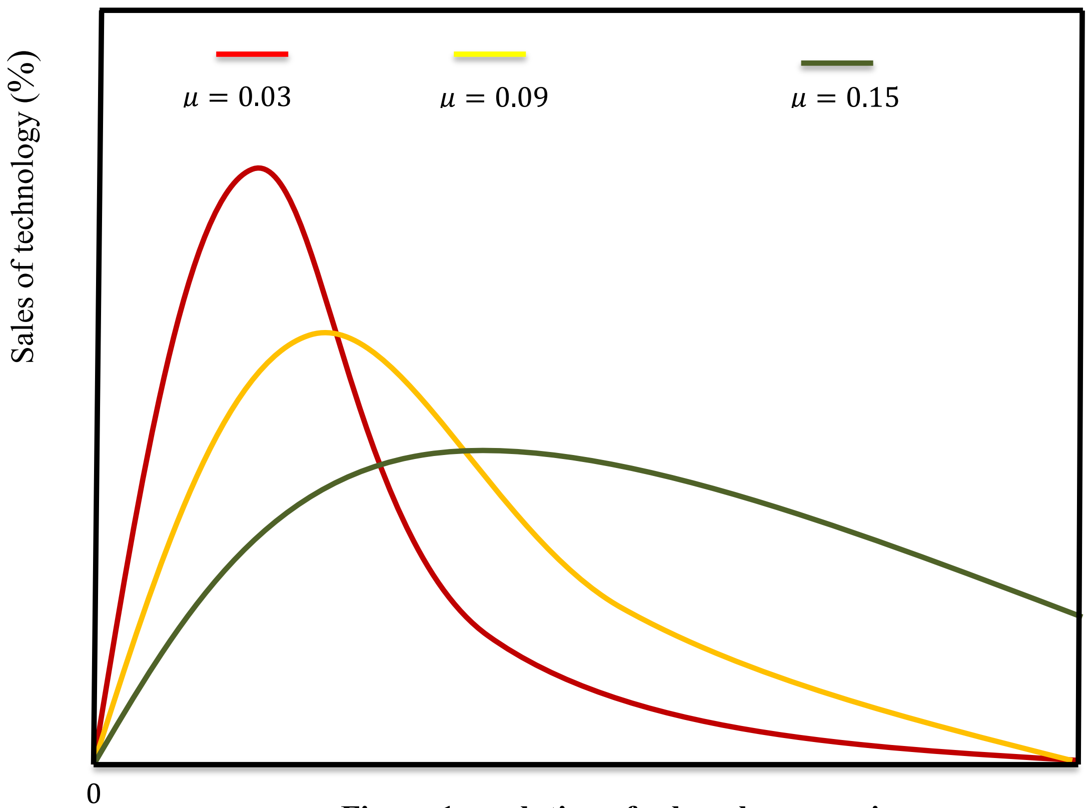

Figure 1: evolution of sales when μ varies

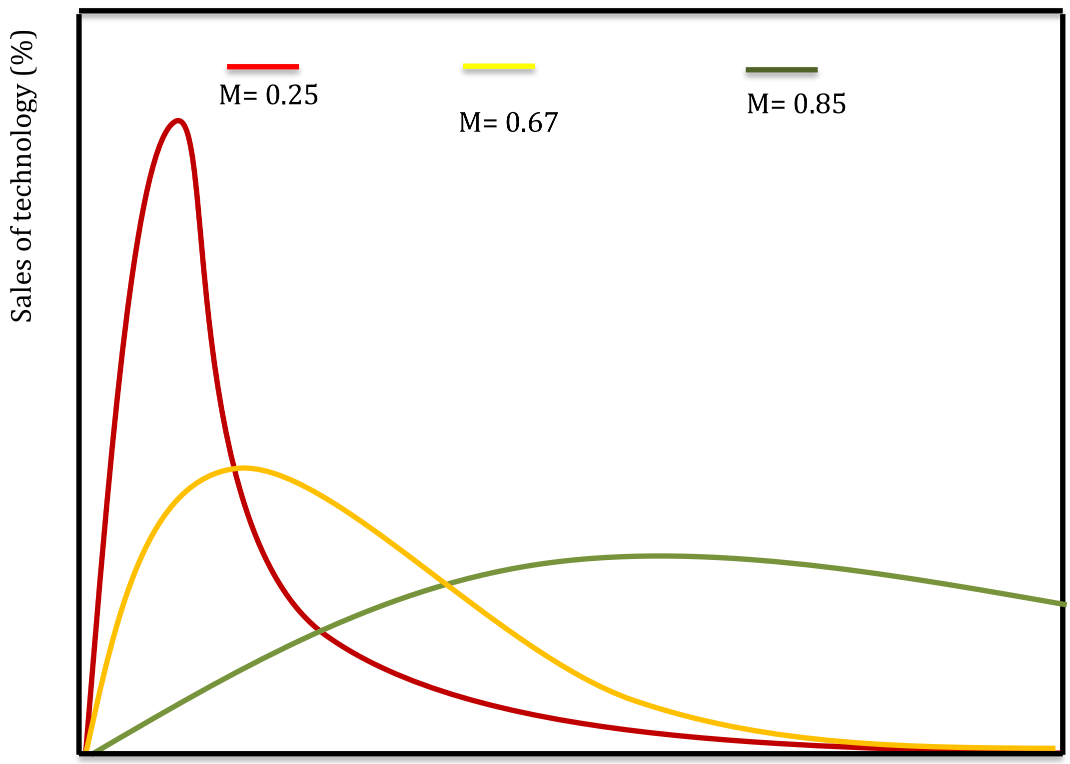

Figure 2: evolution of sales when M varies

3.3 Latent class analysis

Latent class analysis (LCA) is used in this work to account for preference heterogeneity and to release the restrictive assumption of IID of error terms, usually hypothesized under a number of discrete choice techniques, such as multinomial logit. The underlying argument, supported by economic stylized facts is that consumers who belong to the same class (such as education, income) tend to have the same behavioral patterns (Swait 1994; Hess and Rose 2009; Gupta and Chintagunta 1994). LCA, in contrast to multinomial logit (MNL) model, assumes that a discrete number of classes are sufficient to account for preference heterogeneity across classes (Hess 2014). Hence, the unobserved heterogeneity is captured by these latent classes in the population, each of which being associated with a different parameter vector in the corresponding utility. Therefore in our model of (S) classes $\beta_i(L = l, \ldots, s)$ specific parameters would be estimated with the possibility of some β_i remaining constant across some of the classes. However, it is important to emphasize that additional techniques could also be used to account for preference heterogeneity. For example, one can relax the assumption of homogeneous preferences and include interaction terms between individual-specific characteristics and case-specific attribute levels. This approach accounts for the influence that sociodemographic and attitudinal characteristics have on preferences, but it does not relax the potentially unrealistic assumptions of independence of irrelevant alternatives (IIA) and uncorrelated unobserved error over time. An alternative approach that exists is a random parameter model (RPM). RPM assumes that preference parameters are randomly distributed across the population and, as a result, model parameters vary randomly across individuals. A recent development in the econometric techniques allows to perform LCA. The technique is also used to account for attribute non-attendance (ANA), in which responders ignore one or more of the attributes when making their choices. LCA accounts for preference heterogeneity by simultaneously estimating probability of class membership and preference parameters, based on individual characteristics. The technique uses a probabilistic class allocation model.

Based on AIC and BIC criteria, three different classes were identified: (i) risk averse, (ii) innovators, and (iii) supporters of greywater technology. The class "risk-averse" is made of responders who believe in the occurrence of Day Zero. Risk-averse households are responders who trust the city officials and think if no action is taken the city will run out of water. Therefore, this implies that the public campaign by the city has