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Capturing and analysing heterogeneity in residential greywater reuse preferences using a latent class model

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ABSTRACT

To legally permit greywater reuse as a management strategy, it is necessary to establish allowed uses, as well as guarantee legitimacy, safety and maintain public trust. Cities with previous experience in greywater reuse have reconfigured their regulations according to their own evidence with decentralized water reuse systems. This has allowed them to encourage or restrict certain indoor uses of treated greywater. However, cities starting to use these residential schemes lack the experience to reconfigure

24 their water and sanitation regulation, and thus need “blindly” decide on the type of greywater uses to
25 allow in order to achieve a balance between users’ acceptability and avoiding public health problems.

26 In this research, we analyse hypothetical situations of greywater reuse based on real evidence related to
27 decentralized water systems. The main objective of this study is to evaluate the heterogeneity of
28 individuals' preferences regarding residential greywater reuse for six intended indoor uses, using stated
29 choice experiments and a latent class model. Hence, we obtain preliminary evidence about the direction
30 that the regulation or pilot tests should take. We use the context of Santiago (Chile) as a reference,
31 where although allowed, greywater reuse is not taking place widely. Our results show that survey
32 respondents can be classified into four classes (enthusiasts, greywater sceptics, appearance conscious
33 and water expenditure conscious), according to the preferences for the different types of indoor
34 greywater reuse and the appearance of the treated greywater. From a policy perspective, our results
35 show differences across classes as a function of socioeconomic characteristics and previous greywater
36 reuse knowledge, as well as wider household characteristics, including the presence of sensitive
37 individuals (under 15 and over 74 years old), number of residents, number of sanitary devices, and
38 location and type of garden. Along with presenting empirical results for the specific case of Santiago
39 de Chile, the paper provides a demonstration of the method that can be replicated in other countries that
40 need an empirical approach to acquire knowledge about people’s preferences for greywater reuse
41 allocation, before including greywater reuse schemes in their water and sanitation regulation.

42 **Keywords:** *Greywater reuse preferences, choice modelling, latent class model, class allocation.*

43 1. INTRODUCTION

44 Opportunities for using new alternative sources of water supply for households and the availability of
45 new technology for reusing water are reshaping the way water is managed in cities (Wilcox et al., 2016).
46 In particular, now there exist decentralized hybrid water supply systems that draw only part of the water
47 from the mains network (between 50-70%) while the remainder (50-30%) comes from reused greywater
48 that is locally treated (Lefebvre, 2018; Vuppaladadiyam et al., 2019). The source is greywater from the

49 same household, that is, water that is free of faeces, food residues, oil and fats, collected from washing
50 machines, showers, tubs, and washbasins (Lambert & Lee, 2018).

51 Experience in urban settings such as the Persian Gulf region and the broader Middle East (Lambert &
52 Lee, 2018), and Sydney (Pham et al., 2011), indicates that individuals prefer to allocate reclaimed water
53 for two non-potable purposes, namely toilet flushing and garden irrigation. Both uses are very attractive
54 due to a higher perceived safety (i.e. no direct contact with the skin) and lower treatment costs, as high-
55 quality standards are not needed, and also because they are two of the uses that consume the largest
56 water volumes in the household (Roshan & Kumar, 2020). However, at certain times of the year (e.g.
57 winter or rainy months), garden irrigation is not a daily practice, or depending on rainfall, may not be
58 required¹. As a result, at those times, the amount of greywater available would be higher than what
59 consumers can use for other residential uses Dolnicar & Schäfer, 2009). Discharging the extra greywater
60 to the conventional sewage system would be an economic loss for users who pay for the maintenance
61 and operation of the treatment technology (Lambert & Lee, 2018). Thus, if allowed by law, allocating
62 treated greywater for other uses could be beneficial since a higher volume of the greywater that was
63 treated can be used.

64 The perceptions that consumers hold about greywater reuse are fundamental for the success of a
65 decentralized hybrid water supply system, since they are the primary agents that interact with the
66 greywater, as well as operate and take care of the technology (Domnech & Saurí, 2010). To ensure that
67 laws, regulations, and policies contribute to making these systems more attractive and to remain
68 successful over time, an understanding of the key determinants of consumer preferences is essential
69 (Mukherjee & Jensen, 2020). Several studies on water reuse have empirically demonstrated that there
70 is heterogeneity in preferences and that this is mainly linked to socio-demographic characteristics, and
71 other psychological constructs (Amaris et al., 2021; Oteng-Peprah et al., 2020). The starting point of
72 our work is that even within the same sociodemographic group, differences in preferences may exist,
73 in terms of which (if any) uses of greywater are desirable, and what the role of the appearance of the
74 water is (Amaris et al., 2021). We postulate that classes or groups of individuals can be established to

¹ <https://www.organicgardener.com.au/blogs/watering-winter>

75 capture this heterogeneity, and that consumer characteristics can be used to at least partially explain
76 which group an individual is more likely to belong to (Hess, 2014). In particular, our study focuses on
77 exploring different population segments, each with its own behaviour (choice regarding preferences) in
78 the allocation of treated greywater for six domiciliary uses that vary according to the level of skin
79 contact, based on our earlier survey work in (Amaris et al., 2020).

80 Our modelling context is based on hypothetical scenarios that replicate real experiences of water reuse
81 in dwellings in Spain (Domnech & Saurí, 2010) and South Africa (Ilemobade et al., 2013). This method
82 uses SC experiments to explore the preferences of respondents for the qualitative and quantitative
83 characteristics of mutually exclusive alternatives (Louviere et al., 2000). Due to the nature of the data
84 and our study objectives, we analyse the choices in the hypothetical scenarios using latent class discrete
85 choice models allowing for heterogeneity in preferences across consumers. These types of data and
86 models are becoming more common in studies of technological innovations (Su et al., 2018;
87 Franceschinis et al., 2017), mainly because they can produce insights on preferences in the absence of
88 an existing market (Ortúzar & Willumsen, 2011, sec. 8.6.3.2). They also offer a way of knowing about
89 how feasible and successful a project can be and understanding which characteristics should be
90 improved to achieve higher acceptability before it goes on the market, or prior to regulations being
91 established.

92 Discrete choice models of the type used here explain choices under the assumption that consumers
93 maximize the “utility” or benefit they receive by choosing a particular alternative. This utility is based
94 on the characteristics or attributes that define the alternative (Ortúzar & Willumsen, 2011, sec. 7.1), and
95 the sensitivities of the user towards them. In the particular context of our study, the characteristics
96 defining treated greywater in the hybrid water system are: (i) its different levels of colour and odour,
97 (ii) possible uses (e.g. toilet flushing) and (iii) the resulting savings in mains water. Our work seeks to
98 uncover different classes of respondents, with different sensitivities to the attributes, and to understand
99 why individuals belong to each class. We leave aside traditional economic theory (which would
100 consider a full cost-benefit approach), since, although the cost of technology is known to be highly
101 influential, the inclusion of cost would have dominated the scenarios and precluded our focus on

102 understanding other subjective elements that may influence individuals' acceptability of treated
103 greywater, and the heterogeneity in this across people.

104 The study context is Santiago, the capital city and largest conurbation in Chile (INE, 2017), a place with
105 seasonal water availability problems, and where its population has no previous experience about
106 greywater reuse (even the concept itself is largely unknown). Although mandatory water quality
107 standards are not established, the permitted uses for greywater are known to be garden irrigation and
108 toilet flushing (as prescribed in the law 21,075²). With this research we aim to provide evidence, with
109 statistical support, to show that regulations could allow other greywater uses considering the preferences
110 in different population segments. We also provide statistical evidence suggesting that it is possible to
111 preserve the balance between recovered water volumes and the amount of water used, while ensuring
112 that the system's operation provides the greatest benefits without compromising individuals' health.
113 Along with presenting empirical results for the specific case of Santiago de Chile, the paper provides a
114 demonstration of the method that can be replicated in other countries that need an empirical approach
115 to acquire knowledge about people's preferences in greywater reuse allocation, before including
116 greywater reuse schemes in their water and sanitation regulation.

