Is it up to business, governments, or individuals to tackle the marine plastic problem? A Hybrid Mixed Logit Approach

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Abstract

Marine plastic pollution is one of the most talked about environmental issues of our time. While marine plastic pollution generally originates from mismanaged waste from land, waste from ships and fishing gear produce a unique threat to the global seas. Using a choice experiment, we explore preference for a marine debris removal and prevention programme focusing on derelict fishing gear. Additionally, we explore preferences for increasing removal efforts of debris in the North Western Hawaiian Islands. We find overwhelming support for these interventions; however, we find evidence that change, and therefore subsequent action, is strongest for individuals who believe that governments hold the majority of the responsibility for reducing and cleaning plastic pollution in marine environments.

Keywords:
derelict fishing gear, discrete choice experiment, hybrid choice model

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I. Introduction

Awareness of the harms of marine plastic pollution has gained recent traction. Plastic, despite only being around since the 1950s, has become ubiquitous in today's society. Marine plastic pollution was first documented in the 1970s (Barboza et al., 2019) and it is estimated that without improvements to waste management, marine plastic pollution will increase between 15- 40% by 2025 (Jambeck et al., 2015). Marine debris causes direct harm to marine mammals, fish, seabirds, invertebrates, plankton, etc through plastic entanglement, ingestion, or smothering, and causes general harm to environmental health (for impact on mamals, birds and reptiles see: Battisti et al., 2019; Eleonora et al., 2017; Staffieri et al., 2019, respectively). As a result, marine plastic pollution is affecting the ecosystem services of our oceans and is an ongoing major environmental crisis.

Plastic waste deposited in the environment is usually the cause of mismanaged landfills that are not properly contained, human behaviour (e.g. littering), or incidental pollution (Barnes, Galgani, Thompson, & Barlaz, 2009; Hammer, Kraak, & Parsons, 2012). Jambeck et al. (2015) estimated the amount of plastic pollution waste created by coastal populations across the planet. They classify that between 4.8 and 12.7 million metric tonnes of waste reached the oceans from land-based sources in 2010. However, ocean-based sources serve as another cause of plastic pollution. In an earlier estimate, Hammer et al. (2012) stated that 5.6 million tons of debris were generated from ocean-based sources, which they estimated to be 85% of the total marine debris input. Marine debris removal and prevention is key to mitigating ongoing and future harm from plastic waste, however the costs of these types of programmes can be daunting for policymakers without a direct understanding of the relative economic benefits. To address this, we administered an economic survey to establish willingness to pay values for a marine debris removal and prevention programme. This study is a first attempt to elicit willingness to pay, through a field choice experiment, to remove and prevent marine debris, focusing on ocean-based source inputs.

Ocean-based sources of marine debris range from public ships (e.g. ferries, cruise liners), research/government vessels (e.g. Navy ships), industries (e.g. oil platforms), and fishing vessels (Hammer et al., 2012). The largest contributor is likely to be from the latter, with 50-90% of all marine debris estimated to originate from fishing vessels (Hammer et al., 2012). Fishing gear is likely to end up as marine debris due to abandonment or loss, either of which can occur due to extreme weather, change in tides, damage, or the monetary or time cost of extraction. Our study will focus on fishing behaviours and incentive mechanisms that can be used to reduce the amount of fishing gear that is abandoned and increase the amount of lost fishing gear that is reported.

Furthermore, marine plastic has become more widespread in the public eye with television programmes like Blue Planet II presenting the problem unequivocally to viewers. Concern has therefore increased regarding local beaches as well as more remote marine environments. Whether thinking of the remote Arctic (Abate et al., 2020) or one's local beach (Leggett et al., 2018; NOAA, 2019) the marine plastic problem is ubiquitous, and these ecosystem services hold an economic value and are therefore affected by degradation due to marine debris. This study will focus on the North Western Hawaiian Islands (NWHI), an archipelago located North West of Kauai, which is particularly susceptible to marine debris pollution.

We administered a discrete choice experiment (DCE) which is an economic stated preference survey, that asks respondents to state their preferred alternative among two or more multi-attribute goods (see Hanley, Mourato, & Wright, 2002; Johnston et al., 2017). These surveys are commonly used in environmental, health and transport economics and are particularly useful for understanding preferences, and associated willingness to pay values, for policies which are not yet in place. They therefore provide an extremely useful tool for estimating preferences for future marine pollution control.

Our model explores the effect of latent attitudes towards the management of plastic pollution. Using information on who respondents indicate as being the most responsible for cleaning up and reducing plastic pollution (i.e. individuals, businesses or government) we look at respondents' preferences towards a new marine pollution reduction scheme using a hybrid mixed logit model. Hybrid mixed logit models are the most recent advancement in random utility theory that allow for researchers to delve into the role attitudes and behaviours have in the decision making process (Motoaki & Daziano, 2015). We further elicit willingness to pay values for implementing a Marine Debris removal and prevention programme focusing on derelict fishing gear and removal efforts of debris in the North Western Hawaiian Islands.[1] In Section II we discuss the literature on marine pollution as well as specific stated preference studies which have explored plastic consumption and/or reduction. Section III outlines the study design and is followed by the choice experiment methodology in Section IV. We present the results in Section V and Section VI concludes our study.

II. Literature Review

Marine plastic pollution affects the economy and ecology of the environment. Beaumont et al. (2019) examined the social and ecological impacts of marine plastic pollution. They highlight ecosystem services which are highly impressionable to plastic pollution: fisheries, aquaculture, heritage, and recreation. They estimated that between $3300 and $33,000 damages are caused per tonne of plastic. Vince and Hardesty (2016) discuss market-based approaches to deal with marine plastic debris. Policies designed to reduce plastic consumption by changing consumer behaviour are vital, as is, source-reduction and removing existing plastic pollution (e.g. Ocean Clean Up Project, cameras aboard ships to detect debris, rubbish traps at river mouths).

2.1 Discrete Choice Experiment Overview

Discrete choice experiments have been widely used to evaluate preferences and assign value to ecosystem services and environmental protection policies. They make use of Lancaster's (1966) theory that a good can be described in terms of its attributes and random utility theory (McFadden, 1974). Through these survey techniques, an intervention is described in terms of the (1) services it provides and/or (2) environmental outcomes. For example, Matthews et al. (2017) used a DCE to understand preferences for coastal erosion management by describing the management programme in terms of type of erosion protection (i.e. sea wall or dune), extent of headland development, and cost to households. Other DCEs describe a programme in terms of the ecosystem services it provides; for example, Roberts et al. (2017) describes a coral reef management programme in terms of underwater visibility, percentage coral cover and percentage fish decline. In DCEs respondents are repeatedly asked to select their preferred alternative between two or more interventions, and typically a 'do- nothing' or status quo alternative. DCEs typically include a payment vehicle such that researchers are able to look at how individuals make trade-offs between what is being offered with respect to how much they are being asked to pay. This allows for estimation of willingness to pay values for the different management characteristics (e.g. building a sea wall or improved underwater visibility) as well as welfare analysis to estimate willingness to pay for a holistic programme which includes a combination of attribute levels.

