Microplastic in the oceans: preferences and willingness to pay to tackle the issue in Australia

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Abstract

Microplastic is becoming a more and more tangible problem worldwide. Wildlife ingests tiny particles of plastic that may end up in human bodies via food chain. While literature still debates on the potential harm to humans, it is evident that microplastic is damaging the marine ecosystem. Policy makers have the duty to reduce, if not to eliminate, microplastic pollution on beaches and oceans. Many countries, including Australia, have moved first steps in this direction, however the challenge remains enormous.

Currently, there exists no market to reveal the preferences for reducing microplastic in the world's oceans, nor to determine whether people are willing to play a role in such a reduction. This research investigates the preferences for management policies tackling the issue of microplastic in the ocean off New South Wales (Australia) by means of a stated preference experiment. Findings suggest that residents of NSW would support policies that focus on microplastic pollution reduction and would be willing to contribute financially paying a levy.

Furthermore, the paper supports policy makers by providing information specific to different clusters within the population, identifying three segments with preferences spanning from "very caring of the marine environment" to "not caring at all of the marine environment".

Keywords: microplastic; willingness to pay; choice model; stated preference; ocean; microplastic pollution;

Highlights:

- There is little knowledge around preferences for reducing microplastic pollution
- Three quarters of the sample would approve policies pro-reduction of microplastic
- Residents of NSW are willing to pay a levy to reduce microplastic pollution
- Preferences can be clustered in three segments ranging from pro- to indifferent

1. Introduction:

The mass production of plastic has improved the quality of life for people around the world. The properties of plastics (e.g., lightweight, malleability, durability, cost) has made the transportation and storage of goods easier which has resulted in decreased costs and increased accessibility to wider populations (Macintosh et al., 2018). Whilst globalisation has boosted the demand, the lowering of costs has promoted less durable and higher turnover of products, with many products being used for only a single consumption occasion. Unfortunately, single-use plastic is the antithesis of what plastic was originally created for and represents one of the biggest threats for the marine environment (Xanthos and Walker, 2017).

Many studies have focused on the impact that single-use plastics have had on the marine environment, including plastic bags (e.g., Muthu et al., 2012; PlasticOceans, 2020), plastic straws (e.g., Wagner and Toews, 2018), plastic cups (e.g., Changwichan and Gheewala, 2020) and fishing equipment (e.g., Wilcox et al., 2016; Roman et al., 2020; DelBene et al., 2021). Microplastics (MP), considered to be plastic particles less than 5 mm in diameter, have attracted recent research attention, particularly with respect to their impact on the marine environment (e.g., Bravo Rebolledo et al., 2013; Critchell et al., 2019). Two types of microplastics have been identified as being of concern, these being primary and secondary microplastics. Primary microplastics are used mainly in personal care products including exfoliating scrubs and toothpastes (e.g., microbeads), but it also derives from microfibers shed from clothing and other textiles. Secondary microplastics are the result of a breakdown of larger plastic pieces. In particular, microbeads and microfibers, which are not captured by most wastewater treatment systems, often find their way into the ocean when washed down the drain after use or during washing cycles.

Woodall et al. (2014) argue that once in the ocean, microplastics are likely to sink and accumulate into the deep-sea sediment, with the current quantity of microplastics located in deep sea sediments likely to be up to four orders of magnitude greater than those located on the surface. Marine organisms of any size (from plankton to whales) that ingest microplastics, bio-accumulate chemical pollutants and suffer liver toxicity and pathology (Rochman et al., 2013). Although the investigation of adverse effects of microplastics on human health is still limited and the object of controversy (Barboza et al., 2018), the real threat posed by microplastics may extend to the whole eco-system, including to humans via the food chain.

This paper investigates the stated intentions of New South Wales residents to contribute to tackle the issue of microplastic in the ocean. To achieve this goal, we implemented a stated preference experiment that elicits preferences towards marine policies aimed at reducing the quantity of microplastics in the ocean and on the beach as well as the impact on marine and seabird populations. The inclusion of a household levy in the experiment allows the computation of household's willingness to pay (or contribute) to tackle this important issue. Data is analysed via a latent class model in order to better understand the preferences of different (latent) segments the population.

The contribution of the present study is twofold. First, the paper explores the willingness to pay of New South Wales residents to reduce the impact of microplastics on the marine environment on the Australian coast. Recently, this topic has gained increasing attention within the literature, with similar studies being undertaken in locations such as the European Arctic (Abate et al., 2020), South Korea (Choi and Lee, 2018), Norway, Germany and Portugal (Misund et al., 2020). Second, the paper seeks to support policy makers with information specific to different clusters within the population. The econometric model adopted allows the segmentation of the population based on the characteristics of the respondents, providing segment-specific preferences which can be used for the purposes of policy development and acceptance.

The remainder of this paper is structured as follows. Next section includes a brief description of the policy implemented by the Australian government to reduce the impact of microplastic on the marine environment. Section 3 presents the methods, including the stated preference experiment and an overview of the statistical approach employed to analyse the data. Results are presented in Section 4 and then discussed in Section 5.

2. Microplastic in Australia

By taking samples from the Great Australian Bight, the amount of microplastics located on the ocean floor has recently been estimated by Barrett et al. (2020) to be 14 million tonnes. Despite being such a large amount, microplastics are difficult to locate in the ocean by the naked eye, however, the general population is becoming increasingly more aware and educated with respect to the catastrophic effects on many organisms, including fish and birds that microplastics are having. To demonstrate the (invisible) impact of microplastic on the Australian aquatic environment, the Total Environment Centre launched the Australian Microplastic Assessment Project (AUSMAP) which allows community members to locate where microplastics have been found via a searchable and interactive map (https://www.ausmap.org/hotspot-map; see Figure 1). As suggested by this tool, microplastic pollution tends to accumulate in more densely populated areas, such as along Sydney coast.