influenced their beliefs. The class "innovator" refers to households that have already (at the time of the survey) adopted greywater technology. Finally, the last class, "supporters of greywater technology," is made up of households that think in-house treatment of greywater must be allowed through implementation of specific legislations. This last group is expected to adopt the technology in the future. Households within that group have an inherent belief system that supports dissemination of greywater technologies.

Following the above classification we use the random utility theory framework to determine the socioeconomic and attributes that influence adoption of water-saving practices. Let's assume that individual i belonging to class s has a utility U_{is} that is derived from adoption (j = 1) or non-adoption (j = 0) of greywater treatment technologies. Examples of positive utility provided by adoption of such technologies are reduction in global water consumption, reduced water bills, and lower reliance on water supplied by the municipality for non-potable water consumption within the households. This formulation is a typical representation of a random utility model (RUM) that has deterministic and random components (Lancaster 1966) for each class. The functional form of the utility function is given in Equations (8) and (9) below.

$$U_{in/s} = V_{in/s} + \varepsilon_{in/s} \tag{8}$$

with

$$V_{inj/s} = f\left(X_{\mathrm{in}\,j}; Z_{it} / \beta_s\right), \tag{9}$$

where V, represented by $f\left(X_{inj}; \beta_s; Z_{it}\right)$, is a function of the water-saving technology attributes of alternative n faced by individual i; X_{inj} is the matrix of attribute levels for the new greywater equipment; Z_{it} the vector of individual characteristics, and β_s the vector parameters specific to the selected class. After having observed X_i, Y_i and Z_i, the class likelihood (s) is determined as follows in Equation (10):

$$L\left(\beta, Z_{is}\right) = \prod_i \left[\Pr\left(Y_i : X_i, Z_i\right)\right] = \prod_i \left[\sum_{s=1}^{S} \Pr\left(Y_i : X_i / s\right) \Pr\left(s : Z_i\right)\right], \tag{10}$$

where $\Pr\left(s : Z_i\right)$ represents the probability that an individual i belonging to class s, and $\Pr\left(Y_i : X_i / s\right)$ is the probability of observing a response from individual i to the choice set, conditional of her belongs to class s

Finally, we estimate the marginal effects of each attribute in order to allow our results to be more policy relevant. Equation (11) represents the willingness to pay (WTP) for the greywater technology:

$$WTP = -\left(\frac{\beta_s attribute}{\beta_s \cos t}\right) \tag{11}$$

Although latent class analysis (LCA) is the main methodology of the paper, we also run multinomial logit (MNL) and conditional logit (CL) models. This allows us to compare our result with a baseline scenario that does not capture heterogeneity between responders.