Discrete choice experiments are typically estimated in the simplest form with a multinomial logit model (MNL). These models, while informative, are unable to capture individual heterogeneity and

[1] This project was funded by SULSA Postdoctoral and Early Career Research Exchange in collaboration with ECONorthwest, Seattle.

therefore are often outperformed by more sophisticated models such as mixed logit model (MXL) or latent class models (LCM) which allow for parameter heterogeneity either continuously across individuals (in the case of MXL) or in discrete segments (for LCM).[2] Hybrid Mixed Logit Models (HMXL) are a sophisticated estimation technique that allows for heterogeneity of preferences across individuals but also allows for inclusion of phycological information (e.g. attitudinal data) which in and of itself tend to have measurement error. These 'soft variables' are only approximations of underlying latent variables and direct inclusion can lead to increased measurement error (Ben-Akiva et al., 2002; Faccioli et al., 2020). As such, we make use of a HMXL to include latent variables which help explain preference heterogeneity in our model.

2.2 Marine Pollution Literature

Very few stated preference surveys have been administered that look at consumer preferences for reducing marine plastic pollution. A stated preference survey was conducted in 2019 to quantify how changes to marine debris would impact recreational values to beach communities in four US states (Alabama, Delaware, Ohio and California). They estimated that reducing the amount of marine debris in these communities would increase recreation days between 2.2-9.5%, with a 35% increase in Ohio (NOAA, 2019). Abate et al. (2020) estimate Norwegian willingness to pay (WTP) to reduce marine plastic pollution in Svalbard using the contingent valuation approach. They estimated a WTP of $642 per year per household to reduce plastic pollution in this Arctic region. Concern over plastic pollution, preservation of the arctic, gender, age and education were all significant predictors of higher WTP values. A similar approach was taken by Smith, Zhang & Palmquist (1997) who estimated WTP to reduce debris on beaches as well as estuarine reserves. They set out to present scenarios that differ in terms of local conditions, coastal resources affected by debris, amount /character of debris and payment mechanism. Using images, they depict the current situation and the scenario under a control programme. Respondents were asked to select which option they preferred, making a trade-off between the improvement scenario and an associated monetary cost. They found respondents were willing to pay between $20-70 in increased taxes to reduce marine debris. Finally, Birdir et al. (2013) estimated WTP to improve beach quality (through reduced washed up litter and man-made debris) in Turkey. Using a beach access fee, they estimated between €1.77-2.33 WTP.

Other stated preference studies have evaluated consumers' willingness to pay to switch to more sustainable products. For example, stated preference studies have examined WTP for moving away from non-degradable shopping bags (Chan-Halbrendt, Fang, & Yang, 2009) and purchasing biodegradable containers over plastic (Barnes, Chan-Halbrendt, Zhang, & Abejon, 2011; Yue et al., 2010). To the best of our knowledge, no study has examined willingness to pay for specific programmes that would fund increasing marine debris clean-up, as well as reducing marine debris through incentive-based programmes. Moreover, no study has used a hybrid choice modelling framework of analysis to understand the effect of latent attitudes on individual's propensity to pay for programmes to reduce marine plastic pollution.

In addition, we examine the specific case study of the NWHI, one of the largest marine protected areas in the world (Pichel et al., 2007). It is estimated that over one third of floating plastic marine debris accumulates in the North Pacific gyres, just north of the Hawaiian Islands (Barboza et al., 2019). The NWHI lie in the centre of this current, and as a result collect extreme amounts of marine debris, mainly derelict fishing gear (Dameron, Parke, Albins, & Brainard, 2007). It was estimated in 2007 that 52 metric tons of debris accumulate in the NWHI annually. The marine plastic

[2] For more information on MXL and LCM see Greene & Hensher (2003).

accumulation in these island causes extreme harm to the endangered species and the shallow coral reefs of the area, but also cause damage and entanglement to passing vessels. While individuals are unable to visit these islands, the accumulation of debris and the degradation of the ecosystem services they provide are subject to non-use values, causing an economic loss estimated to be worth millions of dollars (Pichel et al., 2007).

III. Survey design and implementation

The survey was designed after extensive discussion with Marine Debris Division at the National Oceanic and Atmospheric Administration (NOAA). Employees in the Marine Debris Division were asked about (1) the biggest factor to marine pollution; (2) what their ideal prevention programme would entail; (3) the most effective means of cleaning up pollution; (4) financing options for prevention/removal; and (5) factors contributing to international cooperation. Evident from these conversations was that derelict nets are a predominant source of marine pollution and the largest impact would be to target derelict and ghost fishing gear. To do so we developed a proposed marine debris prevention and removal programme that focuses on (i) prevention of fishing gear being abandoned and (ii) removal of existing derelict fishing gear. Three attributes were included in programme the which are aimed at better understanding the extent of lost fishing gear, preventing waste, and funding removal projects. We will now describe each attribute in turn.

The first aspect of the initiative would be mandatory reporting of lost fishing gear. It is estimated that 50-90% of marine debris is derelict fishing gear (Hammer et al., 2012). Fishing gear is lost due to weather or collisions, where fishermen are forced to cut their gear free or abandon it. For removal efforts, much of this debris is never found due to the small percentage of lost gear that is reported and can therefore be tracked, collected, and disposed of properly. Reporting the time and location of lost gear would make it easier to track and remove. The revenue to fund this aspect of the marine debris programme would go towards enforcement actions and imposing fines on fishermen who fail to report lost gear, as well as creating a database where derelict gear can be documented and tracked.

The second aspect of the programme examined behavioural tools that can be used to prevent the abandonment of fishing gear. To do so we consider a derelict gear buyback programme. As such, fishermen will be paid for every pound of derelict fishing gear returned to specified ports for proper disposal. Through this buyback programme, we anticipate that fishermen will be incentivised to find, collect, and return to shore any derelict fishing gear they either lose or encounter while at sea.