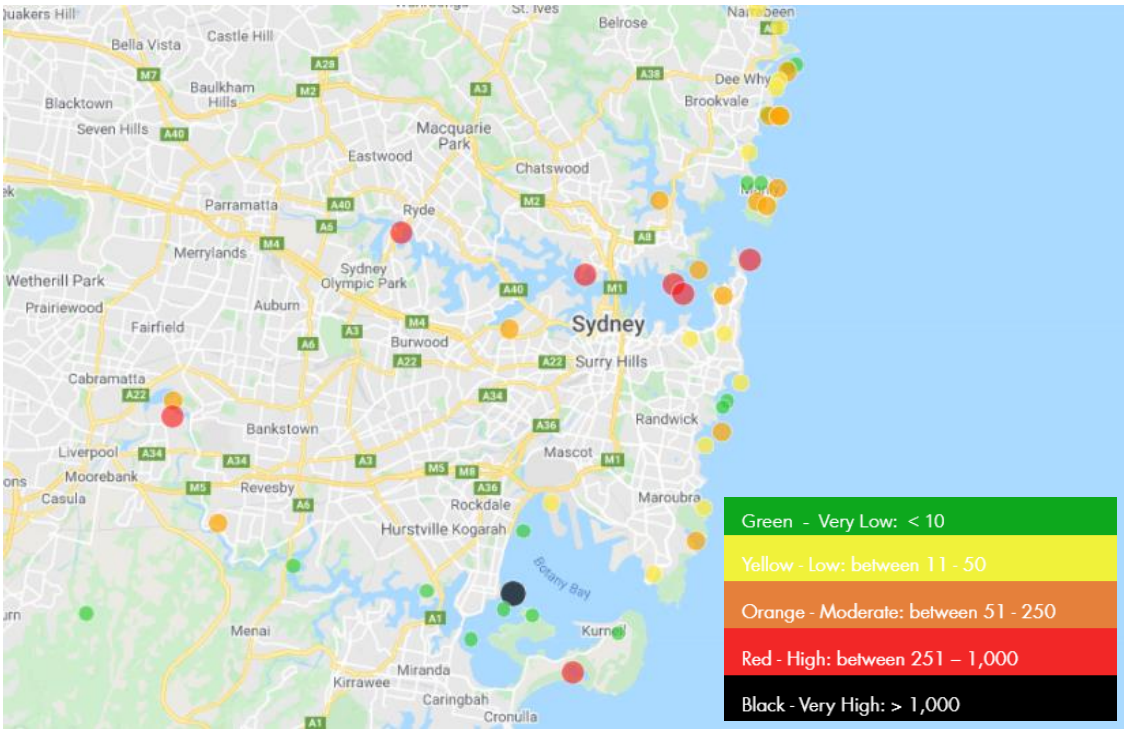

Figure 1: Average number of pieces of microplastic per m^2 along NSW coast. Source: AUSMAP – Total Environment Centre

To tackle the issue of microplastics, the Australian Government introduced a voluntary industry phase-out of plastic microbeads in 2016, led by Accord Australasia and overseen by the Commonwealth Department of Agriculture, Water and the Environment and the NSW Environment Protection Authority. This phase-out included all rinse-off personal care, cosmetic and cleaning products that can end up in the water system after use. The protocol did not however include wiped-off cosmetic products (e.g., make up and lipsticks) and plastic fibres from washing clothes, among other common products. Between November 2017 and February 2018, an independent assessment found that 94 percent of personal care and cleaning products did not contain microbeads or other non-soluble plastic polymers. In 2019, the National Waste Policy Action Plan included a target to phase out 100 percent of microbeads from rinse-off cosmetics and personal care products. An independent assessment confirmed that the target had been almost reached in 2020, with only 0.7 percent of products still containing microbeads. It is worth noting that these strategies focus only on rinse-off products and that microplastic derived from other products, such as wiped-off products, synthetic clothes fibre, plastic microbeads contained in industrial cleaning products used in closed systems, plastic microbeads in medicine, can still end up in the ocean, requiring new strategies and policies to be implemented.

3. Materials and Methods

3.1. The questionnaire

An online survey was administered to residents of NSW aged 18 years and over between the 19th February and 23rd March 2021 (the survey instrument is reported in Appendix). The questionnaire was structured into three main parts. After an introduction and screening questions for quota purposes, respondents were presented with four information screens describing what microplastics are, how much there are, their impact on wildlife and which NSW locations are mostly affected by the issue. This information was provided to increase respondents' awareness of what microplastics are and the issues surrounding their release into nature. The second part of the questionnaire presented respondents with a stated preference (SP) experiment designed to elicit their preferences for different management options related to the issue of microplastic in the ocean. The SP experiment included six tasks, each with three competing options (two hypothetical options plus a status quo alternative). The alternatives were each specified by means of six attributes describing the quantity of microplastics left on the beach and in the ocean (Beach, Ocean), its impact on the wildlife (Seabird, Fish, Marine life) and a monetary contribution for the management policy (Household levy). The attributes were adapted from research on this topic in the recent literature (e.g., Abate et al., 2020; Mackintosh, 2019). The full list of attributes and levels adopted in the design are reported in Table 1.