4. Design of the choice experiment

4.1: Design of the attribute space

The selection of attributes included in the survey has important implications for the results of the choice experiment. We rely on the previous literature to identify the factors that drive adoption of new technologies within households. Table 1 provides an overview of the attributes and the attribute levels considered. Previous studies highlight the *lifetime of the technology* as one of the major factors that influence adoption of technology (Comin and Habijn 2010; Ahsanuzzaman 2015). Households are more willing to adopt new equipment that is perceived to be reliable and have longer lifetime. The two levels of this attribute are: short, and long term. The second attribute identified was *ease of use*, which is perceived as an important determinant in technology adoption. For quite a number of technologies, diffusion has not been widely observed because potential adopters find it costly and time-consuming to acquire skills that are needed to use the technology (Mukoyama 2004; Bartel and Lichtenberg 1987; Doms et al. 1997). Beyond learning cost and time spent at the early stage of adoption, ease of use encompasses any effort made to run, repair, and maintain the selected technology at its best standard. Two levels are selected for the second attribute: easy (when no extra training is required before usage of the technology), and difficult (when intensive pre- and post-usage training is necessary for a well-functioning technology). Technology adoption is also driven by externalities associated with the usage of that technology. After consultation with water policymakers in the region, we include two plausible externality effects: smell, and health-related externalities. Some greywater treatment technologies release a smell, which affects not only the household in which the technology is installed, but also the neighboring households. Many different cases are observed in which neighbors complain about the bad smell coming out of greywater systems installed in their surroundings. Two levels are assigned to each of these attributes: low and high (for smell) and high-risk and safe (for health-related externalities), respectively. Health-related externalities (waterborne diseases, trauma, and discomfort) can result from a bad smell or any physical contact made with the greywater without having taken precautionary sanitary measures. Several studies have shown the extent to which health-related benefits drive adoption of some technologies (WHO, UNICEF 2017; Drummond et al. 2013; Faulkner 2009; Buxton and Chambers 2011; Dishman 2012). Finally, costs were introduced as an attribute to account for the technology. In addition to our literature review, we conducted several focus group discussions (FGDs) with water policymakers, private companies that design greywater treatment technologies, and selected households. Participants of the FGDs were recruited through their local associations or non-government organizations (NGOs). We conducted a series of workshops with policymakers and local authorities who assisted us in recruiting the participants. A total of four FGDs were conducted in different locations, making sure that participants came from different segments of the society, namely, low-, middle-, and high-income groups. On average, each FGD had 12 participants in total and four participants were invited from each segment. Through FGDs, we were able to develop a localized understanding of important concepts associated with attributes and a way to convey them to the respondents. All the identified attributes were discussed with these stakeholders, and they were validated by the experts. The expert group was composed of researchers and officials from the municipality in Cape Town.

Table 1: Definition of attributes and their levels

Attributes	Definition and attribute levels	Levels of attributes
Lifetime of the technology	This indicates the number of years the technology can be used within households.	Short: less than 5 yrs. Long: 15 years.
Ease of use	This refers to whether the technology is easy to use with no prior training required. However, training becomes mandatory if the technology is difficult to use.	Difficult: when very sophisticated and intensive training is needed before and after installment of the technology Easy: when no extra training is required before usage of the technology
Bad smell (negative externality)	This indicates the likelihood of the technology to produce a bad smell during its usage. This disturbs household and neighbors	Low: selected greywater technology emits some smell when installed, but the smell is acceptable and can be treated by using basic chemical products. High: The installed technology carries strong smell. But the smell is not dangerous for human health.
Possibility to engender diseases when in contact with greywater	This captures the technical inefficiency that is associated with the design of greywater treatment technology.	High: greywater treatment could carry waterborne disease, when in contact with the wastewater. No disease: the wastewater is treated and there is no waterborne disease associated with the usage of the wastewater
Costs	Cost of purchasing a technology	R5,000; R10,000; R15,000; R20,000; R25,000 US $1 = 14.5 ZAR

4.2: Experimental design

The main objective of experimental design in choice experiments is to develop designs that yield efficient and unbiased estimates of preference parameters and value estimates (Johnston et al. 2017). Table 2 provides an example of the choice experiment scenarios that were presented to the respondents. With four attributes varying across two levels each, and one attribute varying across five levels, there were 80 ($2^4 \times 5^1$) possible combinations of the attributes and their levels. In order to minimize bias, a full factorial orthogonal design of 24 alternative profiles was created using NGENE[6] 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 an efficient design with one status quo and two non-status quo alternatives per choice set, and four choice sets arranged in six survey blocks/cards. Each choice set presents the characteristics of the technologies. Respondents were randomly assigned one of the six survey blocks/cards which had been prepopulated in six different questionnaire versions.

[6] The program is an intellectual property of ChoiceMetrix (www.choice-metrics.com).

Table 2: **Sample of choice set**

Attributes	**Technology 1: surface tank that collects and stores wastewater for re-usage), but not integrated to the toilet**	**Technology 2: Underground tank that collects and stores wastewater, and is connected to the toilet. This wastewater can be directly used to flush the toilet without using buckets to transport the wastewater.**
Lifetime	Short	Long
Ease of use	Easy (no training required, maintenance at low transaction costs)	Difficult (frequent trainings required and high transaction costs)
Smell	High	Low
Waterborne diseases	No disease	High
Costs	5,000 ZAR	25,000 ZAR

4.3: Survey design

Stated preference (SP) studies should elicit evidence that pieces of information are understood, accepted, and viewed as credible by respondents (Johnston et al. 2017). To elicit household preferences for attributes, the study used a survey-based choice experiment. The survey method allowed enumerators to convey the message and explain difficult concepts. The questionnaire had various sections on socioeconomic characteristics of households and a choice experiment composed of the alternative policy scenarios, including the baseline. As part of the introduction to the survey, respondents were told that the city of Cape Town is planning to introduce water conservation measures in response to water shortages as a result of frequent droughts. As part of the water conservation measure, city authorities will disseminate information about various water-saving technologies available on the market and supply them to buyers at a cost. Since dissemination of technologies has other cost implications for both the supplier and the buyers themselves, such as information cost, the city will bear most the burden associated with the cost of getting information in order to cushion its customers. This cost is accounted for by the attributes. With respect to this, the respondents were asked to pay a once-off levy to the city in exchange for a water-saving technology of their own choice.[7] The respondents could choose to maintain the status quo and pay nothing. The status quo represents the current situation of the household, i.e., what they are doing now, whether they have a technology installed or not. The payment vehicle selection was informed by pretesting to minimize unintended effects on value estimates (Johnston et al. 2017).

Respondents were then presented with a series of choice alternatives, differing in terms of their attributes and levels, and asked to choose their most "preferred water-saving technology" among a range of alternatives presented to them. Five undergraduate students were recruited from the University of Cape Town as enumerators, and a two-day training session was administered in order for them to internalize the information being conveyed by the choice sets. As recommended by Johnston et al. (2017), a pilot study was also conducted on the third day in an area not selected for the main survey as part of training to ensure that the respondents understood the attributes and to refine the survey instrument.