The third attribute focused on increasing removal efforts. We specifically focused on the North Western Hawaiian Islands as a location where the stockpiling of marine debris has become increasingly detrimental. Currently, NOAA runs an organised removal effort every three years. During this time, a small team of scientists spend between 30 and 100 days removing and collecting marine debris from these islands. These trips are estimated to cost between $1.1-1.2 million. Dameron et al. (2007) calculated that 52 metric tons of debris accumulate in the NWHI per year. In 2019, the removal team collected 74 metric tons of waste, composed of mainly derelict fishing gear (NOAA, 2020). The removal efforts are therefore only capturing a fraction of the pollution accumulation. Our third attribute considers increasing these removal efforts from the current state (every three years) to either every, every other, or every two years. The attributes and their levels can be seen in Table 1.

Table 1- Attributes and levels

Variable name	Attribute	Levels
Reporting	Lost gear reporting	Mandatory reporting No mandatory reporting*
Buyback	Derelict fishing gear buyback	Buyback programme No buyback programme*
Clean up	North-western Hawaiian Islands clean-up	Every three years* Every other year Every year Twice a year
Cost	Yearly tax increase	\$150, \$200, \$250, \$300
ASC	Alternative Specific Constant	Option is the Status Quo* Option is a programme

Note: * denotes the level used in the status-quo alternative.

All attributes were included as dummy variables in the model, aside from the payment vehicle (Cost) which was included as a continuous variable. The status quo was described as the current scenario with no mandatory reporting, no buyback programme, and NWHI clean ups every three years.

The survey is composed of three sections. First, respondents received an explanation of the survey and the different attributes, followed by five choice tasks. Afterwards, respondents were asked several attitudinal questions about marine plastic pollution, behaviours towards reducing plastic consumption, followed by standard demographic questions. Given the four different attributes each with respective different levels there are 64 possible combinations (2^2 x 4^2). As it is unpractical to ask all possible combinations to each respondent, researchers tend to reduce the number of choice sets into efficient experimental designs, which aim to minimise the estimated standard errors (Walker et al., 2018). We used a D-efficient design, which are commonly used in the choice experiment literature (Johnson et al., 2013)[3]. The choice experimental design was done in Ngene (ChoiceMetrics, 2018).[4] The survey had three blocks, with each respondent receiving five choice questions. Each choice task consisted of three alternatives: two programmes and one status-quo. An example choice question can be seen in Figure 1. The survey was created in Sawtooth Software and SurveyMonkey. The survey was administered via a web-panel through SurveyMonkey Audience, specifying a desired completed sample size of 500 from the Western United States,

[3] For more information on the effects of different experimental designs, see Bliemer and Rose (2011).
[4] Ngene is statistical software that is able to generate sophisticated experimental designs (ChoiceMetrics, 2018).

targeted to be representative of the general population according to age and gender.

Figure 1- Example choice card

The survey was administered in September 2019 to a panel of residents in the United States "West Census Region" and a final 531 responses were gathered. Table 2 outlines the breakdown of our sample by age, gender, employment, education, and income levels.

Table 2- Summary statistics

Sample	# of observations
Age	
18-20	15
21-29	69
30-39	109
40-49	81
50-59	77
60+	180
Employment status	
Employed, full time	280
Employed part-time	60
Unemployed, searching	24
Unemployed, not searching	27
Retired	120
Disabled	20
Education level	
less than HS	5
HS	46

some college	127
Associate degree	45
Bachelor degree	150
Graduate degree	158
Household income	
<$10,000	23
10,000-24,999	41
25,000-49,999	74
50,000-74,999	86
75,000-99,999	60
100,000-124,999	61
125,000-149,999	37
150,000-174,999	28
145,000-199,999	13
200,000+	44
Prefer not to state	64
Female	268
Households with children under 18	110

According to the U.S. census bureau, the median household income in the Western United States was (in 2018) $69,605, median age of 38.2, an employment rate of 63.8%; 10.6% had a bachelor's degree or higher, and 18% had children under 18 in the home (“U.S. Census Bureau,” 2019). Our sample is therefore slightly older and more educated than the average Western USA resident. Figure 2 maps where our sample respondents live across the Western United States.

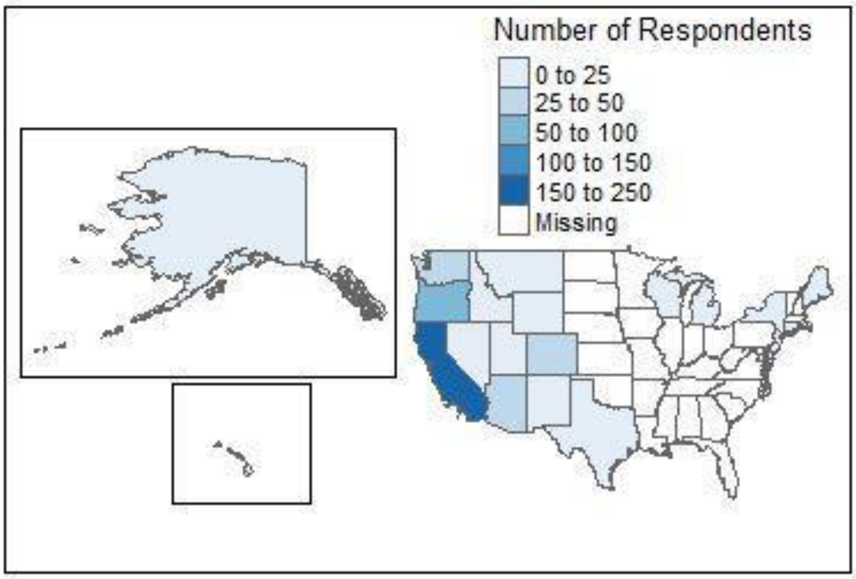

Figure 2- Map of sample residency across states

The majority of respondents lived in California (N = 209), Oregon (N = 73) or Washington (N = 45). Otherwise, only eight individuals lived in Hawaii and a handful individuals listed post codes from the East Coast. Respondents were asked several attitudinal questions used in the analysis, the responses of which are presented in Table 3.

Table 3 – Responses to a selection of attitude questions

Variable name	Question		# of individuals
Clean_up	In general, who do you think is responsible for cleaning up marine debris?	Governments	149
		Individuals	102
		Businesses	151
		I don't know	37
		Other	92
Reduce	In general, who do you think is most responsible for reducing the amount of waste that creates marine debris?	Governments	80
		Individuals	182
		Businesses	204
		I don't know	12
		Other	53

Note: Respondents who selected "I don't know" or "Other" were recoded into one category which was used as the baseline in estimation.

The majority of respondents (N = 421, 79%) had heard of the marine debris problem; however, many were unaware about NOAA's removal efforts regarding the NWHI (N = 446, 84%). When asked who respondents think is most responsible for cleaning up marine debris, the sample is split fairly evenly across government, individuals and businesses. When considering reducing the amount of plastic that creates marine debris, most respondents believed that businesses followed by individuals, then governments, are responsible. Regarding the severity of marine plastic pollution, the majority of respondents (64.7%) believe that it is a serious problem. Most individuals were concerned with plastic pollution in the environment (87%) and indicated they were taking steps to reduce their own plastic consumption (83%).