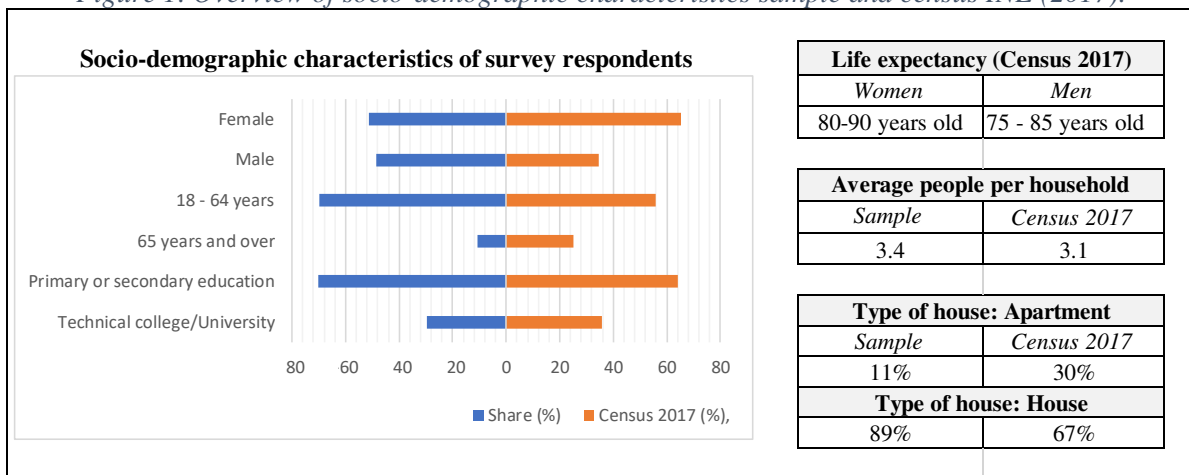
117 **2. DATA**

118 Data for our analysis come from a Stated Choice (SC) survey carried out in Santiago. The Metropolitan
119 Region, where Santiago is located, has water stress problems nowadays (with periods of one to four
120 weeks with very low flows, (Vicuña et al., 2018) and is predicted to become the area with highest deficit
121 in Chile by 2025 (Valdés-Pineda et al., 2014). Currently, residential water demand per capita varies
122 between 150 l/day and over 600 l/day depending on the irrigation of green areas (Bonelli et al., 2014),
123 while water losses due to pipe leaks in the mains water system are around 30% (Aguas Andinas, 2019).
124 Although the main water supply system has been strengthened over the years, it continues to be fragile
125 in the face of significant threats due to climate variability, climate change and population growth
126 (Vicuña et al., 2018).

² <https://www.bcn.cl/leychile/navegar?idNorma=1115066>

127 The survey was carried out *face to face* in 29 of the 37 municipalities of the city, and only household
 128 heads or their partners over 18 years of age were interviewed. The information was collected by a
 129 company with experience with this type of survey. Municipalities were selected from the city areas with
 130 drinking water and sanitation services provided by *Aguas Andinas*, the main water company. In each
 131 municipality, the survey was carried out in different non-neighbouring blocks and the households
 132 participating in the survey were randomly selected. A final sample of 510 individuals were retained for
 133 analysis, of which 65.3% were women, 55.9% were between 18 and 54 years of age, 64.1% had lower
 134 than secondary educational level, and 71.4% had no previous knowledge about greywater reuse. These
 135 characteristics partially replicate census data reported by (INE, 2018) as shown in Figure 1.

136 *Figure 1. Overview of socio-demographic characteristics sample and census INE (2017).*



137

138 2.1. Survey overview

139 Although allowed and regulated by Law 21,075, greywater reuse in Chile is not a common practice at
 140 present. Hence, the survey first presented individuals with a schematic representation to explain the
 141 concepts of greywater and sewage, and showed them how a greywater reuse technology system would
 142 work inside their homes. In the next sections, the survey collected answers/ratings related to individuals'
 143 reactions to the concept of greywater reuse, characterization of the household (e.g. age, gender), the
 144 dwelling (e.g. house size, presence of garden and coverage percentage, kind of coverage – grass or
 145 another kind of vegetation). The choice experiment and the development of the survey are described in
 146 Amaris et al., (2020), and supplementary materials in the present paper gives more detail about the

147 survey form. In what follows, we give an overview of the parts most relevant to this paper (i.e. personal
148 water reuse choices).

149 2.2. Choice context

150 Personal greywater reuse choices have been studied using hypothetical SC scenarios that were based
151 on real experiences in Spain (Domnech & Saurí, 2010), South Africa (Ilemobade et al., 2013) and the
152 USA (Wester et al., 2016). The aim of the SC component was to estimate the acceptability of reusing
153 treated greywater for different purposes inside the home, measuring respondents' sensitivities to
154 changes in the type of use and changes in water appearance and water bill savings.

155 Each respondent was shown six different choice scenarios (see Figure 2 for an example of choice
156 scenario), leading to a final sample of 3,060 observations. Each scenario had three alternatives for water
157 supply inside the home, from which the respondent had to choose only one. One of these alternatives
158 was to continue using the conventional water supply system (*status quo*), while the other two used a
159 hybrid water supply that allowed the reuse of greywater for a specific purpose and mains water for other
160 uses.

161 *Figure 2. Example choice scenario 1*

| CHOICES | | | |
|---|--|---|--|
| We will now show you different situations. You will compare the attributes of each alternative and select the alternative you prefer the most. Remember that the device would already be in your home and you would not pay for this. | | | |
| A1 | ALTERNATIVE A | ALTERNATIVE B | ALTERNATIVE C |
| Water supply system | REUSE TREATED GREYWATER FOR: GARDEN IRRIGATION | REUSE TREATED GREYWATER FOR: SHOWER | MAINS WATER FOR ALL USES |
| | Tap water for other uses | Tap water for other uses | |
| Attributes of water service: | | | |
| Colour caused by treatment | Transparent | Light Blue | Transparent |
| Odour caused by treatment | Strong chlorine odour | Odourless | Odourless |
| Monthly savings expected on the water bill | Saving \$ 3.00 | Saving \$ 8.00 | Saving \$ 0.00 |
| Select the alternative of your preference: | | | |
| | <input type="radio"/> I prefer alternative A | <input type="radio"/> I prefer alternative B | <input type="radio"/> I prefer alternative C |

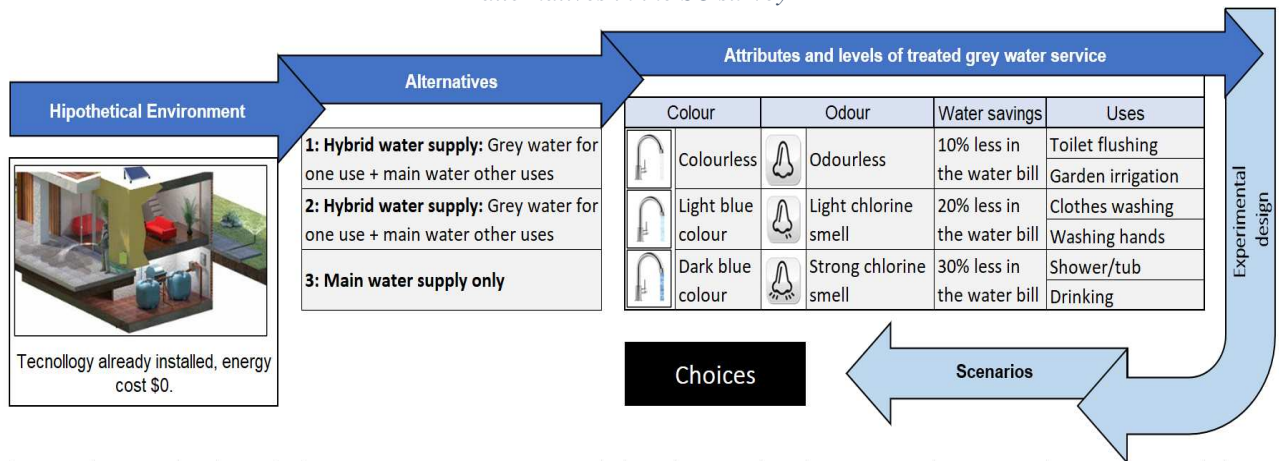
162

163 In the case of the hybrid system the individual had to assume that the greywater treatment device was
164 already installed, was as easy to use as a washing machine, and that there was no additional energy cost,

165 as a solar panel was also already installed. For the two reuse alternatives in the SC scenarios, the treated
 166 greywater in the hybrid system was described by four characteristics at different levels (Figure 3): (i)
 167 type of use, (ii) colour (iii) odour, and (iv) the percentage savings on the water bill (shown as the actual
 168 amount of money saved).