Table 1: attributes and levels of the SP experiment. Elements in italic represent the status quo values

Attribute	Level 1	Level 2	Level 3	Level 4	Level 5
Ocean: pieces per square km of ocean	2,500	3,000	3,500	*4,000*	4,500
Seabird: number of birds impacted	75%	80%	85%	*90%*	95%
Marine life: number of animal deaths per year	70,000	80,000	90,000	*100,000*	110,000
Fish: average number of microplastics digested per fish	1.5	2	2.5	*3*	3.5
Beach: average number of microplastics per sqm	95	115	135	*155*	175
Household levy: yearly amount for 10 years	*$0.00*	$30.00	$60.00	$90.00	$120.00

An example of choice scenario demonstrating the task respondents were asked to complete is shown in Figure 2. Thirty such tasks were constructed as part of the experiment, of which respondents were shown six. Rather than allocate the attribute levels randomly to the tasks, an experimental design was employed. The experimental design underlying such SP experiments play an important role in determining the final results of the study. Exactly how analysts distribute the levels of the design attributes over the course of an experiment, as determined by the underlying experimental design, has been shown to play a significant role in whether or not an independent assessment of each attributes contribution to the choices observed to have been made by sampled respondents can be determined. Further, the allocation of the attribute levels within the experimental design may also impact upon the statistical power of the experiment insofar as its ability to detect statistical relationships that may exist within the data. Given a set of attributes and attribute levels, the problem for the analyst is thus how best to allocate those levels over the course of the experiment. In the current study, a Bayesian D-optimal design was employed (see Rose and Bliemer, 2014). Uninformative Bayesian priors were used to indicate the expected direction of the parameter estimates, with the mean of each prior selected so as to give equal weighing to the overall contribution of the various attributes.

Suppose Options A, B and C were the ONLY management options available to deal with issues of microplastics in the ocean. Which would you realistically choose?

	Option A Maintain current situation	**Option B**	**Option C**
Microplastic Pieces per square km of ocean	4,000	3,500	3,500
Seabird population Number of birds impacted	90.00%	85.00%	85.00%
Marine life Number of animal deaths per year	100,000	110,000	100,000
Fish population Average number of microplastics digested per fish	3.00	2.50	2.50
Beach pollution Average number of microplastics per square meter	155	115	135
Household levy Household to pay this amount per year for next 10 years	$0.00	$60.00	$120.00

Option A	Option B	Option C
○	○	○

Figure 2: example of choice task

The final section of the survey collected socio-demographic characteristics of the respondents, including education, occupation, income and household structure.

3.2. Econometric analysis

At present, there exists no market to reveal the preferences for reducing microplastics in the world's oceans, nor to determine how much people are willing to pay for such a reduction. Thus, whilst Governments can implement policies specifically designed to reduce the amount of microplastics entering the ocean, there currently exists no mechanism to establish how citizens will react to such policies, or whether they support such policies in the first place. For this reason, we have implemented a multi-attribute stated preference experiment, which allows for the recovery of preferences within a population for currently non-existing technology or policy settings. The econometric analysis of such data is routed in the random utility interpretation of multinomial analysis of qualitative choices (McFadden, 1974).

The primary focus of such econometric analysis in this instance is to establish the preferences, as well as economic values, residents of NSW place on reducing not only microplastics within the ocean and on the beaches, but also on lessening the impacts microplastics have on wildlife dependent on the ocean. In the current paper, to obtain the values of interest, we use a latent class model (LCM) (see Kamakura and Russell, 1989 or Scarpa et al., 2003). The LCM model offers several advantages over other discrete choice models. First, the model is able to identify the presence of different latent preference segments within the sample, meaning that the analyst is not required to search for systematic sources of preference heterogeneity by specifying different interaction effects. Secondly, once latent preference classes have been identified, the model allows these to be linked to different socio-demographic characteristics in such a way that allows the analyst to understand, up to a probability, how diverse groups within a population have different preference structures.

Rather than estimate the number of latent preference segments or classes, the LCM requires that the analyst specifies the number of classes, *C*. Instead of deterministically assigning respondents to a class, the LCM model assumes that each decision maker belongs to each of the *C* classes up to a probability. The probability that respondent *n* belongs to class *c* is given by the familiar logit formula

$$P_{nc} = \frac{\exp\left(V_{nc}\right)}{\sum_{c \in C} \exp\left(V_{nc}\right)}, \tag{1}$$

where $V_{nc} = \sum_{l=1}^{L} \delta_{cl} z_{nl}$, represents the observed component of utility and δ_{cl} a parameter associated with covariate z_{nl}. For model identification, the parameters, δ_{cl} for one entire class are normalised to zero. The inclusion of covariates, z_{nl}, into the class assignment model allows the analyst to determine what characteristics of sub-segments within the population are more or less likely to belong to a particular latent class.

Next, conditional on belonging to a class, respondent *n* is assumed to derive utility for alternative *j* in choice task *s* equivalent to

$$V_{nsj|c} = \sum_{k=1}^{K} \beta_{k|c} x_{nsjk}, \tag{2}$$

where $\beta_{k|c}$ is a parameter to be estimated representing preferences for the k^{th} attribute used to describe the j^{th} alternative. The resulting conditional choice probability is given as

$$P_{nsj|c} = \frac{\exp\left(\sum_{k=1}^{K} \beta_{k|c} x_{nsjk}\right)}{\sum_{j=1}^{J} \exp\left(\sum_{k=1}^{K} \beta_{k|c} x_{nsjk}\right)}. \tag{3}$$