IV. Methodology and model specification

In order to test the effect of attitudinal statements in preferences, we use a hybrid mixed logit model (HMXL)[5]. In the hybrid choice modelling approach, unobservable respondent characteristics (i.e. environmental attitudes) are captured by one or more latent variables. The unobservable characteristics become observable through their association with attitudinal indicators and can be included directly into the choice model (Ben-Akiva et al., 2002). These types of models also have modelling advantages, as they avoid endogeneity and measurement bias issues associated with the inclusion of self-reported attitudinal indicators directly into the utility function (Czajkowski, et al. 2017; Daly, Hess, Patruni, Potoglou, & Rohr, 2012), and permit the accounting of the ordinal nature of Likert scale statements (Bahamonde-Birke et al., 2017). Please refer to Appendix A to see the detailed model specification.

The HMXL has recently been used in the environmental literature as a means of making use of stated attitudes and beliefs as well as stated choice data. For more details we refer readers to recent environmental applications including preference for peatlands in Scotland (Faccioli et al., 2020) and environmental quality in Latvia and Estonia (Boyce, Czajkowski, & Hanley, 2019).

Using the indicator attitude variables outlined in Table 3, we conducted a Principal Component Analysis (PCA) (Appendix B), a factor reduction method that is used to identify the number of latent variables to use. Variables Clean_up and Reduced are treated as three dummy

[5] In Appendix C, we provide the results from the simple MNL as well as the MXL model with all attributes, aside from cost, normally distributed with 1000 sobol draws (for more information on MXL models see Ortúzar & Willumsen, 2011; Train, 2009).

variables each, with the baseline level being 'I don't know/Other'; i.e. Clean up- government =1 if respondent indicated that government should be responsible for cleaning up, and 0 otherwise.

We found evidence of three latent attitudes. These latent variables can be categorised *ex post* as relating to who is responsible for marine plastic pollution mitigation: businesses, government, or individuals. As these variables do not vary across choices, they cannot enter the model directly, as such enter the model through influencing the status quo parameter (i.e. the parameter associated with the status quo variable which is equal to 1 if the option is the status quo alternative and 0 otherwise). The latent construct can therefore enter the model through the utility function for bundle *i*. Figure 3 shows how these attitude questions relate to the latent variables, and the economic preferences.

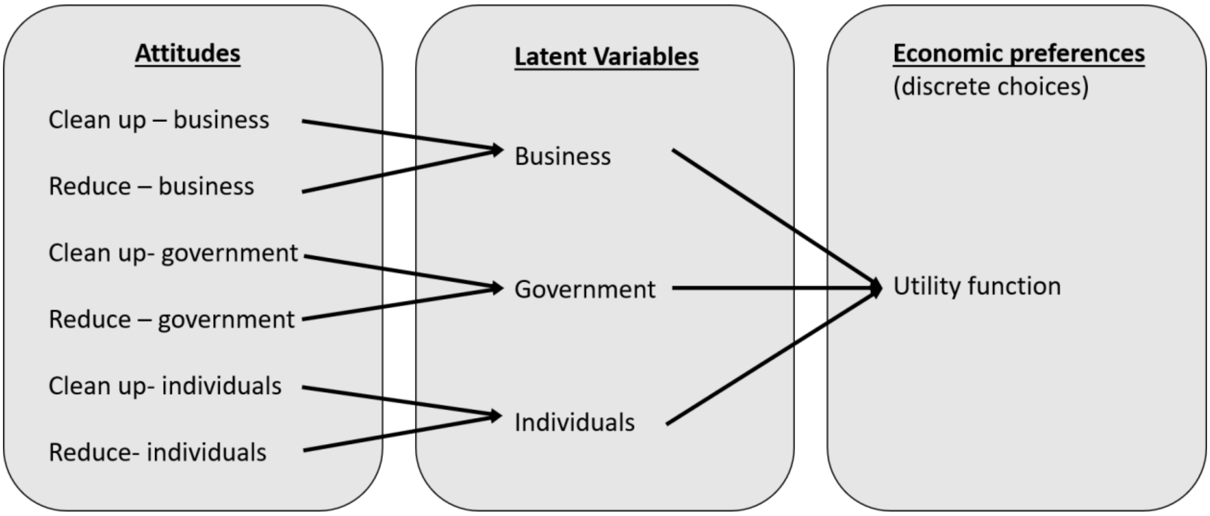

Figure 3- Hybrid Choice Model Structure

V. Results[6]

We estimate a HMXL with three latent variables (LV1-Business, LV2-Government, and LV3-Individuals). The top half of Table 4 represents the mean and standard deviation of the marginal utility estimates for each attribute, as well as the interaction between the alternative specific constant (ASC) which represents the status quo alternative, and the three latent variables. All DCE attributes were assumed to be normally distributed, except for cost, which is assumed to be fixed.[7]

[6] All results were estimated in R using the Apollo Choice Modelling package (Hess & Palma, 2019; Hess et al., 2019).

[7] We assumed cost to be fixed for ease of estimating willingness to pay estimates as convergence issues are common when all coefficients are specified as random (Revelt & Train, 1996). It is common for the cost to be assumes to be lognormally distributed; however, the long right tail of the lognormal distribution can also lead to unrealistic WTP estimates (Sillano & de Dios Ortúzar, 2005).

Table 4- Hybrid model results

	Means	Standard Deviation	Interaction with LV1-Business	Interaction with LV2-Government	Interaction with LV3-Individuals
	Estimate (st. err)	Estimate (st. err)	Estimate (st. err)	Estimate (st. err)	Estimate (st. err)
ASC	-3.68***	7.19***	0.003	-3.652***	-0.329
	(-0.59)	(-0.71)	(0.347)	(0.518)	(0.609)
Reporting	0.99***	-0.74***			
	(-0.10)	(-0.12)			
Buyback	1.14***	0.81***			
	(-0.10)	(-0.14)			
Clean up					
Every 2 years	0.81***	-0.33			
	(-0.19)	(-0.46)			
Every year	1.04***	-0.39			
	(-0.14)	(-0.28)			
Twice per year	1.26***	0.00			
	(-0.13)	(-0.27)			
Cost	-0.56***				
	(-0.10)				
Measurement components [a]					
			LV1-Business	LV2-Government	LV3 - Individuals
Businesses are responsible for:					
	Cleaning up plastic		0.265***		
			(0.067)		
	Reducing the amount of waste		0.320***		
			(0.081)		
Government is responsible for:					
	Cleaning up plastic			0.304***	
				(0.054)	
	Reducing the amount of waste			0.118***	
				(0.025)	
Individuals are responsible for:					
	Cleaning up plastic				0.240***
					(0.059)
	Reducing the amount of waste				0.326***
					(0.077)
LL	-1988.409				
BIC	7674.45				

Note: *p-value <0.10, ** p-value<0.05, *** p-value <0.01

[a] The remaining parameters from the measurement equations (parameters of the indicator variables) are not reported here for brevity. They are reported in Appendix D.