169 The values for each attribute in each scenario were determined on the basis of a D-efficient experimental
 170 design (cf. Rose & Bliemer, 2014). The type of greywater uses corresponded to the six most common
 171 uses within the house, which consider different levels of contact with the skin. Colour and odour (both
 172 with three levels) after treatment, could be caused by the type of treatment (e.g. water purification
 173 tablets), or could be introduced deliberately to indicate the contaminant removal success, or to
 174 distinguish treated water from that of the mains system (Domnech & Saurí, 2010). Water savings are
 175 the result of the lower use of mains water at home due to greywater reuse (Lambert & Lee, 2018; Chen,
 176 et al., 2017) . This attribute (also with three levels) differed across two reference groups in the choice
 177 scenarios: *group 1* with 290 households (T1) and *group 2* with 220 households (T2); these groups were
 178 associated with a monthly water consumption bill below and above US\$ 28.8, respectively.

179 *Figure 3. Attributes and levels of treated greywater in hybrid decentralized water supply system*
 180 *alternatives in the SC survey*



181 **3. MODEL FORMULATION AND SPECIFICATION**

182 We formulated and estimated a latent-class (LC) choice model to identify different segments in the
 183 population, each with its own preferences for reusing treated greywater in different uses inside the
 184 house. A LC model probabilistically segments the sample population into a number of segments with

185 different behaviour/preferences. In our application, each class was based on random utility theory,
 186 which postulates that individuals form a utility for each alternative, based on their perceptions about
 187 what characteristics describing a good or service are desirable or undesirable. Decision makers then
 188 choose the option that provides them with the highest utility. As the process of utility formation is not
 189 observed by the analyst, the models incorporate a random component and the choices become
 190 probabilistic (Train, 2009). In our LC model, the different classes are characterised by different
 191 sensitivities to the characteristics of the greywater system (Greene & Hensher, 2003). We now describe
 192 the two main components of the analysis, namely the model specification and estimation, and the post-
 193 estimation processing of the estimates.

194 **3.1. Model specification and estimation**

195 The LC model uses a probabilistic class allocation model, where respondent n belongs to class k (out
 196 of a total of K classes) with probability $\pi_{n,k}$, where $0 \leq \pi_{n,k} \leq 1 \forall k$ and $\sum_{k=1}^K \pi_{n,k} = 1, \forall k$. LC models
 197 are generally specified with an underlying multinomial logit (MNL) model inside each class, but can
 198 easily be adapted for more general underlying structures (Hess, 2014). Let $P_n(j_{n,t} | \beta_k)$ give the
 199 probability of respondent n choosing alternative j in task t , conditional on respondent n falling into class
 200 k , where the model in this class uses the vector of parameters β_k .

201 We observe a sequence of T_n choices for person n , say j_n^* , where alternative $j_{n,t}^*$ is chosen in choice
 202 situation t . With an underlying MNL model, we have that:

$$203 \quad P_n(j_{n,t}^* | \beta_k) = \frac{e^{V_{j_{n,t}^*}}}{\sum_{j=1}^J e^{V_{j_{n,t}}}} \quad (1)$$

204 where $V_{j_{n,t}}$ is the deterministic component of utility (i.e. the fraction of utility associated with attributes
 205 that the analyst can measure or observe) for person n , alternative j , in choice situation t , given by:

$$206 \quad V_{j_{n,t}} = f(x_{j_{n,t}}, z_n, \beta_k) \quad (2)$$

207 where $x_{j_{n,t}}$ are characteristics of alternative j in choice situation t , z_n are characteristics of individual n ,
 208 and β_k are parameters to be estimated. The functional form $f(x)$ is typically linear in attributes.

209 Equations (1) and (2) are conditional on respondent n falling into class k , but this is not observed by the
 210 analyst. The unconditional (on k) choice probability for this sequence of choices for respondent n ,
 211 $L_n(j_n^* | \Omega)$, is then given by:

$$212 \quad L_n(j_n^* | \Omega) = \sum_{k=1}^K \pi_{n,k} \left(\prod_{t=1}^{T_n} P_n(j_{n,t} | \beta_k) \right) \quad (3)$$

213 that is, the weighted sum across the K classes of the probabilities of the sequence of choices, with the
 214 class allocation probabilities being used as weights. The vector Ω groups together all parameters used
 215 in the model.

216 As seen in Equation (3), the LC model uses a weighted summation of class-specific choice probabilities.
 217 In the most basic version of an LC model, the class allocation probabilities are constant across
 218 respondents, such that $\pi_{n,k} = \pi_k, \forall n$. However, the real flexibility arises when the class allocation
 219 probabilities are not constant across respondents and a class allocation model is used to link these
 220 probabilities to characteristics of the respondents. Typically, these characteristics take the form of socio-
 221 demographic variables, such as income, age and employment status. With z_n representing the vector of
 222 characteristics for respondent n , and with the class allocation model taking a MNL form, the probability
 223 of respondent n falling into class k is given by:

$$224 \quad \pi_{n,k} = \frac{\left(e^{\delta_k + g(\gamma_k, z_n)} \right)}{\sum_{l=1}^K e^{\delta_l + g(\gamma_l, z_n)}} \quad (4)$$

225 where δ_k is a class-specific constant, γ_k is a vector of parameters to be estimated, and $g(\cdot)$ corresponds
 226 to the functional form of the utility function in the class allocation model.

227 Here, a major difference arises between class allocation models and choice models. In a choice model,
 228 the attributes vary across alternatives while the estimated coefficients (with a few exceptions) stay
 229 constant across alternatives. In a class allocation model, the attributes normally stay constant across
 230 classes while the parameters vary across classes, and are set to zero for one class for normalisation. This
 231 allows the model to allocate respondents to different classes depending on their socio-demographic
 232 characteristics. For example, a situation where high-income and low-income respondents are allocated
 233 to two classes could be represented with a positive income coefficient for the first class (with the

234 coefficient normalised to zero for the second class). In a LC model, taste heterogeneity is accommodated
235 as a mixture between a deterministic and a random approach.

236 A probabilistic model is used to allocate respondents to the different classes that characterise different
237 tastes in the sample. However, the class allocation in Equation (4) is not purely random, but a function
238 of socio-demographic characteristics of the respondents. In addition, it is also possible to incorporate
239 heterogeneity in preferences directly in the utility functions in Equation (3), for individual classes, rather
240 than in the class allocation model. In some cases, such as for example an income effect on cost
241 sensitivity, it also makes sense to keep these effects the same across classes.

242 The LC model was estimated using Apollo v 0.1.1 (Hess & Palma, 2019). The estimation of a discrete
243 choice model involves the maximisation of the likelihood of the observed choices, where we typically
244 work with the log-likelihood function, given by:

$$245 \quad LL(j_n^* | \Omega) = \sum_{n=1}^N \log (L_n (j_n^* | \Omega)) \quad (5)$$

246 where N is the number of individuals, $L_n (j_n^* | \Omega)$ is given by Equation (1), which itself uses Equations
247 (2) and (4). The log-likelihood function for a LC model is notoriously difficult to maximise, with a risk
248 of convergence to poor local optima. We address this issue by moving away from gradient based
249 approaches and using an expectation-maximisation process (Train, 2009, Chapter 14).

250 **3.2. Posterior analysis**

251 The estimation of a LC model provides parameters for the choice model used inside each class, in this
252 case always a MNL model. In addition, we obtain estimates for the parameters used in the class
253 allocation models. The utility parameters provide insights into the preferences and sensitivities within
254 each class, while the class allocation parameters explain the allocation of individuals to different classes.
255 The differences in parameters across classes give insights into the sample level patterns of
256 heterogeneity. Each individual belongs to each class up to a probability, where this probability varies
257 across individuals as a function of their characteristics. For example, in a model that retrieves two
258 classes characterised by differences in the sensitivity to cost, the class allocation model will likely show

259 that higher income individuals have a higher probability of belonging to the class with lower cost
 260 sensitivity. However, this treats two individuals who are identical on the socio-demographics used in
 261 Equation (4) as also having identical sensitivities, contrary to the notion of random heterogeneity. In
 262 addition, it does not provide information about how preferences may vary as a function of socio-
 263 demographic (or other) characteristics that were not included in Equation (4).

264 Further insights can be obtained, post estimation, in a Bayesian manner by calculating information
 265 relating to a given individual's sensitivities on the basis of the sample level model estimates and her
 266 observed choices. Let us return to the example with the classes used above. Two individuals with the
 267 same income may still make different choices in our data. Bayesian analysis then allows us to further
 268 disaggregate the class allocation of these individuals. If one of the two chooses more expensive options
 269 than the other on average, her likelihood of falling into the low cost sensitivity class is higher. On the
 270 other hand, if we have two individuals with different income but the same choice patterns, then the
 271 person with lower income will still have a lower probability of falling into the low cost sensitivity class.
 272 This is an illustrative example, just to explain the concept, which is now formalised using Bayesian
 273 analysis as follows.