To facilitate the interview, we provided each respondent with a separate fact card describing the attributes in English. Each option in the choice set provided respondents with different attributes of a technology (e.g., a technology with a short lifetime, easy to use, with high likelihood of generating a bad smell or disease). Due to the subjective nature of verbal description and to ensure that respondents have a common understanding of the subject matter, each technology was visualized through digital manipulation of a control picture. This was made to insure that different types of technologies and changes in the attribute levels were

[7] The decision context dictates that a willingness to pay (WTP) measure could be more appropriate as opposed to a willingness to accept (WTA), since we are not dealing with losses or damages.

easily illustrated without biases that may have arisen from differences in the respondents' levels of education.

4.4: Data

The data were collected in Cape Town, South Africa. Various districts of the city were sampled to account for various important characteristics of the city. We collected data from 465 households in April 2018.[8] A team of eight enumerators was recruited and spread around the city. Areas from the Southern (Plumstead, Rondebosch, Kensington, Wynberg, Southfield), Central (Goodwood, Maitland) and the Northern (Brackenfell, Northpine, Oakdale) parts of Cape Town were randomly selected. We obtained information about the households and streets in each suburb from the city authorities. Each day, a street name was randomly selected and allocated to a designated enumerator. Thereafter, a systematic random sampling was applied by the enumerator to identify and select the next respondent by skipping households according to a sampling interval (n), computed as the total number of households in a given area, divided by the sample size in that area. For instance, when the number of questionnaires required in a specific area were not received, enumerators were instructed to make a left turn before they reached the end of the street and continue. Alternatively, we instructed enumerators to request a different street name to be randomly generated from the office. Figure A.3 in the appendix presents the areas that have been surveyed. Table 3 shows the summary statistics of the selected variables. The data was captured such that each individual was entered 12 times to include the choices they made for three options and four different choice sets. Responders averaged 53 years of age, and their average number of years in school was 13. A greater proportion (62%) of the sample was composed of male respondents. Quite a significant proportion (46%) of the respondents did not believe that Day Zero actually exists.

[8] This period corresponds with a severe drought in Cape Town and the scheduled Day Zero was a few days ahead of the interviews

Moreover, the average income is R17048.83 (US $1,183) per month, while the average water bill is R159.30 per month. The average cost of a technology is R9732.30, based on market prices collected at the time of the survey. We observed a great variability associated with income and technology cost, suggesting that most of the responders were middle aged, educated up to matric level, and belonged in the middle-income category. The alternative specific constant (ASC) in Table 3 commonly reflects the status quo bias, and it measures the difference between status quo and non-status quo alternatives.

Table 3: Summary statistics

Variable	Obs	Mean	Std. Dev.
School Years	5,580	13.47	3.58
Gender	5,580	0.62	0.49
Day Zero	5,580	0.54	0.50
Innovators	5,580	0.10	0.30
Risk Adv	5,580	0.89	0.31
Support	5,580	0.85	0.36
ASC	5,580	0.33	0.47
Water Bill	5,580	159.30	237.00
Ce Cost	5,580	9732.00	8906.00
Income	5,580	17048.83	14120.90

5. Results and discussion

We start by analyzing the results of the CL and MNL together, and we then proceed to discuss the LCA results. Table 4 represents the results of the conditional logit (CL) and the multinomial logit (MNL) models with and without interaction terms. The models with covariate interactions were run to evaluate the effects of individual characteristics on technology preferences. Table 5 presents the results of the LCA model. According to the measures of good fit (AIC and BIC criteria), the LCA model provides a better fit to the data than the CL and MNL models.

However, we will discuss the results of all the models, because they introduce different flavors to the analysis.

5.1: CL, MNL, MNL-interaction and CL-interaction results

The specification of the CL and MNL uses the attribute levels and the ASC to explain the alternatives selected by responders in the choice sets (Vermunt et al. 2008). The coefficients in the CL and MNL models are all statistically significant at the 1% level. The signs of the attributes lifetime and disease are consistent with expectations, whereas the sign of bad smell despite being significant is not consistent with expectation. We expect households to consider bad smell as a negative externality, which decreases the probability of adoption. However, households may still choose greywater-saving technologies, although they generate a bad smell during their use, as long as the technologies contribute at saving water and hence reducing the water bill. Therefore, despite their ability to generate bad smell, greywater technologies still remain an appealing water-saving strategy in the study areas. This is supported by the fact that adoption of greywater can be combined with utilization of chemical scrubbers (gas and liquid oxidation, carbon/permanganate absorption, $FeCI_3$ addition, etc.) that allow a mitigation of the negative effects associated with bad smell in order to reduce the odor sources within the household. Another alternative is using underground greywater conservation tanks, which limit (neutralizes) the effects that the smell has on the household and the neighborhood. The positive coefficient of ASC in the base model is statistically significant, suggesting a significant status quo effect. The results show that ease of use is significant at 1% with expected sign of the coefficients.

In both the CL and MNL interactions model, Easyuse, Badsmell, and Disease are statistically insignificant. Lifetime is statistically significant and has the expected sign of the coefficients. In these models, the coefficients on choice attributes represent the preferences of base-case responders. By assumption, the base-case might represent responders who prefer a technology with a relatively longer lifespan, that is easy to use, that has a very low likelihood of generating bad smell and diseases at an affordable cost. As with the base-case models, the interactions models have a positive and significant ASC, indicating that responders had a preference for the status quo option, regardless of the change in the levels of the attributes. Therefore, these results show the importance of key attributes in explaining adoption of greywater technology within households.