In the current study, each respondent was observed to make choices in six different choice tasks. Given these observed choices, y_{nsj}, the probability, conditional to belonging to class *c*, that respondent *n* is observed to make a sequence of choices of *s* choice scenarios is represented as

$$P^{*}_{n|c} = \prod_{s=1}^{S} \prod_{j=1}^{J} P_{nsj|c}^{y_{nsj}}. \tag{4}$$

Finally, maximum likelihood is used to estimate the model parameters, δ_{cl} and $\beta_{k|c}$. The log-likelihood function of the model is

$$LogL = \sum_{n=1}^{N} \ln\left(\sum_{c=1}^{C} P_{nc} P^{*}_{n|c} \right). \quad (5)$$

3.3. Sample

Data was collected during four weeks period spanning from the 19th February to the 23rd March 2021. Respondents were recruited using an online panel, Quality Online Research (QOR). Data, collected using an online questionnaire created in Qualtrics, was obtained from 1,580 residents of New South Wales, Australia. Data cleaning was undertaken such that respondents that took less than four minutes (median duration was 12 minutes) were excluded from the analysis. The final number of respondents in the sample after this data cleaning was 1,502.

The sampling strategy was based on interlocked quotas for gender and age, and residence (metropolitan versus regional) and is therefore representative of the NSW resident population in respect to these variables (Table 2). The median and average income reported by the sample is very similar to the population levels; however in terms of education distribution, the sample seems to be more educated, although the official statistic of the Australian Bureau of Statistics reports more than 10 percent of inadequately described records (versus. 0.4 percent in the sample).

Table 2: sample and population characteristics

		Sample	Population
Gender	*Male*	48.2%	48.6%
Age	*<34*	27.1%	27.6%
	35 – 49	26.9%	26.5%
	50 – 64	24.5%	24.4%
	65+	21.7%	21.6%
Residence	*Metropolitan*	62.1%	64.5%
Weekly income	*Median*	$900	$958
	Mean	$1,099.8	$1,199.5
Education	*School qualification*	32.5%	39.1%
	Certificate	13.4%	18.1%
	Diploma/Advanced Diploma	11.8%	8.9%
	Graduate Diploma/Graduate Certificate	4.6%	1.7%
	Bachelor degree	25.9%	16%
	Postgraduate degree	11.4%	5.7%
	Prefer not to say	0.4%	10.5%

4. Results

After testing different specifications, a model based on three classes displayed the best fit in terms of indices and provided the clearest behavioural insights[1]. This three-class specification has been extensively tested to identify linear and non-linear effects of the attributes on the individual choices. The final model includes linear effects for all six attributes. Figure A.1 in the Appendix reports a table that compares the goodness of fit indexes for 18 additional specifications that have been tested against the linear in parameters model.

[1] Models with two, three and four classes have been tested and compared by means of LRTs. The model presented in this paper (i.e., three classes) has a better fit in terms of adjusted R^2, AIC and BIC than the model with two classes (adjusted R^2 = 0.178 BIC = 16,410; LRT p-value = 0.000). The model with four classes presents slightly better fit indexes (adjusted R^2 = 0.204; BIC = 16,004) and is statistically superior (LRT p-value = 0.000); however, two classes present estimates not statistically different for four out of six attributes of the discrete choice model (i.e., Beach, Seabird, Ocean, Marine) in the specification with four latent classes.

Table 3 reports the parameter estimates for the discrete choice (top table) and the class assignment models (mid table). Parameters associated with Class 1 have the strongest influence on individual utilities for all the attributes, except that measuring the effect of household levy. Respondents aligned with Class 1 strongly favour the non- status quo management options over the status quo, prefer less microplastic on the beach and in the ocean, and clearly support animal welfare. Those belonging to the second class have preferences for that follow a similar pattern, however they have smaller marginal impact on individual utilities when compared to those who belong to Class 1. Class 3 includes respondents who are mostly indifferent towards the issue of microplastics. Indeed, the hypothetical management options are not preferred over the status quo, the presence of microplastics in the ocean and on the beach does not impact the preferences of this segment, whilst they only marginally care about the welfare of seabirds. Finally, they are highly influenced by the household levy, with the magnitude for this attribute being seven to nine times larger than for Classes 1 and 2 respectively.

The average willingness to pay (WTP) values per each class have been reported next to the parameter estimates. Note that for Class 3, the WTP is not different from zero for all the not significant attributes. All the WTP related to the attributes of the choice experiment are positive, suggesting that respondents would be willing to accept a levy of that value to decrease the level of the attribute by one unit. For instance, on average Class 1 displays a WTP of \$34.61 to reduce the amount of microplastic by 1,000 pieces per square km of ocean, and \$4.16 to decrease the number of birds impacted by 1 percent. For the same improvements, the average WTP for Class 2 are \$11.93 and \$0.80 respectively.

Table 3: Parameter estimates of the LCM. Significance: *** = 0.99; ** = 0.95; * = 0.90