Based on the Choice Model Log Likelihood of the HMXL (LL = -1988.41) and the comparable Log Likelihood of its reduced form (i.e. MXL model in Appendix C) (LL = -1988.22) we can conclude the two models are marginally similar. However, the hybrid approach allows us to better understand preference heterogeneity through the use of the latent constructs.

The negative ASC marginal utility suggests that there is a preference for programme bundles over the current status quo. All attribute estimates have the expected sign (i.e. positive for non-monetary attributes and negative for the monetary attribute) and are significant. The largest marginal utility is derived from increasing the NWHI clean ups from once every three years to twice yearly ($\hat{\beta}$ = 1.26) and introducing the buyback programme ($\hat{\beta}$ = 1.13).

The negative and significant cost coefficient suggests that respondents prefer cheaper management options when all other attributes remain constant. The NWHI Clean Up attribute was included as three dummy variables in the model for whether the programme introduced additional clean up missions every other year, every year, or twice a year (the base level being the current situation where clean up happens every three years). The coefficients indicate positive and increasing marginal utility increments for more frequent NWHI clean up missions relative to the current situation of expeditions every three years.

The only significant interaction between the ASC and the latent variables is with LV2-Government. This suggests that on average, there is a marginal disutility for the ASC of 3.6 and that respondents whose attitudes reflect a stronger emphasis on the responsibility of government have a significant preference to pay for developing the programme to reduce marine plastic pollution. Respondents who believe Businesses (LV1-Business) or Individuals (LV3-Individuals) are more accountable for plastic mitigation are not significantly more averse to the status quo than the average.

The bottom half of Table 4 outlines how our unobservable latent variables are linked with the responses to the attitude questions outlined in Table 3. All our attitude statements significantly and positively relate to the three latent variables, meaning that respondents with higher levels of the latent variables are more likely to agree with the statements. LV1-Business thus represents a strong feeling the businesses are responsible for cleaning and reducing plastic waste, while LV2-Government suggests that it is government's responsibility. LV3-Individuals reflects a high level of individual motivation for plastic mitigation.

Table 5 – Marginal Willingness to Pay

Attribute	Mean	C.I. low	C.I. high
Reporting	182.981	134.569	263.462
Buyback	209.702	156.23	300.418
Clean up every 2 years	149.077	77.36	250.761
Clean up every year	189.666	144.045	260.615
Clean up twice per year	230.875	165.953	338.143

Using the estimates from Table 4 we can calculate the willingness to pay values for the various attributes, which are shown in Table 5.[8] Households are willing to pay the most for clean up to the NWHI to increase to twice yearly ($231/year), followed by the introduction of a buyback programme ($209/year). Increasing the number of clean up expeditions to every two years, already yields a willingness to pay per household of $149 per year. This suggests strong support for programmes to reduce visible marine litter as well as clean-up efforts targeting distant nature preserves. Additionally, these willingness to pay values for additional NWHI clean ups greatly exceed the potential costs of doing so. Allocated evenly across the 18.2 million households in Hawaii, California, Oregon, and Washington, twice yearly clean ups would cost each household approximately 17.5 cents per year (compared to a WTP of $231 per year), while a clean up

[8] WTP estimates and confidence intervals were estimated using the Delta method (Greene, 2002).

expedition every two years would cost each household approximately 4.4 cents per year (compared to a WTP of $149 per year). This indicates, that from a policy perspective, marine debris removal efforts convey substantial value on residents.

VI. Conclusion

This paper outlines analysis on a choice experiment regarding initiatives to prevent and remove derelict fishing gear from the Pacific Ocean. Marine plastic pollution is an increasing problem; as such policies are needed that not only prevent the amount of waste that becomes marine pollution, but also extensively remove marine pollution. Furthermore, campaigns addressed at reducing community's consumption of plastic, illegal dumping, and improving social consciousness can have a significant impact in the marine debris problem.

This study uses data from 531 individuals' responses to a choice experiment conducted in the United States, focusing primarily on individuals who reside along the West Coast. We were particularly interested in eliciting public support for programmes that would help self-regulate derelict fishing gear. We find that individuals are willing to pay non-trivial amounts for programmes that introduce fishermen buyback schemes and help regulate self-reporting of lost fishing gear. Additionally, there is strong support to increase the expeditions that remove derelict fishing gear from the remote NWHI.

Furthermore, we identify that individuals who believe the government should be responsible for marine debris removal and prevention efforts, have a stronger preference for a programme over the status quo, compared to respondents who believe individuals or business are responsible. This suggests that highlighting the role government is undertaking in tackling marine debris could increase public support. However, we must be cautious when making policy recommendations using a hybrid choice model. This is because the latent variables are measured only once per individual, therefore only between-person comparisons are possible, as opposed to any within-person conclusions (Chorus & Kroesen, 2014).[9]

Programmes that tackle marine debris, specifically derelict and ghost fishing gear, already exist in the United States, and tend to focus on one particular body of water. NOAA's (2020) report highlight some of these efforts. For example, removing crab traps in the Lake Pontchartrain Basin; locating and removing derelict fishing gear in the Long Island Sound; raising awareness to encourage individuals to spot and remove waste discarded by others in the San Francisco Bay; and establishing community-based clean ups and net recovery patrols off the coast of Hawai'i. These programmes have proven capable of removing a considerable amount of derelict fishing gear from the environment, but are predominantly community-led campaigns, often in partnership with local government and non-profit organisations. Our study highlights individual's willingness to support a national approach to marine debris prevention and removal programmes; specifically, programmes which encourage fisherman to reduce and remove their own derelict fishing gear, and that of others. We also show that individuals are willing to support programmes which focus on out-of-sight marine environments, in particular clean ups to the marine protected NWHI.

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[9] As we only observe differences across individuals in latent variables, we can only stipulate that if person A scores higher on the latent variable LV2-GOV than person B, they are more likely to choose an intervention over the status quo. However, we cannot sate that if person A increases their LV2-GOV score, then they would be more likely to choose an intervention over the status quo.