The coefficients of the interaction terms describe the effects that individual characteristics have on preferences for each attribute. The significant negative coefficient on Innovators × Lifetime, Gender × Disease, Waterbill × Easyuse, and Income × Cost indicate that early adopters prefer technologies that are less difficult than late adopters. Women are more sensitive to technologies that have a high probability to generate diseases than men. Responders who believe that greywater helps to reduce the water bill prefer relatively easy technology than their counterparts. The significant and positive coefficient for Support × Cost, Gender × Cost, Waterbill× Badsmell, and Income × Lifetime indicate that greywater supporters are less sensitive to changes in costs associated with investment in water-saving technologies than non-supporters. Men are less sensitive to costs than women, those who believe that the use of greywater technologies actually reduce a water bill do not care much about bad smell than others (as explained earlier). However, those with higher incomes seem to care about the lifespan of the technology than responders with lower incomes.

Table 4: Results of the MNL and CL (with and without interaction)

	Base CL		CL Interaction		Base MNL		MNL Interaction	
	Coefficients	Std. Err.	Coefficients	Std. Err.	Coefficients	Std. Err.	Coefficients	Std. Err.
Lifetime	0.46***	0.08	0.43**	0.19	0.62***	0.08	0.58***	0.21
Easyuse	0.20***	0.07	-0.06	0.20	0.26***	0.08	-0.003	0.22
Badsmell	0.13**	0.06	0.10	0.21	0.17***	0.06	0.19	0.23
Disease	-0.21***	0.07	-0.217	0.21	-0.27***	0.07	-0.13	0.23
Cost	-1.16e-05	7.76e-06	-4.65e-05*	2.63e-05	-1.47 e-06*	8.57e-06	-4.67e-05*	2.92e-05
ASC	1.73***	0.60	1.7***	0.61	2.40***	0.64	2.44***	0.66
Innov × Lifetime			0.01	0.11			0.01	0.12
Innov × Easyuse			-0.19*	0.11			-0.24*	0.12
Innov × Badsmell			-0.04	0.12			-0.05	0.13
Innov × Disease			0.16	0.13			0.22	0.14
Innov × Cost			3.22e-06	1.57e-05			4.73e-06	1.78e-05
Riskadv × Lifetime			0.04	0.11			0.06	0.12
Riskadv × Easyuse			0.13	0.12			0.14	0.13
Riskadv × Badsmell			0.07	0.13			0.07	0.14

Riskadv × Disease	0.04	.13	0.01	0.14
Riskadv × Cost	-1.33 e-05	1.59 e-05	2.10e-05	1.76e-05
Support × Lifetime	-0.015	0.09	-0.02	0.18
Support × Easyuse	0.07	0.10	0.08	0.12
Support × Badsmell	-0.15	0.10	-0.19*	0.11
Support × Disease	-0.01	0.11	-0.02	0.12
Support × Cost	2.62e-05*	1.40e-05	3.11e-05**	1.56e-05
Gender × Lifetime	-0.01	0.06	-0.01	0.07
Gender × Easyuse	0.01	0.07	0.01	0.07
Gender × Badsmell	0.04	0.07	0.04	0.08
Gender × Disease	-0.13*	0.07	-0.19**	0.08
Gender × Cost	2.56e-05**	1.00 e-05	3.12e-5***	1.56e-05
Schoolyear × Lifetime	-0.01	0.01	-0.01	0.07
Schoolyear × Easyuse	0.01	0.01	0.01	0.01
Schoolyear × Badsmell	-0.0042	0.01	-0.01	0.01
Schoolyear × Disease	-0.005	0.01	-0.01	0.01
Schoolyear × Cost	1.40e-06	1.41e-06	-1.84e-07	1.59e-06

Waterbill × Lifetime		-4.00e-05	1.4e-04		-5.6e-05	1.65e-4
Waterbill × Easyuse		-2.8e-05**	1.30e-04		-4.18e-4***	1.59e-4
Waterbill × Badsmell		2.4e-04*	1.4e-04		3.03e-4*	1.62e-4
Waterbill × Disease		1.91e-04	1.46e-04		1.97e-4	1.66e-4
Waterbill × CostA		1.72e-08	1.94e-08		1.78e-08	2.24e-08
Income × Lifetime		5.18e-06**	2.48e-06		6.71e-06**	2.91e-06
Income × Easyuse		2.04e-06	2.62e-06		1.18e-06	3.04e-06
Income × Badsmell		4.29e-06*	2.66e-06		4.76e-06	3.06e-06
Income × Disease		5.00e-06 *	2.77e-06		4.04e-06	3.15e-06
Income × Cost		-8.06e-10**	3.49e-10		-1.40e-9***	3.97e-10
Log-likelihood	-1845.89	-1793.71		-3273.80	-3224.94	
AIC	3703.786	3667.42		6561.61	6531.89	
BIC	3743.544	3932.47		6608.00	6803.60	
Obs	5,577	5,577		5,580	5,580	

* $p < 0.10$. **$p< 0.05$. *** $p <0.01$.

5.2: Latent class model

The specification of the LCA model was performed using all of the variables that appear in the CL and MNL interactions models. Out of all model specifications, a three-class model was selected as the best specification based on AIC and BIC criteria. As shown in Table 5, the coefficient on Badsmell, Cost and ASC for class 1 are statistically significant. The coefficients for Easyuse and Cost are significant for class 2, while the coefficient of Easyuse, Badsmell, Disease, and Cost are highly significant for class 3. There is consistency on the sign of the coefficients for Easyuse, Badsmell, and Diseases for all classes except for Cost in class 3.

Class 1 has the least class membership and accounts for 15% of responders. Class 1 characterizes responders who think that adoption of greywater technology would contribute to reduced water scarcity and postpone occurrence of Day Zero. For that class, adoption of water-saving equipment is naturally perceived as a tangible option that could help mitigate water crisis, alongside other water-demand management options. This class is labeled as risk averse. The class has the youngest (52 years) members and relatively more women (41%). Our study supports other studies that find women to be more risk averse than men (Charness and Gneezy 2012). Our results show women have a strong preference for change away from the status quo (negative and significant ASC). The mean willingness to pay for Badsmell and Diseases are higher for class 1, suggesting that members of this class put more weight on Badsmell and Diseases. Relative to classes 2 and 3, members of class 1 are significantly less likely to adopt technologies that yield Badsmell and Diseases. Relative to members of class 2, they are also significantly less likely to innovate or to be leaders in technology adoption.