274 The first step is to calculate posterior class allocation probabilities, where the posterior probability of
 275 individual n for class k is given by:

$$276 \quad \widehat{\pi}_{n,k} = \frac{\pi_{n,k} L_{n,k}(j_n^* | \Omega_k)}{L_n(j_n^* | \Omega)} \quad (6)$$

277 where $\pi_{n,k}$ and $L_n(j_n^* | \Omega)$ are given by Equations (4) and (3), respectively, and where $L_{n,k}(j_n^* | \Omega_k)$ is
 278 the likelihood of the observed choices for individual n , conditional on class k , that is, the term inside
 279 the sum across classes in Equation (3).

280 We then use the output of Equation (6) to produce a membership profile for each class. From the
 281 parameters in the class allocation probabilities, we know which class is more or less likely to capture
 282 individuals who possess a specific characteristic. Crucially, this can be done for characteristics not
 283 included in the model specification during estimation. Let us use the example of a given socio-

284 demographic characteristic z_c . We can then calculate the likely value for z_c for an individual in class k
 285 as:

$$286 \quad \widehat{z}_{c,k} = \frac{\sum_{n=1}^N \widehat{\pi}_{n,k} z_{c,n}}{\sum_{n=1}^N \widehat{\pi}_{n,k}} \quad (7)$$

287 where $z_{c,n}$ is the value for this characteristics for individual n . Thus, Equation (7) considers the weighted
 288 average of the value for characteristic z_c for all individuals in class k , using the posterior class
 289 allocations from Equation (6) as weights. Alternatively, we can also calculate the posterior probability
 290 of an individual in class k having a given value κ for z_c by using:

$$291 \quad P(\widehat{z}_{c,k} = \kappa) = \frac{\sum_{n=1}^N \widehat{\pi}_{n,k}(z_{c,n} == \kappa)}{\sum_{n=1}^N \widehat{\pi}_{n,k}}, \quad (8)$$

292 where $(z_{c,n} == \kappa)$ will be equal to 1 if and only if $z_{c,n}$ equals κ .

293 The calculation of these posterior values for characteristics in each class opens up the possibility of
 294 graphical analysis, using three dimensions, as we will demonstrate in Section 4.2.2. In particular, this
 295 allows us to study the relationship between the posterior class allocation probabilities (Z dimension)
 296 and two different socio-demographics (X and Y) at the same time. In the graphical analysis, the inverse
 297 distance weighting method (IDW) was implemented to interpolate the estimates of Z within the data
 298 range, which implies that the assigned weights will be bigger at the points closest to the prediction
 299 location and that these will decrease as a function of distance. The reason for this is that the IDW method
 300 assumes that closer points are more similar than those that are further away. To have a common
 301 reference system, the data used for the X and Y axes were standardized.

302 **3.3. Initial model specification considerations**

303 A number of decisions are needed prior to specify the models. These decisions relate to the levels used
 304 as reference for categorical variables, the inclusion of socio-demographic characteristics in the model,
 305 the existence of any generic parameters across classes, and the number of classes to use.

306 The survey used three alternatives, two of which were greywater reuse (GWR) options, and the third
 307 implied using mains water. We specified mains water as reference and, thus, a parameter for each of

308 the six types of greywater reuses could be estimated. In addition, we estimated a constant for the left-
309 most alternative, to capture any left-to-right (reading) bias in the data. The other categorical variables
310 were related to odour and colour; here we again used dummy coded coefficients, with the best level (i.e.
311 clear for colour, and odourless for odour) being the reference and fixing its parameter to zero for
312 identification.

313 In LC models, the socio-demographic parameters are typically used only in the class allocation model,
314 (i.e. to explain which types of individuals are more or less likely to fall into given classes). For extra
315 flexibility, we additionally incorporated some socio-demographic variables directly in the utility
316 functions. These variables related to differences in the preferences for different GWR uses as a function
317 of gender and past knowledge, and in the sensitivity to water bill savings as a function of the current
318 level of water expenditure in the household. These socio-demographics were kept generic (i.e., with the
319 same parameter) across classes. In addition, the sensitivity to the water bill savings was kept constant
320 across classes, as earlier results showed that segmenting by level of expenditure was sufficient to
321 capture the heterogeneity in cost sensitivity.

322 Within individual classes, we also tested for the significance of differences between parameters, and
323 imposed some constraints where appropriate; for example, if the preferences for two or more uses were
324 found not significantly different from each other. These constraints are highlighted in the presentation
325 of the results. Similarly, some parameters were excluded from specific classes if the associated
326 attributes did not have a significant impact on utility in those classes (marked in the tables as n.s., for
327 non-significant to distinguish from those parameters fixed to zero as reference). Finally, socio-
328 demographic characteristics were also incorporated in the MNL class allocation model. For
329 identification purposes, we set class 1 as reference and estimated an offset (δ_k in Equation (4)), as well
330 as socio-demographic effects (γ_k), for the other classes.

331 A key decision in specifying a LC model relates to the number of classes to use. We evaluated different
332 models to define the optimal number of classes (Table 1). The log-likelihood (LL) improves with
333 additional classes, but at the cost of additional parameters. In line with best practice for LC models, we
334 compared models on the basis of the Akaike Information Criterion (AIC) and Bayesian Information

335 Criterion (BIC). While the former favoured a 5-class model, the latter narrowly favoured a 3-class
 336 model. The 4-class model provided a good balance between the two, with additional behavioural
 337 insights over the 3-class model. Some further parameter constraints (i.e. removing insignificant
 338 parameters) in this model led to our final specification.

339

Table 1. Determining the number of classes

| Number of classes | LL | N° of parameters | AIC | BIC |
|---------------------------------|-----------|------------------|----------|----------|
| 1 | -3,129.02 | 18 | 6,294.04 | 6,370.25 |
| 2 | -2,398.48 | 31 | 4,858.96 | 4,990.23 |
| 3 | -2,319.93 | 45 | 4,729.85 | 4,920.40 |
| 4 | -2,282.31 | 58 | 4,680.63 | 4,926.22 |
| 5 | -2,262.79 | 69 | 4,663.58 | 4,955.75 |
| 4 (with additional Constraints) | -2,304.57 | 34 | 4,677.15 | 4,882.04 |

340

341 4. RESULTS AND DISCUSSION

342 4.1. Estimation results for final model

343 When working with LC models, an analyst needs to make a decision between an “exploratory” LC
 344 model and a “confirmatory” LC model (cf. Hess, 2014). While “confirmatory” LC is useful for testing
 345 for the presence of specific behavioural traits, “exploratory” LC lets the data “speak”, that is, the
 346 preferences in the classes as well as their composition are revealed by the data, rather than pre-imposed
 347 by the analyst. We use such an “exploratory” LC model, where the four classes can then be interpreted
 348 by studying the estimated sensitivities to different characteristics, including the type of use and the
 349 appearance of the treated greywater.

350 The results in Table 2 show the parameter estimates (which give the impact on utility by a given
 351 attribute) alongside the robust t-ratios (given by dividing estimates by their robust standard errors, with
 352 for example 1.96 implying a 95% significance level for rejecting the null hypothesis that the parameter
 353 is not different from 0 in a two-sided test). The parameters show the impact of the attribute on utility,
 354 with a negative sign implying a reduction in utility (i.e. an undesirable attribute), and the opposite
 355 applying for a positive estimate.