	Class1		Class 2		Class 3	
	Par (rob. Std. err)	WTP	Par (rob. Std. err)	WTP	Par (rob. Std. err)	WTP
ASC_hyp1	4.180 (1.560)***	-\$ 485.48	0.833 (0.132)***	-\$ 73.07	0.279 (0.338)	\$ -
ASC_hyp2	4.030 (1.560)***	-\$ 468.06	0.339 (0.138)***	-\$ 29.74	0.027 (0.308)	\$ -
Ocean	-0.298 (0.040)***	\$ 34.61	-0.136 (0.045)***	\$ 11.93	-0.134 (0.098)	\$ -
Seabird	-0.036 (0.004)***	\$ 4.16	-0.009 (0.005)*	\$ 0.80	-0.013 (0.006)*	\$ 0.15
Marine (in ‘000)	-0.026 (0.003)***	\$ 3.01	-0.007 (0.004)**	\$ 0.62	0.005 (0.01)	\$ -
Fish	-0.280 (0.038)***	\$ 35.52	-0.073 (0.044)*	\$ 6.44	-0.131 (0.086)	\$ -
Beach	-0.006 (0.001)***	\$ 0.69	-0.004 (0.001)***	\$ 0.37	-0.003 (0.002)	\$ -
Household levy	-0.009 (0.002)***	-	-0.011 (0.001)***	-	-0.083 (0.011)***	-
	Class assignment model					
ASC for class			2.430 (0.520)***	4.673	1.010 (0.502)**	2.012
Age			-0.028 (0.005)***	-5.340		
Master degree	0.467 (0.280)*	1.668	0.467 (0.280)*	1.668		
Beach lover	0.872 (0.479)*	1.820				
Mountain lover	1.210 (0.493)***	2.454				
Lover of both	1.020 (0.475)**	2.147				
Solar panel	0.404 (0.152)***	2.658	0.404 (0.152)***	2.658		
Adults in the household			0.047 (0.026)*	1.824		
Income (in ‘000)					-0.019 (0.081)	-0.230
Visit 1 per month	0.345 (0.182)*	1.896				
Visit 1 per season					-0.863 (0.226)***	-3.819
Visit < 1 per season					-0.533 (0.186)***	-2.866
	Model fit					
LL(0)	-9,900.69					
LL(β)	-7,930.99					
ρ^2	0.1989					
Adj. ρ^2	0.1952					

AIC	15,935.98
BIC	16,132.61
Observations	1,502
Parameters	37

The LCM allows for insights on the composition of the various class segments. Respondents having very high education (i.e., master degree, master degree by research or a PhD) are more likely to belong to Classes 1 or 2, as are those who have solar panel installed at their place of residence. Self-reported nature (beach, mountain and both) lovers are more likely to have preferences aligned with Class 1, whilst younger respondents and those sharing a household with a larger number of adults are more likely to belong to Class 2. Those who report visiting a beach once per month are more likely to be belong to Class 1, whilst those who spend time at the beach only once per season or less are less likely to belong to Class 3. Whilst this last result might be somewhat unexpected, it is worth noting that that a lack of actual visitation does not reflect a desire to go to the beach. Indeed, these people may wish to go to the beach more often, but cannot due to different constraints they face (e.g., they may live far from the beach in rural areas, etc.).

The model employed assigns respondents to a class up to a probability. Table 4 provides summary statistics of the class assignment probabilities. Given the minimum probability for each class is non-zero, this means that even a respondent having all the sociodemographic characteristics in line with a specific class will display a non-null probability for the remaining two classes. For example, a (real) respondent who has a master degree, loves both the mountain and the beach, has solar panels installed on their dwelling and visits the beach once a month displays preferences in line with Class 1 for about 61 percent, with Class 2 for about 21 percent and with Class 3 for about 18 percent. On average, respondents have the highest probability of belonging to Class 2, and the lowest to Class 3, indicating that most of the sample believes that microplastics are an issue that should be managed by policy makers (Class 1 and Class 2 have strong preferences for alternative specific constants over status quo).

Table 4: Class assignment probabilities

	Class 1	Class 2	Class 3
Min	7.29%	15.75%	3.01%
Average	35.16%	41.39%	23.45%
Max	61.03%	89.44%	54.96%

In addition to understanding preferences, it is possible using Bayes theorem to compute individual specific parameter estimates (see Greene and Hensher, 2003), which in turn can then be used to derive individual willingness to pay (WTP) estimates for the different attributes of the choice experiment. The individual WTP estimates are given as

$$WTP_{nk} = \sum_{c=1}^{C} \left(\frac{P^{*}_{n|c} P_{nc}}{\sum_{c=1}^{C} P^{*}_{n|c} P_{nc}} \frac{\beta_{nsjk|c}}{\beta_{nsj,levy|c}} \right), \tag{4}$$

Which takes into account the class specific preferences for the different attributes $\beta_{nsjk|c}$ and the non-null class assignment probabilities.

The WTP distributions of the five attributes are reported in Figure 3. The different class preferences that emerged via the model estimation process are reflected in the tri-modal WTP distributions of all the attributes. On average, respondents are willing to pay $0.02 to decrease the quantity of microplastics in the ocean by one unit per square km and $0.41 to reduce the amount of microplastics on the beach by one unit per square metre. The large difference in WTP can be explained by the "out of sight, out of mind" construal level theory (Trope and Liberman, 2010; Barnes, 2019), according to which people tend to take a simplified view of phenomena as (psychological) distance from a situation or problem increases. The average WTP for animal welfare ranges from $1.30 to save 1,000 animal deaths per year and $1.83 to reduce the number of birds impacted by one percent, to $14.48 to reduce the average number of microplastics digested per fish by one piece.

To link the WTP values to the sample characteristics, the individual WTP distributions have been aggregated into four categories identified by the first quartile, the median and the third quartile. For each attribute, the resulting categorical WTP takes values Q1 if the continuous WTP value is below the first quartile of the distribution, Q2 if is between the first quartile and the median, Q3 if it is between the median and the third quartile and Q4 if it is greater than the third quartile. The attribute related to Marine Life has a fifth category labelled Negative, which includes all the negative WTP values. By means of a correspondence analysis, it is possible to plot the categorical WTP variables and the socio-demographic variables that played a significant role in the class assignment model. The result is a visual contingency table, which contains information of the multivariate frequency distribution, of individual demographics and values of willingness to pay. The plot reported in Figure 4 is bi-dimensional and explains 92.51 percent of variance. The first dimension seems to represent mostly household composition (number of adults and age define the two extremes), whilst the second is driven by the WTP values (the higher the value on Dimension 2, the lower the WTP).