Class 2 has the largest share of responders with 49% and, by default, it is used as the reference class. Determinants of class membership for the other alternative classes are interpreted with respect to class 2. Members of class 2 are the innovators and leaders in using water-saving technologies. During our experiment, these were members who already adopted greywater technologies before our survey was administered. Members of class 2 are mature (56 years), slightly more educated (13.7 year of school) than the mean, and composed of fewer women (26%), compared to other classes. The household marginal MWTP for Lifetime (527.79) and Easyuse (-1426.69) are higher for class 2, suggesting members of this class care about the lifespan and ease of use of the technology (Table 6). The ASC is not significantly different from zero, suggesting the absence of status quo bias, and members in class 2 are indifferent between the status quo and other alternatives. This seems to suggest that members of class 2 might view greywater technologies as an appealing water-saving strategy, if benefits are greater than the costs of adopting the technology.

Class 3 is the second largest of the classes, representing 35% of responders. They have been labeled "greywater supporters." This class characterizes responders who support initiatives that facilitate adoption of greywater technologies. Members of class 3 are mature (54 years), and women constitute 37%. Again, the ASC is not statistically different from zero, suggesting the absence of status quo bias. This suggests that members of class 3 were indifferent between the status quo and moving away from it. Class 3 has the least MWTP for all attributes (Table 6). The positive and significant cost coefficient in this class suggests that responders were ignoring the cost associated with each alternative, or selecting alternatives with higher cost with all else held constant. Although this is not consistent with expectations, the explanation could be that greywater supporters were willing to adopt any technology that can reduce household demand for freshwater to prevent a water crisis. This may be because the publicity provided by officials about the likelihood for the city to run out of water has contributed to rising concerns about future water crises.

Table 5: Latent class analysis (LCA) results

	Class 1 (Risk Averse)		Class 2 (Innovators)		Class 3 (Supporters)	
	Coefficients	Std. Err.	Coefficients	Std. Err.	Coefficients	Std. Err.
Marginal utilities						
Lifetime	-0.06	0.36	0.68	0.22	0.98	0.13
Easyuse	-0.19	0.32	0.25***	0.209	0.60***	0.11
Badsmell	0.44*	0.25	-0.29	0.18	0.21***	0.09
Disease	-0.29	-0.31	-0.17	0.189	-0.12**	0.10
Cost	-0.0004***	0.00005	-0.00015***	0.00002	0.0001***	0.000013
ASC	-5.36**	2.60	2.37	2.37	1.66	1.00
Class membership parameters						
Innovators			-0.04	0.13	-0.09	0.13
Risk Averse			-0.51***	0.14	-0.19	0.15
Supporters			0.03	0.11	0.22*	0.12
Gender			0.18**	0.07	0.54***	0.08

Constant			1.50***	0.14	0.48***	0.16
Posterior membership probability	15.27		49.46		35.27	
Log-likelihood	-130.98		-331.22		-395.27	
AIC	273.96		674.44		802.5464	
BIC	302.45		709.97		836.055	
Obs	852		2,757		1,968	

* p < 0.10. ** p< 0.05. *** p <0.01.

5.3: Marginal willingness to pay and aggregate willingness to pay

When we consider the marginal willingness to pay (MWTP) across models, we observe that both the CL and MNL base-case models have the highest MWTP for Lifetime, Easyuse, and Badsmell, while the LCA has the highest MWTP for Disease. Mean MWTP for Lifetime, Easyuse, and Badsmell are higher in the CL/MNL base model, while the mean MWTP for Disease is higher in the MNL interactions model. Overall, Lifetime has the largest MWTP, followed by Easyuse, and Badsmell. In general, responders had a negative MWTP in all models for a technology that is likely to generate Disease. This is not necessarily true when we consider the mean MWTP across classes for a technology that generates Disease as in class 1 and class 3. It makes sense for both classes to have positive values, since the innovators and supporters of greywater have a higher likelihood of finding new or innovative ways to neutralize the negative externality associated with usage of greywater. What is more important is adoption of wastewater conservation practices that contribute to reducing the expenditures on Waterbill, which in turn is expected to prevent water scarcity.

According to the three measures of goodness of fit (log-likelihood, AIC, and BIC), the LCA model provides a better fit to the data, followed by the CL models and, finally, the MNL models. For ease of exposition, we eliminate the MNL models and compare estimates of aggregate MWTP from the LCA, CL interaction, and CL base models in Table 6. All the attributes carry negative signs in the LCA model. The CL base model has positive signs for all attributes but Disease, while the CL-interaction model has negative signs for Easyuse and Disease, and positive signs for Lifetime and Badsmell. All the models converge on the negative sign of Disease.

Since the LCA provides a better fit, the remainder of the discussion focuses on the results of the LCA model. The mean annual household MWTP for each attribute is aggregated for the

3.8 million households in Cape Town (STATS SA 2018) that were sampled to represent the study area. This is then multiplied by the figures in Table 6 for the LCA. The LCA produced higher mean MWTP estimates for Disease (-R45 068 000), followed by Lifetime (-R5 337 670 000), Easyuse (-R5 582 162 000) and, lastly, Badsmell (-R5 992 296 000). The signs of the MWTP for Lifetime and Easyuse are not consistent with theory. The MWTP values for Disease and Badsmell are negative, indicating a MWTP for decreases (or to avoid increases) in the levels of those attributes. In making their choices, responders prefer technologies that have a very low probability of generating Disease than other attributes. Responders seem not to consider Badsmell to be a very important attribute when making a choice about technology adoption.