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Appendix A Technical details of the hybrid mixed logit

The basis for analysing discrete choice data is the random utility model (McFadden, 1973). In this framework, the utility that respondent i derives from alternative j in the choice occasion t can be expressed as:

$$\mathrm{U_{ijt}} = \mathbf{X}_{\mathrm{ijt}}\boldsymbol{\beta}_{\mathbf{i}} + \mathrm{ASC}_{ijt}\gamma_i + \alpha_{\mathrm{j}}\mathrm{c_{jt}} + \varepsilon_{\mathrm{ijt}} \qquad \text{(A.1)}$$

where X_{ijt} is the vector of non-monetary attributes of the marine debris programme, ASC is an alternative specific constant (ASC) which represents a dummy variable equal to one if the option is the status quo and c_{jt} is cost of the programme. β_i and γ_i correspond to the individual-specific preferences towards the project attributes and the ASC, respectively. α_j is the parameter to be estimated for cost, and ε_{ijt} is the random component capturing the factors that affect utility but are not observed by the modeller and are assumed to be Type-1 Extreme Value distributed. The assumption of the error term is so that the probability that an option *j* is chosen over alternative *k* can be expressed through the logistic distribution (McFadden, 1973).

In our model, we assumed that all non-cost attribute parameters (β_i and γ_i) were normally distributed, which allows us to examine respondent heterogeneity towards programme characteristics. We assume cost to be fixed to avoid problems of lack of convergence that often happens when all coefficients are specified as random (Revelt & Train, 1996) and because the long right tail of the cost lognormal distribution can lead to unrealistic WTP estimates (Sillano & de Dios Ortúzar, 2005).

We expand upon the traditional mixed logit model and estimated a hybrid mixed logit (HMXL) in order to explore unobserved influences in the utility function. HMXL models make use of latent variables, which because they do not vary across choices (i.e. they are individual specific), must enter the model through interactions with a component of the choice model. In our model, we assume the parameter on the ASC (γ_i) is dependent on unobservable latent variables, such that:

$$\gamma_i = \boldsymbol{\Gamma}'\boldsymbol{LV}_i + \boldsymbol{\gamma}_i^* \qquad \text{(A.2)}$$

LV_i is a vector of unobservable latent variables, and $\boldsymbol{\Gamma}$ is a matrix of coefficients to be estimated. $\boldsymbol{\gamma}_i^*$ is the ASC individual-specific preference parameter of this model, and follows a priori specified multivariate normal distribution with a vector means and a covariance matrix.

We specified three latent variables as identified by the PCA analysis: $LV_{Business}, LV_{Government}$ *and* $LV_{Individuals}$. Each latent variable is unobserved by the researcher, but may be linked to attitudinal statements. As explained in Figure 3, the $LV_{Business}, LV_{Government}$ *and* $LV_{Individuals}$ use two binary variables indicators (Clean_up and Reduce) as indicator questions. Responses to these indicator questions are assumed to be driven by respondents' true attitudes, the latent variables. The measurement components for $LV_{Business}, LV_{Government}$ *and* $LV_{Individuals}$ are specified as follows:

$$\mathrm{I}_i = \zeta' LV_i + \eta_i, \qquad \text{(A.2)}$$

where I_i are the responses to the indicator variables (Clean_up and Reduce) that are linked to the latent variables, ζ is a matrix of coefficients and η_i denotes a vector of error terms assumed to have a normal distribution with zero mean and a standard deviation of 1.

Combining all the model components: the choice equation, the structural equation(s) and measurement equations(s), we obtain the full-information likelihood function for the HMXL model:

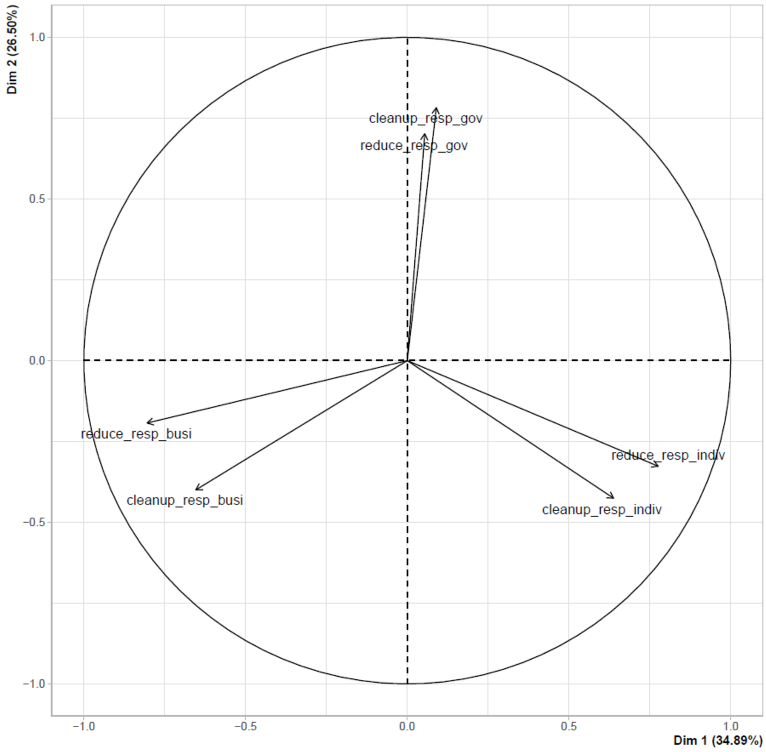
$$L_i = \int P(y_i | X_i, LV_i, \beta_i, \alpha, \gamma_i^*, \Gamma, \zeta) P(I_i | LV_i, \Gamma, \zeta)\,, f(\gamma_i^*) d(\gamma_i^*) \tag{A.5}$$

Where y_i represents an individual *i*'s choices. As random disturbances γ_i^*, as well as latent variable LV_i , are not directly observed, they are integrated out of the conditional likelihood. In practice, the joint likelihood equation does not possess a closed-form solution, but this multi-dimensional integral can be approximated using a simulated maximum likelihood approach.

Recent examples of Hybrid Mixed Logit Model include: Zawojska et al. (2019) and Faccioli et al. (2020).