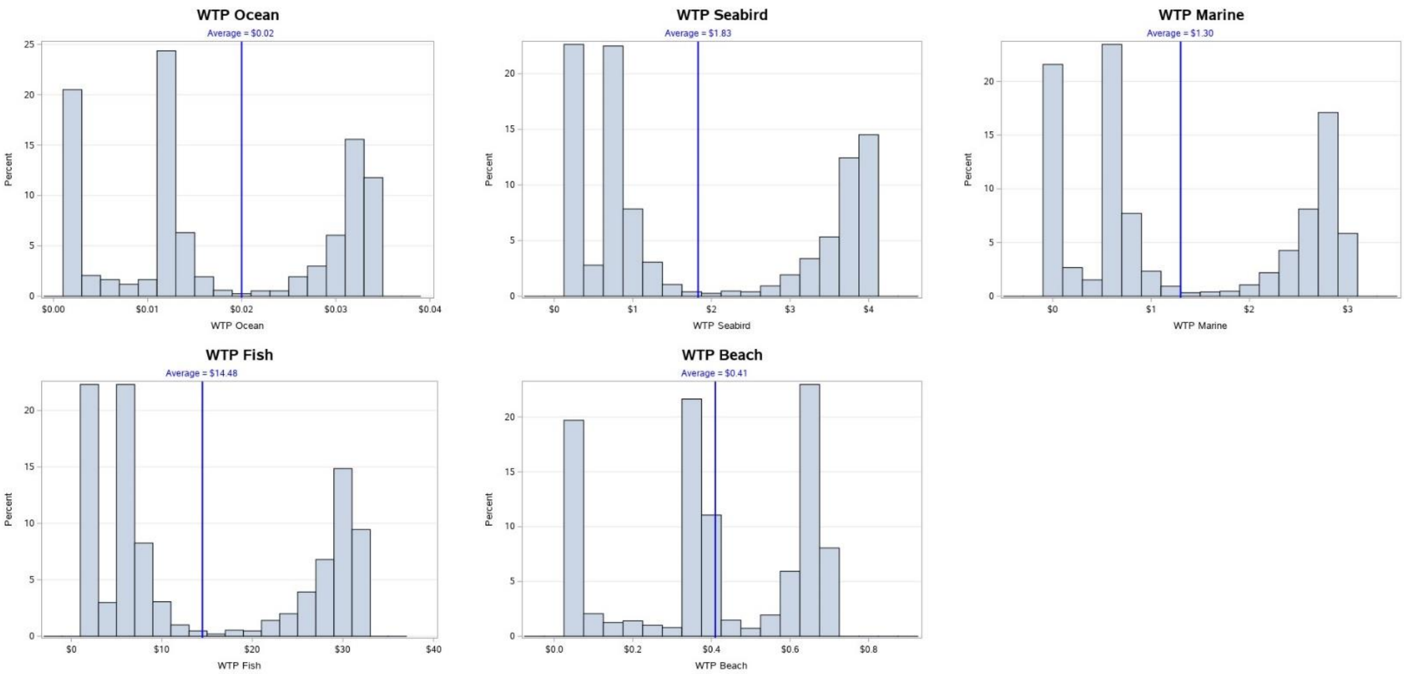

Figure 3: Individual WTP distributions for Ocean, Seabird, Marine (in '000), Fish and Beach

In the plot, the categories of the WTP for the different attributes cluster very closely. In the first quadrant (highest position with respect to Dimension 2), the categories Q1 and Negative are mapped close to the characteristics describing beach visitation (never visit and 1 visit per season), single adult household, no solar panel (installed on the property of residence) and no nature lover (although this characteristic is distant from Q1 cluster in absolute terms, it is still the smallest compared to the distance to other clusters). Cluster of Q2 values are displayed in the second quadrant, just above the origin of Dimension 2, while the cluster of Q3 values is in the third quadrant just below the same line. These clusters are surrounded by characteristics of a larger household (3 to 6 adults), a more frequent visitation to a beach (1 per week or 1 per fortnight) and the love for beach and beach and mountain. The final cluster of Q4 values is in the fourth quadrant and is characterised by love for Mountain, visitation to the beach once per month, an intermediate household dimension (2 adults), an older age (56+) and higher education (the distance to Master degree is the smallest compared to the other clusters).

5. Discussion and conclusion

This study investigates the preferences for management policies tackling the issue of microplastics in the ocean off New South Wales (Australia). Data is analysed by means of a latent class model, a model which recovers latent heterogeneity in population preferences. Evidence from the model suggests that the population can be clustered in three segments, whose preferences span from “very caring of the marine environment” to “not caring at all of the marine environment”. Overall, about 76 percent of respondents, on average, would support policies that reduce the impact of microplastics on the ocean (classes 1 and 2).