356

Table 2. Estimation results for latent class model

| | Class 1 | | Class 2 | | Class 3 | | Class 4 | |
|---|--------------------|----------------|---------------------|----------------|--------------------|----------------|---------------------|----------------|
| | Estimate | Robust t-ratio | Estimate | Robust t-ratio | Estimate | Robust t-ratio | Estimate | Robust t-ratio |
| (1) ALTERNATIVE SPECIFIC CONSTANT | | | | | | | | |
| <i>Left alternative</i> [†] | -0.367 | -6.39 | -0.367 | -6.39 | -0.367 | -6.39 | -0.367 | -6.39 |
| (2) GREY WATER APPEARANCE | | | | | | | | |
| Colour | | | | | | | | |
| ... Clear (reference) | 0 | reference | 0 | reference | 0 | reference | 0 | reference |
| ... Light blue | 0 | n.s. | 0 | n.s. | 0 | n.s. | -1.301 [‡] | -2.05 |
| ... Dark blue | -0.313 | -3.13 | 0 | n.s. | -0.619 | -5.09 | -1.301 [‡] | -2.05 |
| Odour | | | | | | | | |
| ... Odourless (reference) | 0 | reference | 0 | reference | 0 | reference | 0 | reference |
| ... Light chlorine | -0.169 | -1.45 | 0 | n.s. | -0.472 | -3.53 | 0 | n.s. |
| ... Strong chlorine | -0.816 | -6.48 | -11.057 | -21.08 | -1.032 | -6.4 | 0 | n.s. |
| (3) USES | | | | | | | | |
| 0. Mains water (reference) | 0 | reference | 0 | reference | 0 | reference | 0 | reference |
| 1. Toilet flushing | 3.963 [‡] | 6.74 | -4.959 [‡] | -9.79 | 0.303 [‡] | 2.14 | 5.957 [‡] | 2.1 |
| ... shift for female [†] | 0.728 | 4.26 | 0.728 | 4.26 | 0.728 | 4.26 | 0.728 | 4.26 |
| ... shift for previous knowledge [†] | 0.375 | 1.35 | 0.375 | 1.35 | 0.375 | 1.35 | 0.375 | 1.35 |
| 2. Garden irrigation | 3.963 [‡] | 6.74 | -4.959 [‡] | -9.79 | 0.303 [‡] | 2.14 | 5.957 [‡] | 2.1 |
| 3. Clothes washing | 3.963 [‡] | 6.74 | -4.959 [‡] | -9.79 | 0.303 [‡] | 2.14 | 0 | n.s. |
| ... shift for female [†] | 0.257 | 1.75 | 0.257 | 1.75 | 0.257 | 1.75 | 0.257 | 1.75 |
| ... shift for previous knowledge [†] | 0.448 | 2.22 | 0.448 | 2.22 | 0.448 | 2.22 | 0.448 | 2.22 |
| 4. Hands washing | 3.71 [‡] | 5.98 | -4.959 [‡] | -9.79 | 0 | n.s. | 0 | n.s. |
| ... shift for female [†] | 0.289 | 2.05 | 0.289 | 2.05 | 0.289 | 2.05 | 0.289 | 2.05 |
| 5. Shower/Tub | 3.71 [‡] | 5.98 | -15.29 [‡] | -18.02 | 0 | n.s. | 0 | n.s. |
| 6. Drinking | 2.397 | 3.88 | -15.29 [‡] | -18.02 | -0.82 | -3.33 | 0 | n.s. |
| ... shift for female [†] | 0.448 | 2.15 | 0.448 | 2.15 | 0.448 | 2.15 | 0.448 | 2.15 |
| (4) SAVINGS ON WATER BILL | | | | | | | | |
| Low water expenditure group [†] | 0.089 | 4.26 | 0.089 | 4.26 | 0.089 | 4.26 | 0.089 | 4.26 |
| High water expenditure group [†] | 0.039 | 3.39 | 0.039 | 3.39 | 0.039 | 3.39 | 0.039 | 3.39 |

| | Class 1 | | Class 2 | | Class 3 | | Class 4 | |
|-------------------------------|----------|----------------|----------|----------------|----------|----------------|----------|----------------|
| | Estimate | Robust t-ratio | Estimate | Robust t-ratio | Estimate | Robust t-ratio | Estimate | Robust t-ratio |
| CLASS ALLOCATION MODEL | | | | | | | | |
| Constant | 0 | reference | -1.574 | -3.7 | -0.595 | -2.41 | -8.091 | -5.52 |
| Low educational level | 0 | reference | 0.723 | 2.75 | 0.471 | 1.79 | -1.046 | -1.95 |
| Garden | 0 | reference | -0.824 | -2.49 | 0 | n.s. | 6.771 | 4.34 |
| House | 0 | reference | 1.402 | 2.98 | 0 | n.s. | 0 | n.s. |
| Class weight | 40% | | 24% | | 30% | | 6% | |

358 †: parameter shared across classes

359 ‡: parameter shared across multiple uses or multiple levels of categorical attribute

360 n.s.: parameter constrained to zero after initial estimate was not significantly different from zero

361

362 **4.1.1. Generic parameters**

363 Parameters indicated with the symbol † in Table 2 are generic across classes. They fall into three
364 categories. First, there is an alternative specific constant (ASC) for the left-most alternative, which
365 captures the difference in baseline utility between the two greywater reuse options. The negative value
366 shows that, all else being equal, respondents will choose the middle option (i.e. the second GWR

367 alternative) more often than the first. There is no apparent reason for this, as the survey design was
368 balanced. Second, there are a number of generic socio-demographic effects. These relate to differences
369 in sensitivities between men and women, and between those with and without prior knowledge. Women,
370 for example, have an additional increase in utility compared to men, if water reuse is for flushing toilets
371 (0.728), laundry (0.257), handwashing (0.289) and drinking (0.448). Previous knowledge only results
372 in an additional increase in utility if water reuse is for toilet flushing (0.375) and clothes washing
373 (0.448). Note that the impact of gender on the utility of reusing greywater for toilet flushing is much
374 larger than that of having prior knowledge, while the opposite is true for laundry.

375 The third and final generic set of parameters relate to the savings in the water bill. This is subject to
376 household water consumption, so the model contains two estimates, one for the low consumption group
377 and another for the high consumption group. Each time, the coefficient multiplies the actual saving
378 expressed in 1000s of Chilean pesos (CLP). The results show that the impact per 1000 CLP in savings
379 for the low water consumption group are more influential (0.089) than for the high water consumption
380 group (0.039). The influence exerted by the savings attribute is positive, which is an indication that this
381 attribute is key to achieving higher acceptability of reusing water for different uses.

382 *4.1.2. Class specific parameters*

383 We now look at those parameters which vary across the four classes, as well as giving a behavioural
384 interpretation to each class.

385 **Class 1 – Enthusiasts:** this class corresponds to individuals who have a positive perception of reusing
386 treated greywater for the six uses considered. Table 2 shows that toilet flushing, garden irrigation and
387 laundry are perceived the same in terms of benefits and are also the uses with greater utility. Reusing
388 greywater for washing hands or shower/tub has the same utility in this group, slightly lower than the
389 previous three uses, but still with a substantially higher utility than reusing treated water for drinking.
390 Regarding the impact of appearance on utility, increased colour (though not if only increasing to light
391 blue) and odour levels negatively influence acceptability, especially if the treated water has high levels
392 of odour (-0.816). In this class, the influence of appearance (colour and odour) on utility is small

393 compared to its influence in the other classes. Furthermore, for this group, the positive impact of using
394 treated greywater on utility is much higher than the negative utility resulting from changes in the
395 appearance that the use of treated greywater would produce.

396 **Class 2 – Greywater sceptics:** this class corresponds to individuals who have a negative perception of
397 greywater reuse, especially those uses that require more direct skin-to-water contact (shower/tub and
398 drinking). The size of the estimates shows that, in this class, the difference in utility between mains
399 water and greywater is much larger than in other classes, with a substantial loss of utility for greywater
400 options. This loss is further amplified if the water has a strong chlorine smell, while colour is not a
401 characteristic that influences the utility in this class.

402 **Class 3 – Appearance conscious:** this class corresponds to individuals who perceive positively
403 greywater reuse for toilet flushing, garden irrigation and laundry if the treated greywater is odourless
404 and clear/transparent. In this class, individuals are more sensitive to changes in the appearance of treated
405 water than to the uses themselves (comparing the weights of the appearance attributes with the weights
406 for uses). The three uses with a positive utility (compared to mains water) are those that require less
407 skin contact.

408 **Class 4 – Water expenditure conscious:** this class corresponds to individuals who have an increase in
409 utility when treated greywater is available for toilet flushing and garden irrigation. We label these as
410 expenditure conscious, as the preferred uses for these consumers are those with highest water
411 consumption (toilet flushing between 10 and 20 litres per flush, while a 100 m² garden area can use up
412 to 1000 litres, SISS, 2019). Additionally, in this class, changes in the colour level of water are highly
413 influential compared to individuals from other classes. However, the utility of using treated greywater
414 for toilet flushing and garden irrigation is much higher than the loss of utility associated with changes
415 of appearance.