Table 6: Household marginal willingness to pay per month, by class

Attributes	Class 1 (Risk Averse)			Class 2 (Innovators)			Class 3 (Supporters)		
	Mean MWTP	95% CI		Mean MWTP	95% CI		Mean MWTP	95% CI	
Lifetime	-162.73	-1947.03	1621.57	4531.507	527.79	8535.218	-10266.75	-11898.60	-8634.91
Easyuse	-483.37	-2005.85	1039.10	1681.66	-1426.69	4790.02	-6313.96	-7788.64	-4839.30
Badsmell	1087.95	-260.37	2436.28	-1947.349	-4173.49	278.80	-2211.20	-3895.93	-526.49
Disease	735.55	-2193.51	722.40	-1146.16	-3458.93	1166.59	1255.21	-1155.70	3666.13

Table 7: Average monthly household MWTP (LCA mean, conditional-base and conditional interaction)

Attributes	LCA Mean[a]			Conditional-Base			Conditional Interaction		
	Average Household MWTP	95% CI		Average Household MWTP	95% CI		Average Household MWTP	95% CI	
Lifetime	-1404.65	-4232.90	1423.59	40506.93	-22944.40	103958.27	9418.36	-3503.93	22340.65
Easyuse	-1468.99	-3758.98	820.99	17542.88	-15773.78	50859.53	-1340.05	-9810.18	7130.08
Badsmell	-1576.92	-3478.06	324.22	11673.78	-11442.15	34789.72	2172.60	-6397.68	10742.88
Disease	-11.86	-2453.35	1980.35	-18333.85	-37403.70	735.99	-4684.552	-16077.30	6708.20

Mean MWTP and confidence intervals for LCA model are calculated as the sum of the MWTP and confidence intervals from each group, multiplied by the respective membership probability,

6: Conclusion and policy implications

This paper has investigated the factors that drive adoption of greywater treatment technology by using a novel econometric technique that accounts for household heterogeneity. The results show that households are sensitive to disease and lifetime duration of the technology, on top of all the provided attributes, when it comes to explaining the attributes that determine adoption. Interestingly, our results show that women are more sensitive to technologies that have a high probability to generate diseases than men. This means female heads of households in our surveyed areas are more cautious about the health status of their children and other family members than men. When running our LCA, almost all the attributes are significant. Based on the goodness of fit of the model, three classes were formed: risk-averse (class 1), innovators (class 2), and greywater supporters (class 3). Class 1 has the least class membership and accounts for 15% of responders. In class 1, bad smell and ease of use are significant. Class 2 has the highest share in our sample size, reflecting the widespread diffusion of greywater technology within urban households in Cape Town. Ease of use and the cost of the technology are significant within that class. Whereas for class 3, ease of use, bad smell, disease, and costs are all significant.

Our results show the importance of better understanding the profile of the potential users in order to promote widespread adoption of greywater technology. Policy interventions may support initiatives that attempt to design better greywater treatment technologies, which control for smell and eliminate any possibility of risk from waterborne diseases. This means that a massive investment in research and development should be promoted around greywater technology advancement. Alongside these technical interventions, our results show the importance of raising awareness, via public campaigns, around attributes that affect greywater technology. The benefits of such public campaigns arise from a better explanation of the real attributes of the technology in order for potential users to differentiate between the true advantages associated with decentralized wastewater treatment and the fake news provided in some media outlets. Finally, costs may also hinder adoption of greywater technology. Policy interventions may be articulated around possible financial support that could assist poor households in acquiring such technology. The intention of this paper was not to study the impacts associated with such financial schemes on adoption rate. That will be addressed in further research. This paper attempted to understand the factors that drive adoption of greywater treatment technology in urban households. The underlying assumption being that adoption of greywater may help the city of Cape Town to reduce the impact of water scarcity.

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Appendix

Table A.1: **Choice of water conservation measures**

Studies	Methodologies	Main factors that influence adoption of water-conservation measures	Locations	Main findings
Renwick and Archibald (1998)	Household panel data	(1) Change in water price, (2) quantity restriction, and (3) subsidies for water efficient technologies	California (Santa Barbara, Goleta)	➢ Demand side management (DSM) policies were effective in reducing water demand. ➢ Price policies will allow a larger reduction in residential water demand in a lower-income community than in a higher-income community, all other factors held constant.
Campbell et al. (2004)	Multivariate regression analysis	(1) Change in water price, and (2) regulation (low-flow fixtures and devices ordinance; wastewater ordinance enforcement; water-	Phoenix	➢ Price increase leads to a reduction in water consumption. ➢ If the ordinance of regulations are designed correctly, they can lead to large water savings.

		saving equipment; education) that induce installation of water-saving devices		
Geller, Erickson and Buttram (1983)	Experimental approach	(1) Educational (distribution of handbooks that describe a) the problems resulting from wasteful water use, b) the relationships between water and energy consumption, and c) methods for implementing water-saving strategies in the home; (2) behavioral (daily written informational feedback with social	Blackburg, Virginia	➢ The ineffectiveness of feedback and education was a function of resources cost (i.e., water prices) and lack of economic incentives for reducing consumption. ➢ The engineering devices were significantly effective in reducing consumption because, once in place, water is saved with little or no inconvenience or need to change ongoing behaviors. ➢ The installation of toilet dams, shower flow restrictors, and faucet aerators should have resulted in much larger water savings.

		recommendation); and (3) engineering strategies that consisted of implementing water conservation devices.		
Perez-Urdiales et al. (2016)	Household level panel data	(1) Attitudinal factors, (2) knowledge and skills, (3) habits and routines, and (4) different water-pricing structures.	Granada, Spain	➢ Water demand management policies should be tailored to specific demand function of a particular group of consumers. ➢ Both pricing and non-pricing policies (education programs, water rationing, retrofit subsidies, and public information campaigns) can be jointly applied to the most price-responsive groups of consumers.
Renwick and Green (2000)	Cross-sectional analysis	(1) Water allocation, (2) use restrictions, and (3) public education.	California	➢ Price and demand side management (DSM) are effective in reducing water demand.
Grafton et al. (2011)	Econometric analysis that	(1) Water pricing, (2) turning off water	10 OECD countries (Canada, Australia,	➢ The results found that a key policy lever in managing water demand is campaigns to