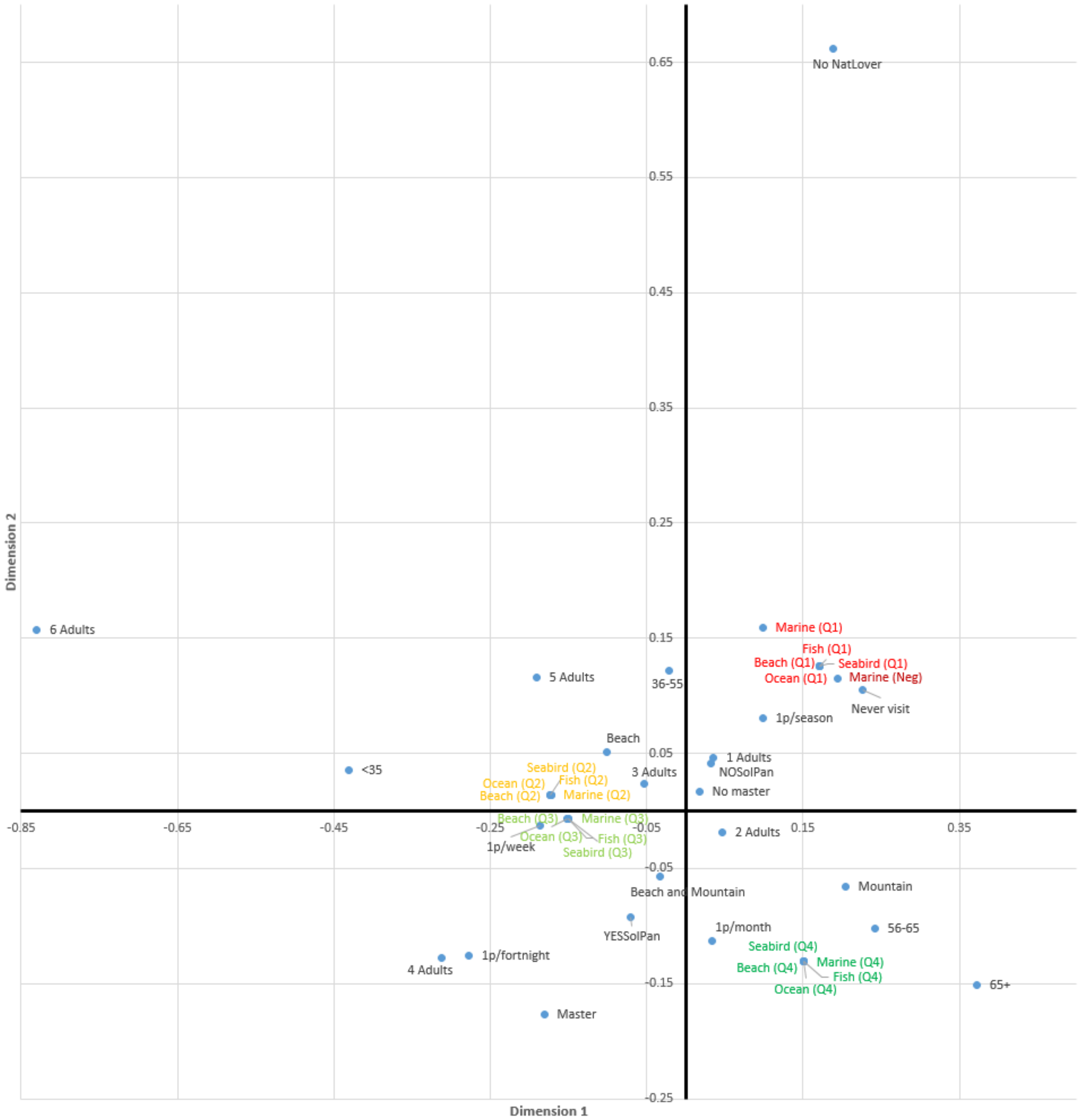

Figure 4: Correspondence analysis WTP/sociodemographic characteristics

At one end of the spectrum, more educated respondents, nature lovers (both beach and mountain), those who live in a dwelling with solar panel installed and those who visit the beach once a month, are more likely to prefer management options that improve the status quo of microplastics in the marine environment. Similar findings are common in the literature (see for instance, Abate et al., 2020; Perkins, 2010). The status quo is more likely to be preferred by those who self-report as not being nature lovers and by those who visit the beach often. Although this latter finding is unexpected, it finds confirmation in the study by Browuer et al. (2017), who found that the longer respondents visit a beach the less likely they are willing to pay for its clean-up. The authors suggest that the familiarity with the beach may be linked to the responsibility for its pollution (the more often someone visits it, the less likely it is that they feel responsible for it). The different preferences towards management options are reflected into heterogeneous intentions to economically contribute to the issue. Besides confirming what emerged in the class assignment model, the correspondence analysis suggests that age and WTP have a U-shaped relationship: the monetary contribution is higher for people under 35 years old or for those older than 55 years old. A similar link is reported in Abate et al. (2020) but contrasts with that found by Choi and Lee (2018).

The preferences obtained via the model can be translated into values of WTP to tackle the issue of microplastics in the marine environment. Consider the hypothetical management options described in Table 1 and presented to the respondents in the stated preference experiment (based on the design). For the non-price attributes, the fourth level represents the status quo value, whilst the levels one to three describe management options that improve upon the status quo. Under those scenarios, the average monetary support ranges from \$46.25 (outcomes all at level 3) to \$138.75 (outcomes all at level 1) per year for the next 10 years per household. This equates to \$141,506,453.75 (lower bound obtained at level 3) or \$424,519,361.25 (upper bound obtained at level 1) overall in New South Wales.

Comparing WTP values with other studies on the topic in the recent literature is unfortunately not straightforward. As a general finding, other studies report a positive willing to contribute financially to the issue of microplastics in the ocean, although substantially different from the amount reported in this research. Abate et al. (2020) estimated an average WTP of Au\$850 to support an initiative that drastically improve the current situation in Svalbard (e.g., from 100 g to 10 g of plastics per square metre of beach; from 90 percent to 10 percent of seabirds having ingesting plastics). Choi and Lee (2018) estimated an average WTP of Au\$3.33 under the scenario that South Korean government establish "some microplastic-related policies such as controlling the usage of microplastics in cosmetics and various daily objects" (p. 94). A more specific comparison is not doable for two reasons: first, the attributes used in the experiments are different (e.g., Abate et al. include "impacts on mammals") or are on a different scale (e.g., percentage of water samples that contain microplastics); second and most important, the method employed (i.e., contingent valuation) does not allow the researchers to compute the willingness to pay for each individual attribute but rather produces an overall measure for the intervention proposed. The LCM presented in this research offers measures of WTP for each attribute, and therefore allows for computation of financial contribution for any combination of attributes (i.e., any hypothetical scenario).