Appendix B PCA Plot

Figure B.1 Biplot of the PCA illustrating the relationships between the self-reported attitudinal indicators



Appendix C MNL and MXL models

	MNL	MXL Model	
	Estimate (st. err)	Estimate (st. err)	Standard Deviations (st. err)
ASC	0.323***	-3.51***	7.672***
	(-0.14)	(0.6109)	(0.8407)
Reporting	0.63***	0.99***	0.730***
	(-0.06)	(0.1015)	(0.1186)
Buyback	0.732***	1.14***	0.827***
	(-0.06)	(0.1034)	(0.1393)
Clean Up			
Every 2 Years	0.443***	0.81***	-0.040
	(-0.12)	(0.1891)	(0.40731)
Every year	0.602***	1.03***	0.288
	(-0.1)	(0.1370)	(0.3971)
Twice yearly	0.84***	1.26***	-0.031
	(-0.09)	(0.1314)	(0.2589)
Price	-0.002***	-0.005***	
	(0.00)	(0.0009)	
LL	-2727.684		-1988.223
BIC	5518.22		4078.94

Note: *p-value <0.10, ** p-value<0.05, *** p-value <0.01

Appendix D Measurement Components for HMXL Model

Measurement components		Coef (st. err)
Businesses are responsible for:		
	Cleaning up plastic	0.365***
		(0.0487)
	Reducing the amount of waste	0.366***
		(0.0694)
Government is responsible for:		
	Cleaning up plastic	0.335***
		(0.0451)
	Reducing the amount of waste	0.338***
		(0.0123)
Individuals are responsible for:		
	Cleaning up plastic	0.314***
		(0.0436)
	Reducing the amount of waste	0.347***
		(0.0713)

Note: *p-value <0.10, ** p-value<0.05, *** p-value <0.01

References

Abate, T. G., Börger, T., Aanesen, M., Falk-Andersson, J., Wyles, K. J., & Beaumont, N. (2020). Valuation of marine plastic pollution in the European Arctic: Applying an integrated choice and latent variable model to contingent valuation. *Ecological Economics*, *169*, 106521. https://doi.org/10.1016/j.ecolecon.2019.106521

Bahamonde-Birke, F. J., Kunert, U., Link, H., & Ortúzar, J. de D. (2017). About attitudes and perceptions: finding the proper way to consider latent variables in discrete choice models. *Transportation*, *44*(3), 475–493. https://doi.org/10.1007/s11116-015-9663-5

Barboza, L. G. A., Cózar, A., Gimenez, B. C. G., Barros, T. L., Kershaw, P. J., & Guilhermino, L. (2019). Macroplastics Pollution in the Marine Environment. In *World Seas: an Environmental Evaluation* (pp. 305–328). Elsevier. https://doi.org/10.1016/B978-0-12-805052-1.00019-X

Barnes, D. K. A., Galgani, F., Thompson, R. C., & Barlaz, M. (2009). Accumulation and fragmentation of plastic debris in global environments. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1526), 1985–1998. https://doi.org/10.1098/rstb.2008.0205

Barnes, M., Chan-Halbrendt, C., Zhang, Q., & Abejon, N. (2011). Consumer Preference and Willingness to Pay for Non-Plastic Food Containers in Honolulu, USA. *Journal of Environmental Protection*, *2*, 1264–1273. https://doi.org/10.4236/jep.2011.29146

Battisti, C., Staffieri, E., Poeta, G., Sorace, A., Luiselli, L., Amori, G., … Servizio, C. (2019). Interactions between anthropogenic litter and birds : A global review with a ‘ black-list ’ of species. *Marine Pollution Bulletin*, *138*(November 2018), 93–114. https://doi.org/10.1016/j.marpolbul.2018.11.017

Beaumont, N. J., Aanesen, M., Austen, M. C., Börger, T., Clark, J. R., Cole, M., … Wyles, K. J. (2019). Global ecological, social and economic impacts of marine plastic. *Marine Pollution Bulletin*, *142*, 189–195. https://doi.org/10.1016/j.marpolbul.2019.03.022

Ben-Akiva, M., Mcfadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., … Munizaga, M. A. (2002). *Hybrid Choice Models: Progress and Challenges*. *Marketing Letters* (Vol. 13). Retrieved from https://link.springer.com/content/pdf/10.1023%2FA%3A1020254301302.pdf

Birdir, S., Ünal, Ö., Birdir, K., & Williams, A. T. (2013). Willingness to pay as an economic instrument for coastal tourism management: Cases from Mersin, Turkey. *Tourism Management*, *36*, 279–283. https://doi.org/10.1016/j.tourman.2012.10.020

Bliemer, M. C. J., & Rose, J. M. (2011). Experimental design influences on stated choice outputs: An empirical study in air travel choice. *Transportation Research Part A: Policy and Practice*, *45*(1), 63–79. https://doi.org/10.1016/j.tra.2010.09.003

Boyce, C., Czajkowski, M., & Hanley, N. (2019). Personality and economic choices. *Journal of Environmental Economics and Management*, *94*, 82–100. https://doi.org/10.1016/j.jeem.2018.12.004

Chan-Halbrendt, C., Fang, D., & Yang, F. (2009). Trade-offs between shopping bags made of non-degradable plastics and other materials, using latent class analysis: The case of Tianjin, China. *International Food and Agribusiness Management Review*, *12*(4), 179–198.

ChoiceMetrics. (2018). Ngene 1.2 User Manual and Reference Guide, *Australia*. Retrieved from www.choice-metrics.com

Chorus, C. G., & Kroesen, M. (2014). On the (im-)possibility of deriving transport policy implications from hybrid choice models. *Transport Policy*, *36*, 217–222. https://doi.org/10.1016/j.tranpol.2014.09.001

Czajkowski, M., Vossler, C. A., Budzí Nski, W., Winiewska, A., & Zawojska, E. (2017). Addressing empirical challenges related to the incentive compatibility of stated preferences methods. *Journal of Economic Behavior and Organization*, *142*, 47–63. https://doi.org/10.1016/j.jebo.2017.07.023

Daly, A., Hess, S., Patruni, B., Potoglou, D., & Rohr, C. (2012). Using ordered attitudinal indicators in a latent variable choice model: A study of the impact of security on rail travel behaviour.