416 ***4.1.3. Class allocation model***

417 The final part of the model estimates relates to the class allocation model (see Table 2). This component
418 explains which respondents are more likely to fall into specific classes. At the sample level, the

419 probability of belonging to Class 1 is 40%, of belonging to Class 2 is 24%, 30% for Class 3 and only
420 6% for Class 4. These sample level class allocation probabilities are driven in large parts by the offset
421 (δ_k in Equation (4)) included in the class allocation model, where with Class 1 taken as reference,
422 negative constants for the remaining classes are observed. These constants relate to an individual in the
423 base socio-demographic group (mid or high education, without a garden and living in a flat), where the
424 probability of belonging to Class 1 is the highest (and the lowest for Class 4). However, these
425 probabilities vary as a function of respondent characteristics. Note that having a lower level of education
426 increases the likelihood of belonging to the sceptic class (Class 2) or the class concerned about
427 greywater appearance (Class 3). Having a garden reduces the likelihood of falling into the sceptic class
428 (Class 2) and substantially increases the likelihood of falling into Class 4, which assigns high utility for
429 using greywater for garden irrigation (with Equation (4) implying a change in probability for class 4
430 from near zero to 14%). Thus, this finding is entirely in line with expectations. Finally, those living in
431 a house as opposed to a flat, have an increased likelihood of falling into Class 2.

432 **4.2. Posterior - analysis**

433 The discussion in Section 4.1.3 focussed on the sample level class allocation probabilities. This process
434 only requires the class allocation model, and thus implies that the class assignment probabilities are
435 identical for individuals with the same characteristics. We now go a step further, making use of the
436 approach in Section 3.2 to determine posterior class allocation, using the estimates of the sample level
437 model and the observed choices of each individual. Unlike the direct results from the class allocation
438 model, this posterior analysis makes use of respondent characteristics that were not included in the class
439 allocation model.

440 *4.2.1. Posterior values of socioeconomic characteristics across classes*

441 In Table 3 we compare the posterior share (cf. Section 3.2) of given sociodemographic characteristics
442 across classes. For each characteristic, the crucial comparison is against the sample average, showing
443 whether individuals with given characteristics are more likely to fall into specific classes. There is also

444 some insight to be gained by comparing the posterior across characteristics (e.g. male vs. female), but
 445 care needs to be taken if there are differences in the sample level representation.

446 *Table 3. Socio-demographic characterization into the classes*

| Socio-economic characteristic | Class 1 | Class 2 | Class 3 | Class 4 | Sample average |
|---|---------|---------|---------|---------|----------------|
| Gender | | | | | |
| ... Male | 0.37 | 0.32 | 0.34 | 0.34 | 0.35 |
| ... Female | 0.63 | 0.68 | 0.66 | 0.66 | 0.65 |
| Age | | | | | |
| ... Under 30 years old | 0.16 | 0.09 | 0.06 | 0.10 | 0.11 |
| ... Between 30 and 60 years old | 0.57 | 0.55 | 0.62 | 0.65 | 0.58 |
| ... Over 60 years old | 0.28 | 0.36 | 0.32 | 0.25 | 0.31 |
| Education level | | | | | |
| ... Elementary school | 0.18 | 0.22 | 0.10 | 0.10 | 0.16 |
| ... High school | 0.37 | 0.48 | 0.54 | 0.24 | 0.44 |
| ... Technical education | 0.17 | 0.13 | 0.14 | 0.21 | 0.15 |
| ... University studies | 0.23 | 0.11 | 0.14 | 0.42 | 0.18 |
| Main occupation | | | | | |
| ... Stay at home | 0.24 | 0.31 | 0.26 | 0.25 | 0.26 |
| ... Retired | 0.15 | 0.19 | 0.15 | 0.12 | 0.16 |
| ... Part-time | 0.05 | 0.04 | 0.06 | 0.12 | 0.05 |
| ... Full-time | 0.48 | 0.41 | 0.50 | 0.40 | 0.47 |
| Income | | | | | |
| ... Under 600 USD | 0.42 | 0.47 | 0.42 | 0.40 | 0.43 |
| ... Between 600 – 1,820 USD | 0.48 | 0.44 | 0.49 | 0.40 | 0.47 |
| ... Over 1,820 USD | 0.10 | 0.09 | 0.09 | 0.21 | 0.10 |
| Previous knowledge about water reuse | | | | | |
| ... None | 0.65 | 0.79 | 0.68 | 0.48 | 0.68 |
| ... Medium | 0.11 | 0.06 | 0.12 | 0.17 | 0.10 |
| ... High | 0.25 | 0.15 | 0.20 | 0.35 | 0.21 |

447
 448 **Gender.** Women have a larger overall representation in our sample. We see only small differences in
 449 the posterior allocation to the different classes. The highest female concentration is in Class 2 and the
 450 highest male concentration is in Class 1. This indicates a more negative view of GWR by women than
 451 by men, which is in agreement with results obtained in other studies (Amaris et al., 2021; Wester et al.,
 452 2015), which have been linked to the higher susceptibility of women to associate reuse with high levels
 453 of risks (Mankad & Tapsuwan, 2011). However, it is important to highlight that other studies have also
 454 found the opposite effect or no relation between gender and water reuse acceptability (Garcia-Cuerva
 455 et al., 2016; Mason et al., 2018).

456 **Age.** Individuals between 30 and 60 years old are predominant in the sample. Our posterior analysis
 457 shows that individuals under the age of 30 have a higher representation in the enthusiasts class (Class
 458 1) and a much reduced share in the class caring about appearance (Class 3). People between 30 and 60
 459 years old have a higher representation in classes 3 and 4, where reusing water is desirable if greywater

460 has a similar appearance to the mains water, or if more indirect uses are considered (i.e. toilet flushing
461 and garden irrigation). Individuals over the age of 60 have a higher representation in Class 2, where
462 reusing greywater for any option is undesirable, and a reduced share especially in Class 4.

463 **Education level.** Our sample had a majority of individuals with high school, followed by individuals
464 with university studies, technical education, and elementary school. Our results show that people with
465 higher educational levels are more likely to belong to classes that have a positive perception of reusing
466 water for two or more uses (classes 1, 3 and 4). People with elementary school only are most likely to
467 belong to Class 2 (water reuse sceptics), people with high school education have a greater frequency in
468 Class 3 (appearance matters), and people with technical or university education have a greater frequency
469 in Class 4 (greywater for indirect uses) and Class 1 (water reuse enthusiasts). In general, our results are
470 consistent with outcomes revealed Gu et al. (2015) who suggest that people with higher educational
471 levels are more willing to reuse greywater. However, our results also show detailed information
472 indicating that according to the educational group of the individual, the appearance and the uses could
473 have a greater or reduced level of importance.

474 **Main occupation.** The sample was composed mainly of individuals working full-time, followed by
475 people that stay at home, old age pensioners and, finally, individuals with a part-time job. Our results
476 indicate that individuals who are at home or retired have a higher concentration in Class 2, i.e. those
477 who would dislike reusing water, people with a part-time job have a greater presence in Class 4, while
478 this class is the least likely one for people with a full-time job.

479 **Income:** Households with the lowest monthly income (under 600 USD) have a higher frequency in
480 Class 2 (greywater reuse sceptics) than in any other class. Households with an intermediate monthly
481 income (between 600 USD and 1,820 USD) have their highest frequency in classes 1 (enthusiasts) and
482 3 (appearance conscious). Finally, households with highest income (over 1820 USD) are more prevalent
483 in Class 4 (water expenditure conscious), and this is likely correlated with having gardens and larger
484 properties.

485 **Previous knowledge about water reuse.** Most individuals in our sample had no previous knowledge
 486 about water reuse, as expected in a country only starting to allow residential greywater reuse. As
 487 anticipated, individuals without previous knowledge about water reuse have the highest presence in
 488 Class 2 (greywater sceptics). In contrast, people with high knowledge have a notable greater presence
 489 in Class 4 (most indirect uses) and Class 1 (enthusiasts); this has also been reported before (Garcia-
 490 Cuerva et al., 2016; Dolnicar et al., 2011). Likewise, individuals with medium knowledge have a similar
 491 incidence in the classes with a positive perception of reusing water for two or more uses (classes 1, 3
 492 and 4).

493 *4.2.2. Posterior values of household characteristics across classes*

494 Section 4.2.1 focussed on socio-demographic characteristics of the survey respondent. As it is quite
 495 conceivable that household and dwelling characteristics might also influence preferences, we extended
 496 the analysis to such variables, focusing on household composition, and two key dwelling influences on
 497 water consumption, namely the number of bathrooms and the presence of gardens. The results of this
 498 analysis are summarised in Table 4, using the same approach as in Section 4.2.1.