Marine wildlife currently is dealing with an increasing amount of plastics that are causing collateral damage to the entire ecosystem, potentially including humans via the food chain. The Australian government has implemented a voluntary industry phase-out of rinse-off products including microplastic and has been able to almost eliminate these products from the internal market. However, rinse-off products are only a fraction of the problem. Indeed, wiped-off products, synthetic clothes fibre, plastic microbeads contained in industrial cleaning products used in closed systems, plastic microbeads in medicine, and secondary microplastic, can still end up in the ocean and therefore more effort is required and needed. Whilst policies targeting the supply play a key role to reduce the amount of microplastic in the marine environment, it is fundamental to address the issue also by looking at the demand side. Pettipas et al. (2016) highlight the importance to focus on education and awareness of young generations, suggesting incorporating ocean education, pollution, and waste management into schools for instance. This policy could be very relevant to the Australian case: findings of this research suggest that young respondents are more likely to have mild pro-environmental preferences, but that education shapes personal preferences in this regard.

The literature on individuals' preferences towards policies aiming at reducing the quantity of microplastic in the marine environment is still very young, but has gained popularity in the past few years (see for example, Abate et al., 2020; Choi and Lee, 2018; Deng et al., 2020; Misund et al., 2020).

Understanding individual opinions and commitments is a useful starting point for policy makers, who should guarantee that more efforts and resources are invested in tackling this issue. This research suggests that residents of NSW would prefer and would be willing to contribute with a levy to the implementation of policies to reduce the amount of microplastic that ends up in the ocean.

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Appendix

Non-linear specifications

We have tested three transformations for each of the six attributes, for a total of 18 models. Figure A.1 reports the goodness of fit indexes for the non-linear models, which are compared to the model reported in the paper (LINEAR). The transformations applied to each attribute include quadratic, logarithmic and exponential effects. Note that when the base attribute level is very large (e.g., OCEAN ranges from 2,500 to 4,500; MARINE LIFE from 70,000 to 110,000; BEACH from 95 to 175; LEVY from 0 to 120), we have rescaled them by factors of 10, 100 or 1,000 to avoid computation issues associated with extremely large values (e.g., exp(4,500) is too large to be computed). Also, the attribute LEVY includes the value 0, therefore it was necessary to apply a different transformation for the logarithm (i.e., log(LEVY + 1)). Info on the rescaling factors are reported in the table in the first row of each model.

The non-linear in effect models have been compared with the base LINEAR model in terms of Adjusted ρ2 and BIC. From the extensive comparison, it emerges that none of the models outperforms the model with linear parameters, although some transformations lead to as good results as the base model (e.g., any transformation to MARINE LIFE leads to very similar indexes). Models that perform similar to the LINEAR model are highlighted in green in the Figure.

	LINEAR	OCEAN			SEABIRD		
TRANSFORMATION	**3 classes**	**Quadratic (/1,000)**	**Logarithmic**	**Exponential (/1,000)**	**Quadratic**	**Logarithmic**	**Exponential**
Final log likelihood:	−7930.988	−7965.675	−7965.947	7965.345	−7953.625	−7953.946	−7953.654
Rho-square for the init. model:	0.199	0.195	0.195	0.195	0.197	0.197	0.197
Rho-square-bar for the init. model:	0.195	0.192	0.192	0.192	0.193	0.193	0.193
Akaike Information Criterion:	15935.975	16005.349	16005.893	16004.689	15981.25	15981.891	15981.307
Bayesian Information Criterion:	16132.614	16201.988	16202.532	16201.328	16177.889	16178.53	16177.946
		MARINE LIFE			**FISH**		
TRANSFORMATION		**Quadratic (/1,000)**	**Logarithmic (/1,000)**	**Exponential (/100,000)**	**Quadratic**	**Logarithmic**	**Exponential**
Final log likelihood:		−7933.466	−7928.675	−7933.205	−7930.89	−7931.586	−7954.466
Rho-square for the init. model:		0.199	0.199	0.199	0.199	0.199	0.197
Rho-square-bar for the init. model:		0.195	0.195	0.195	0.195	0.195	0.193
Akaike Information Criterion:		15940.932	15931.35	15940.409	15935.779	15937.172	15982.933
Bayesian Information Criterion:		16137.571	16127.988	16137.048	16132.418	16133.81	16179.571
		BEACH			**LEVY**		
TRANSFORMATION		**Quadratic**	**Logarithmic**	**Exponential (/100)**	**Quadratic (/10)**	**Logarithmic (+1)**	**Exponential (/10)**
Final log likelihood:		−7952.583	−7932.63	−7929.629	−7930.195	−8055.203	−7988.487
Rho-square for the init. model:		0.197	0.199	0.199	0.199	0.186	0.193
Rho-square-bar for the init. model:		0.193	0.195	0.195	0.195	0.183	0.189
Akaike Information Criterion:		15979.166	15939.259	15933.258	15934.39	16184.406	16050.974
Bayesian Information Criterion:		16175.804	16135.898	16129.896	16131.029	16381.044	16247.613