Transportation, *39*(2), 267–297. https://doi.org/10.1007/s11116-011-9351-z
Dameron, O. J., Parke, M., Albins, M. A., & Brainard, R. (2007). Marine debris accumulation in the Northwestern Hawaiian Islands: An examination of rates and processes. *Marine Pollution Bulletin*, *54*(4), 423–433. https://doi.org/10.1016/j.marpolbul.2006.11.019
Eleonora, S. (2017). Ecological effects of anthropogenic litter on marine mammals : A global review with a “black-list ” of impacted taxa Methods Data collection, *28*(December), 253–264. https://doi.org/10.4404/hystrix
Faccioli, M., Czajkowski, M., Glenk, K., & Martin-Ortega, J. (2020). Environmental attitudes and place identity as determinants of preferences for ecosystem services. https://doi.org/10.1016/j.ecolecon.2020.106600
Greene, W. H. (2002). *ECONOMETRIC ANALYSIS* (5th ed.). Upper Saddle River, New Jersey: Prentice Hall.
Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological*, *37*(8), 681–698. https://doi.org/10.1016/S0191-2615(02)00046-2
Hammer, J., Kraak, M. H. S., & Parsons, J. R. (2012). Plastics in the Marine Environment: The Dark Side of a Modern Gift. In D. M. Whitacre (Ed.), *Reviews of Environmental Contamination and Toxicology* (pp. 1–44). New York, NY: Springer New York. https://doi.org/10.1007/978-1-4614-3414-6_1
Hanley, N., Mourato, S., & Wright, R. E. (2002). Choice Modelling Approaches: A Superior Alternative for Environmental Valuatioin? *Journal of Economic Surveys*, *15*(3), 435–462. https://doi.org/10.1111/1467-6419.00145
Hess, S., & Palma, D. (2019). *Apollo version 0.1.0, user manual*. Retrieved from www.ApolloChoiceModelling.com
Hess, S., Palma, D., Calastri, C., Crasted dit Sourd, R., Daly, A., Dumont, J., … Schmid, B. (2019). *Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application version 0.1.0 User manual*. Retrieved from www.ApolloChoiceModelling.com
Jambeck, J., Geyer, R., Wilcox, C., Siegler, T., Perryman, M., Andrady, A., … Law, K. L. (2015). Plastic waste inputs from land into the ocean. *Marine Pollution*, *347*. https://doi.org/10.1126/science.1260352
Johnson, F. R., Lancsar, E., Marshall, D., Kilambi, V., Bs, B. /, Mü, A., … Bridges, J. F. P. (2013). Constructing Experimental Designs for Discrete-Choice Experiments: Report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force. https://doi.org/10.1016/j.jval.2012.08.2223
Johnston, R. J., Boyle, K. J., Adamowicz, W., Bennett, J., Brouwer, R., Ann Cameron, T., … Vossler, C. A. (2017). Contemporary Guidance for Stated Preference Studies. *Journal of the Association of Environmental and Resource Economists*, *4*(2), 319–405. https://doi.org/10.1086/691697
Lancaster, K. J. (1966). A new approach to consumer theory. *The Journal of Political Economy*, 132–157.
Leggett, C. G., Scherer, N., Haab, T. C., Bailey, R., Landrum, J. P., & Domanski, A. (2018). Assessing the Economic Benefits of Reductions in Marine Debris at Southern California Beaches : A Random Utility Travel Cost Model. *Marine Resource Economics*, *33*(2).
Matthews, Y., Scarpa, R., & Marsh, D. (2017). Using virtual environments to improve the realism of choice experiments: A case study about coastal erosion management. *Journal of Environmental Economics and Management*. https://doi.org/10.1016/j.jeem.2016.08.001
McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics* (pp. 105–142). New York: Wiley. https://doi.org/10.1108/eb028592
McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choices. *Zarembka. P.(Eds): Frontiers*.
Motoaki, Y., & Daziano, R. A. (2015). Assessing Goodness of Fit of Hybrid Choice Models An Open Research Question. *Transportation Research Record: Journal of the Transportation Research*, *2495*, 131–141. https://doi.org/10.3141/2495-14

NOAA. (2019). *The Effects of Marine Debris on Beach Recreation and Regional Economies in Four Coastal Communities: A Regional Pilot Study Final Report*.

NOAA. (2020). *NOAA Marine Debris Program Accomplishments Report*. Retrieved from https://marinedebris.noaa.gov/report/accomplishments-report

Ortúzar, J. de D., & Willumsen, L. G. (2011). *Specification and Estimation of Discrete Choice Models*. *Modelling Transport*. https://doi.org/10.1002/9781119993308.ch8

Pichel, W. G., Churnside, J. H., Veenstra, T. S., Foley, D. G., Friedman, K. S., Brainard, R. E., … Clemente-Colón, P. (2007). Marine debris collects within the North Pacific Subtropical Convergence Zone. *Marine Pollution Bulletin*, *54*(8), 1207–1211. https://doi.org/10.1016/j.marpolbul.2007.04.010

Revelt, D., & Train, K. (1996). Mixed Logit with repeated choices: households' choices of appliance efficiency level. *The Review of Economics and Statistics*. Retrieved from http://direct.mit.edu/rest/article-pdf/80/4/647/1612495/003465398557735.pdf

Roberts, M., Hanley, N., & Cresswell, W. (2017). User fees across ecosystem boundaries: Are SCUBA divers willing to pay for terrestrial biodiversity conservation? *Journal of Environmental Management*, *200*, 53–59. https://doi.org/10.1016/j.jenvman.2017.05.070

Sillano, M., & de Dios Ortúzar, J. (2005). Willingness-to-pay estimation with mixed logit models: Some new evidence. *Environment and Planning A*, *37*(3), 525–550. https://doi.org/10.1068/a36137

Smith, V. K., Zhang, X., & Palmquist, R. B. (1997). Marine Debris , Beach Quality , and Non-Market Values. *Environmental and Resource Economics*, 223–247.

Staffieri, E., Andrea De Lucia, G., Camedda, A., Poeta, G., & Battisti, C. (2019). Pressure and impact of anthropogenic litter on marine and estuarine reptiles: an updated "blacklist" highlighting gaps of evidence. *Environmental Science and Pollution Research*, *26*, 1238–1249. https://doi.org/10.1007/s11356-018-3616-4

Train, K. (2009). *Discrete Choice Methods with Simulation*. *Cambridge University Press*. Cambridge university press.

U.S. Census Bureau. (2019). Retrieved November 21, 2019, from data.census.gov

Vince, J., & Hardesty, B. D. (2016). Plastic pollution challenges in marine and coastal environments: from local to global governance. https://doi.org/10.1111/rec.12388

Walker, J. L., Wang, Y., Thorhauge, M., & Ben-Akiva, M. (2018). D-efficient or deficient? A robustness analysis of stated choice experimental designs. *Theory and Decision*, *84*(2), 215–238. https://doi.org/10.1007/s11238-017-9647-3

Yue, C., Hall, C. R., Behe, B. K., Campbell, B. L., Dennis, J. H., & Lopez, R. G. (2010). Are Consumers Willing to Pay More for Biodegradable Containers Than for Plastic Ones? Evidence from Hypothetical Conjoint Analysis and Nonhypothetical Experimental Auctions. *Journal of Agricultural and Applied Economics*, *42*(4), 757–772. https://doi.org/10.1017/s1074070800003941

Zawojska, E., Bartczak, A., & Czajkowski, M. (2019). Disentangling the effects of policy and payment consequentiality and risk attitudes on stated preferences. *Journal of Environmental Economics and Management*, *93*, 63–84. https://doi.org/10.1016/j.jeem.2018.11.007