499 *Table 4. Household characterization into the classes*

| Socio-economic characteristic | Class 1 | Class 2 | Class 3 | Class 4 | Sample average |
|--|----------------|----------------|----------------|----------------|-----------------------|
| Presence of sensitive population | | | | | |
| ... Homes with kids under 15 | 0.41 | 0.43 | 0.41 | 0.39 | 0.41 |
| ... Homes with adults over 74 years old | 0.17 | 0.22 | 0.14 | 0.18 | 0.17 |
| Number of people living in the same place | | | | | |
| ... 1 to 2 | 0.28 | 0.29 | 0.35 | 0.24 | 0.30 |
| ... 3 to 5 | 0.61 | 0.60 | 0.53 | 0.64 | 0.59 |
| ... Over 5 | 0.11 | 0.11 | 0.12 | 0.12 | 0.11 |
| Number of bathrooms | | | | | |
| ... 1 to 2 | 0.65 | 0.62 | 0.71 | 0.47 | 0.65 |
| ... 3 to 5 | 0.35 | 0.38 | 0.28 | 0.49 | 0.34 |
| Garden | | | | | |
| ... Front garden (1) | 0.25 | 0.25 | 0.27 | 0.18 | 0.25 |
| ... Rear garden (2) | 0.09 | 0.06 | 0.10 | 0.01 | 0.08 |
| ... Front and rear garden (3) | 0.51 | 0.50 | 0.47 | 0.81 | 0.51 |
| ... None (4) | 0.15 | 0.19 | 0.17 | 0.00 | 0.16 |
| Type of garden | | | | | |
| ... Front garden with grass | 0.28 | 0.31 | 0.33 | 0.43 | 0.31 |
| ... Front garden with another type of vegetation | 0.59 | 0.65 | 0.55 | 0.85 | 0.61 |
| ... Rear garden with grass | 0.14 | 0.12 | 0.13 | 0.41 | 0.15 |
| ... Front garden with another type of vegetation | 0.39 | 0.36 | 0.32 | 0.52 | 0.37 |

500

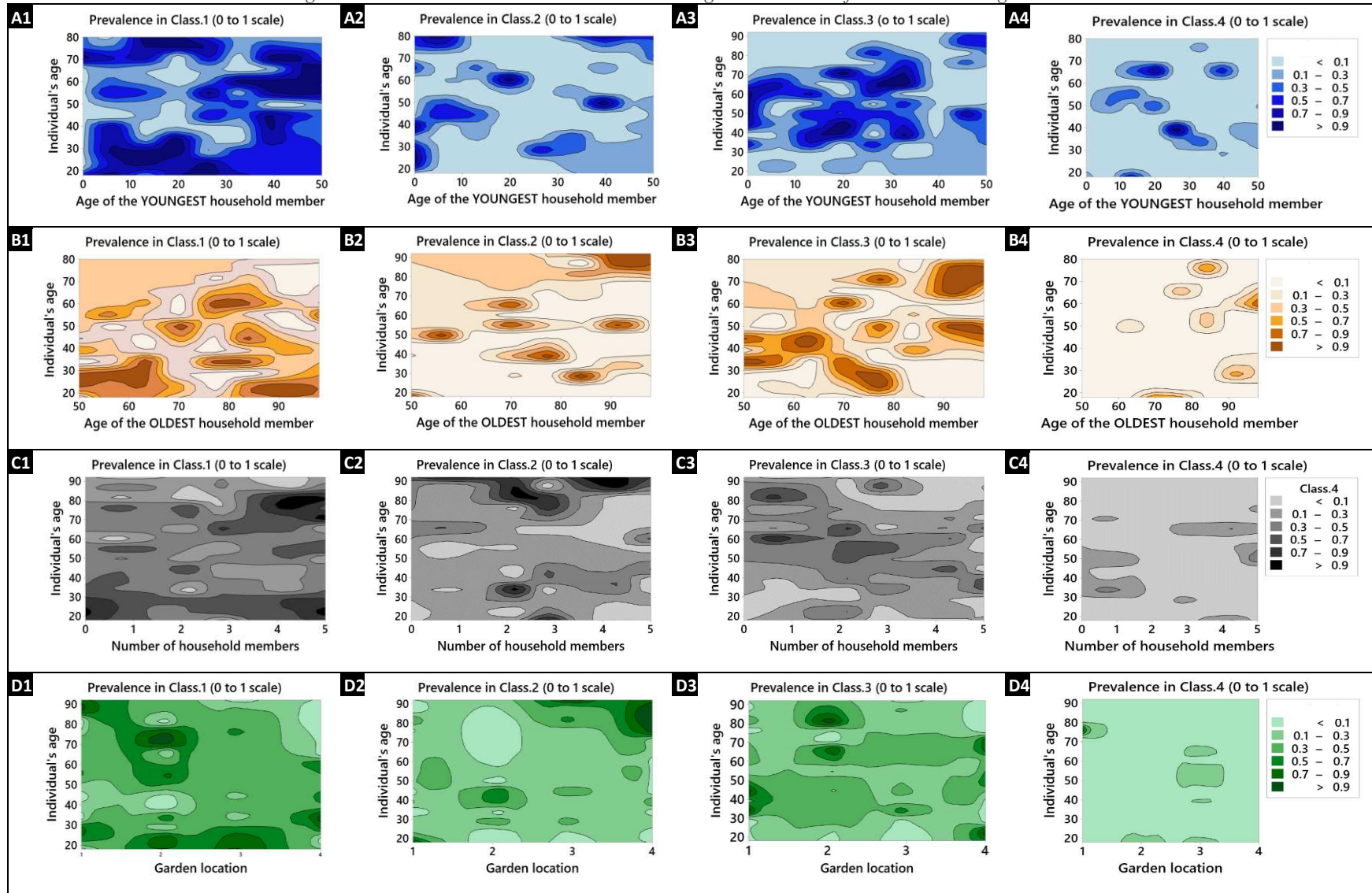
501 In addition, we produced contour diagrams (Figure 3), where we summarize the prevalence of
502 characteristics across classes for the three most influential features of the households: presence of
503 sensitive population (i.e. with people under the age of 15 and over the age of 74), household size, and
504 presence and location of gardens. The highest concentrations are shown in darker colours and
505 correspond to values higher than 0.5 on a 0 - 1 scale. We used three dimensions: (i) the characteristics
506 of the home on the X-axis, (ii) the age of the individual making the decision on the Y-axis, and (iii) the
507 latent classes 1, 2, 3 and 4 in the Z-axis.

508 ***Presence of a sensitive population:*** Respondents whose households include sensitive population were
509 more prevalent in Class 2 (0.43), i.e. the greywater sceptics (Table 4). A reason for this could be that
510 people in these age ranges are more susceptible to acquiring infections (Leng & Goldstein, 2010).
511 Additionally, the prevalence in each class was found to vary as a function of relative age. For example,
512 if the youngest family member is between 0 and 30 years old, then respondents between 20 and 35 have
513 a higher probability of belonging to Class 1 (greywater enthusiasts – Figure 4-A1). If the youngest
514 person among the household’s members is between 20 and 40, then individuals between 50 and 65 have
515 a higher probability of belonging to Class 1. We also found that if the oldest family member was
516 between 50 and 70 or over 85, then individuals between 25 and 30 had a high probability of belonging
517 to Class 1 (Figure 4-B1).

518 In the case of Class 2, individuals whose youngest family members were under the age of five had a
519 higher probability of belonging to this class. Moreover, the highest probability of belonging to this class
520 is for 60-year old individuals with the youngest family member being in their twenties. Concerning
521 people more likely to belong to Class 2, there are different sensitivities between the different age ranges
522 and the age of the household’s members. For example, younger individuals (20 - 35 years of age) are
523 more likely to belong to this class if the oldest family member is more than 80 years old. People in other
524 age ranges are likely to belong to this class if they have family members older than 65.

525

Figure 4. Posterior share in classes according to the most influential dwelling characteristics



528 The predominant individuals in Class 3 would be mainly: (i) people between 20 and 30 years old whose
529 family has one or more adults between 65 and 80 (Figure 4-A3); (ii) individuals between 30 and 45
530 years old with the youngest member of the family being between 15 and 20, and if there are adults over
531 50 years old among the household (Figure 4-B3); (iii) individuals between 45 and 60 years old living
532 with children under the age of 5.

533 Class 4 is dominated by three groups, namely: (i) individuals near to 20 years of age living with younger
534 family members (Figure 4- A4) or family members older than 65 years old (Figure 3- B4); (ii)
535 individuals of approximately 35 years of age, whose family members have similar ages (Figure 4- A4)
536 or family members older than 90 (Figure 4- B4); and (iii) individuals over 50 living in households with
537 one or more individuals aged around 20 years (Figure4-A4, or in the case that there are family members
538 over 70-year-old, Figure 4-B4).