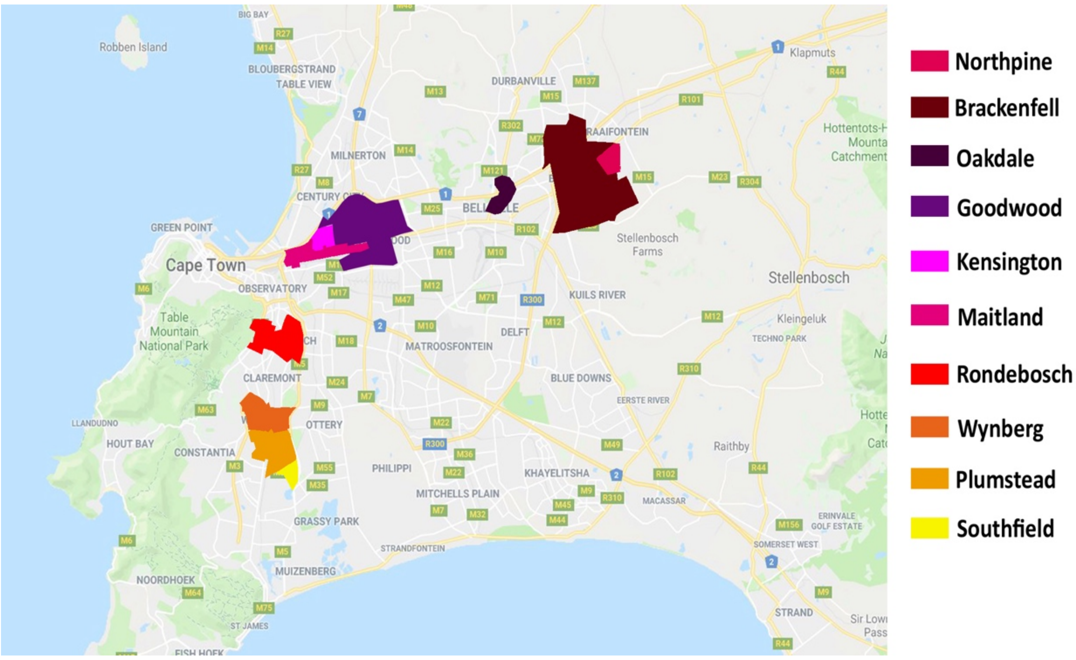
	uses instrumental variable approaches	while brushing teeth, (3) taking shower instead of bath, (4) plugging the sink when washing dishes, (5) watering gardens in the coolest part of the day, (6) collecting rainwater/recycling waste water.	Italy, The Netherlands, Sweden, Norway, Czech Republic, Mexico, South Korea, France)	conserve water use through a change in water-use practices. ➢ Volumetric water charges increase the probability of: a) turning off the water while brushing teeth, b) taking a shower instead of a bath, c) watering the garden in the coolest part of the day, and d) collecting rainwater and recycling wastewater.
Millock and Nauges (2010)	Econometric probit model	(1) Socioeconomic variables	10 OECD countries (Australia, Canada, Czech Republic, France, Italy, Korea, Mexico, The Netherlands, Norway and Sweden)	➢ Environmental attitudes and ownership status are strong predictors of adoption of water-efficient equipment, metering, and individual charge for water consumption, which lead to higher probability of adopting water-saving equipment, compared to households that paid a flat rate.

Nauges and Thomas (2000)	Panel data	(1) Individual metering, (2) average and marginal price, and (3) climatic conditions.	116 local communities in Eastern France	➢ Results indicate that households respond to both average and marginal prices, with significant but low price elasticity of -0.22 in the case of average price. ➢ A significant income effect is found with an income elasticity estimated at 0.1. Residential water consumption is low for individual houses with meter recording. ➢ Non-price factors (low-flow equipment promotion, awareness campaigns and education programs) are more likely to induce a reduction in water consumption as compared to changes in water prices. Water demand remains poorly sensitive to price change.

Lam (2006)	Theory of planned behavior (TPB)	(1) Attitude, (2) normative belief, (3) vulnerability, (4) collective efficacy, and (5) behavioral intention.	Taipei and Kaohsiung (China)	➢ The author highlights that TPB alone was not sufficient to explain people's intention to install water-saving equipment, such as dual-flush controllers in toilets; However, the subjective effectiveness of alternative solutions remains a good predictor for the intention. This is mainly because the dual-flush controller was a new technology to the targeted households. Responders' attitudes, subjective norms, and PBC regarding the retrofit might have been vague. ➢ The author argues that strategies to shape people's psychological aspects may be relatively ineffective. A more powerful strategy would be to publicize the relative advantages of dual-flush controllers and other water-efficient appliances.
Gilg and Barr (2006)	Household data analysis	(1) Social, (2) attitudinal, and (3) behavioral	Devon	➢ Achievement of water-saving targets must account for: a) behavioral complexity, b)

		composition of water saving activities		behavioral groupings, and c) lifestyle of the households.
Berk et al. (1993)	Analysis of survey data	(1) Installation of a water dam in toilets, (2) installation of water-saving toilets, (3) checking for plumbing leaks, and many other water conservation measures.	California (Los Angeles and San Francisco Bay areas)	➢ Households with higher socioeconomic status were more inclined to adopt a greater number of different water-conservation practices.

Figure A.3: Map of the City of Cape Town and areas visited during the survey



Source: Authors elaboration.