539 **Household size:** Single-person household have a greater prevalence in Class 3, where the appearance
540 of greywater matters most. Households with 3 to 5 people have greater representation in Class 4, and
541 households with more than 5 people are homogeneously distributed across classes. Household size is a
542 characteristic that has been previously defined as relevant. For example Mason et al. (2018) found that
543 the likelihood of using greywater during dry seasons increases by 24% for each additional household
544 member. Nevertheless, our results complement that information with a more detailed analysis about
545 uses and types of consumers.

546 **Garden presence and its location:** Overall, households belonging to Class 4 have a higher incidence of
547 gardens, with a prevalence of mixed gardens with vegetation different from grass, mainly in their front
548 yards. Dwellings of respondents belonging to classes 1, 2 and 3 consistently have a small presence of
549 gardens with grass, and a higher presence of front yards with vegetation other than grass. Note that
550 these characteristics, which are associated with bigger dwellings (i.e. large number of bathrooms,
551 presence of gardens), and more household members, are associated with households who tend to have
552 a higher prevalence in class 4.

553

554 **5. CONCLUSIONS**

555 This study aimed to extend our understanding about heterogeneity in the acceptability of uses for treated
556 greywater and the factors that influence it, by focusing on the interaction of variables that rarely receive
557 attention. The most novel finding is associated with the possibility of quantifying the relationship
558 between the acceptability of reusing water, by use, and the characteristics of a consumer, their
559 household and their dwelling. Our approach offers numerical support for making predictions about how
560 different latent classes of individuals may behave when facing different reuse options.

561 In particular, the method implemented has been more commonly used in other disciplines such as
562 transport research, health and most recently in innovation appliances. The latent class approach we used
563 is valuable in showing that a pre-feasibility empirical analysis can be carried out to assess greywater
564 projects or initiatives in zones with no experience in reusing water. Likewise, these results are valuable
565 to demonstrate that uses other than flushing toilets and garden irrigation can also be accepted once the
566 potential users are aware of all possible uses of treated greywater.

567 This study considers the case of residents in future buildings that must adhere to new greywater
568 regulations, which establish that new buildings must have a parallel greywater system. However, future
569 studies should incorporate the cost of technology, operation and maintenance in order to include those
570 consumers that want to adopt these new systems in their existing dwellings. These studies can be based
571 on real-world pilot experiences carried out in areas with a high concentration of people, with
572 characteristics similar to those identified in our study as having the highest level of acceptability of
573 GWR. On the basis of that new evidence, policies can then be updated to produce management
574 strategies that can achieve greater user acceptability.

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584 LIST OF ACRONYMS

585 Acronyms:

586 AIC: Akaike Information Criterion
 587 ASC: alternative specific constant
 588 BIC: Bayesian Information Criterion
 589 CLP: Chilean pesos
 590 GWR: greywater reuse
 591 IDW: inverse distance weighting
 592 INE: National Statistics Institute (Instituto Nacional de Estadísticas)
 593 LC: latent class
 594 MNL: multinomial logit
 595 n.s.: not significant
 596 SC: stated choice
 597 T1: households with monthly water bills below US\$28.8
 598 T2: households with monthly water bills above US\$28.8
 599

600 Symbols in equations:

601 Vectors in data:

602 $x_{j,n,t}$: characteristics of alternative j in choice situation t for respondent n
 603 z_n : characteristics of respondent n
 604 j_n^* : sequence of observed choices for respondent n
 605 $j_{n,t}^*$: observed choice for respondent n in task t
 606

607 Probabilities and likelihoods:

608 $\pi_{n,k}$: class allocation probability for respondent n for class k
 609 $P_n(j_{n,t} | \beta_k)$: probability of respondent n choosing alternative j in task t , conditional on being in class k
 610 $L_n(j_n^* | \Omega)$: likelihood of observed sequence of choices for respondent n , conditional on vector of
 611 parameters Ω
 612 $LL(j_n^* | \Omega)$: log-likelihood of observed sequence of choices for respondent n , conditional on vector of
 613 parameters Ω
 614

615 Parameters and functional form:

616 β_k : vector of utility parameters in class k
 617 $V_{j,n,t}$: deterministic component of utility for person n , alternative j , in choice situation t
 618 $f(x)$: functional form for utility function in within-class model
 619 Ω : vector grouping together all parameters used in the model
 620 $g(\cdot)$: functional form of the utility function in the class allocation model
 621 δ_k : class-specific constant for class-allocation model
 622 γ_k : vector of parameters for class-allocation model utility for class k
 623

624 Indices:

625 j : index for alternatives ($j=1, \dots, J$)
 626 k : index for latent classes ($k=1, \dots, K$)

627 n : index for individuals ($n=1, \dots, N$)
628

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- 743

6. SUPPLEMENTARY MATERIALS

6.1. Survey

SECTION 1 - RESIDENTIAL WATER REUSE OPINION

Here are some questions to do about your opinion on the reuse of water in homes:

1 Before today, had you heard about residential water reuse?

| | | |
|-----|----|--------------------|
| Yes | No | → Skip to 3 |
| 1 | 2 | |

2 From what you had heard about water reuse, how much do you feel you previously knew about this subject? Use a scale from 1 to 5 to respond, with 1 being "little, I've only heard comments" and 5: "a lot, I found out information about it".

| | | | | |
|----------------------------------|---|---|---|---|
| Little, I've only heard comments | | | | A lot, I found out information about it |
| 1 | 2 | 3 | 4 | 5 |

3 Have you ever reused water?

| | | | |
|--|------------------------------|-------------------------|-----------------------------|
| Yes, I reused water, but not any more. | Yes, I currently reuse water | NO, but I would like to | NO, and I would NOT like to |
| 1 | 2 | 3 | 4 |

4 The following questions are related to the reuse of treated greywater inside the home, for that, we want to show you how this system works [SHOW CARD 3]. The water from washing machine, shower/bath and sink, "called grey water" goes through treatment, storage and finally can then be used in various applications. The best treatment conditions allow to obtain water of quality sufficient for several uses. What would you be willing to use your own treated greywater for after such treatment? You can select more than one option.

| | | | | | | |
|------|-------------------|-----------------|-----------------|---------------|--------------|----------|
| None | Garden irrigation | Toilet flushing | Clothes washing | Shower / bath | Hand washing | Drinking |
| 0 | 1 | 2 | 3 | 4 | 5 | 6 |


SECTION 2 - STATED PREFERENCES

To answer this section: Imagine that your home has this device to treat greywater with highest water quality standards, and the device is activated by pressing a button, and the cost of energy is 0.0 USD (Energy: Solar panel).














Other features:

- Saving of drinking water in the house.
- Good water quality at low maintenance costs (2 and 10 USD per month).
- **Limitations:** Depending on the treatment applied to greywater, colour and odour levels may vary as follows:

| | | | |
|---------------|---|---|---|
| Colour |  |  |  |
| | (1) Transparent | (2) Light blue | (3) Dark blue |
| | Odour |  |  |
| (1) Odourless | | (2) Soft chlorine odour | (3) Strong chlorine odour |

CHOICES

We will show you now, different situations. You will compare the attributes of each alternative and select the alternative you prefer the most. Remember that the device would already be in your home and you would not pay for this.

| A1 | ALTERNATIVE A | ALTERNATIVE B | ALTERNATIVE C |
|--|--|---|--|
| Water supply system | REUSE TREATED GREYWATER FOR:  GARDEN IRRIGATION Tap water for other uses | REUSE TREATED GREYWATER FOR:  SHOWER Tap water for other uses | TAP WATER FOR ALL USES |
| Attributes of water service: | | | |
| Colour caused by treatment |  Transparent |  Light Blue |  Transparent |
| Odour caused by treatment |  Strong chlorine odour |  Odourless |  Odourless |
| Monthly savings expected on the water bill |  Saving \$ 3.00 |  Saving \$ 8.00 |  Saving \$ 0.00 |

Select the alternative of your preference:

I prefer alternative A
 I prefer alternative B
 I prefer alternative C

748

SECTION 5 - HOUSEHOLDS AND DWELLING CHARACTERISTICS

Now I'll ask some general questions about household members.

10 Number of people living in the house:

11 How many of the people living in your household are under 18:

12 How many of the people living in your household are over 74:

13 How many of the people living in your household need special care:

14 Indicate the type of dwelling you live in:

House

Apartment

15 This property is

Owned/mortgaged

Rented

Informal settlement

Another condition

Do not know

16 Does your house have a private garden?

Yes No

17 The garden is ...

Front Rear Front and rear

749