Estimation of the Value of Precautionary Restrictions on Microplastics.

Volume 1 of 1

Peter Michael Gregory King

A thesis submitted for the degree of Doctor of Philosophy.

University of Bath

Department of Economics

October 2021

Acknowledgements

"If you admire somebody, you should go ahead and tell 'em.
People never get the flowers while they could still smell 'em". (West, 2007)

First and foremost, I must pay tribute to Dr Alistair Hunt and Dr Lucy O'Shea; your comments, guidance, and insight have always been deeply appreciated. Secondly, I would like to praise the continual contributions and insight from my co-authors, Dr Stavros Georgiou, Richard Dean, Caroline Rainsford, on the 'Economic valuation of benefits from the proposed REACH restriction of intentionally added microplastics.' project. A special thanks to Stavros as well for kicking this all off; it has been a fantastic experience. Thank you to both examiners, Dr Bruce Morley and Professor Susana Mourato, for their help wrapping this up. I am also grateful for the staff and students of the Department of Economics University of Bath, Frankie Cho and everyone who supported my visit to the LEEP Institute University of Exeter, and everyone who provided feedback on my many survey designs. I would additionally like to acknowledge receipt of the University of Bath Research Studentship Award and time spent training in the Sports Training Village. Finally, thanks to Oliver Schofield and the doctoral engagement team for the experiences.

When I started my PhD, my father told me that I should not expect to be the same person afterwards. Like all his generous advice, he has again been proven correct. Mum, David, and Susan, thank you for being you; coming home to see you after long semesters was always something to cherish. Caroline, I am writing this while you are singing in the background doing an assignment. Throughout your own struggles, you have listened, supported, and cared for me from the first, and I hope you know how much I have always appreciated that. There is a thesis of things I want to say about everyone but for now I want to shout out those who were there; Faaris Sheikh and Emmanuel Simukwayi (if we can't do it, it can't be done), Kayleigh (good luck in prison ('s research), you won't need it), Imogen and Darmonelle (thanks for having me at Chelsea Road), Hus (technically, theses are vegan), Tom (all the way from future fitness), Scott (we are never filming another video), Andrew (where is the tipping point?), Kostas (we should control for randomised acknowledgements), Kalyan (endless fun since masters), and all the others I've had the pleasure of working with, thank you.

Be the change you want to see in the world.

Abstract

This thesis estimates the value of precautionary restrictions on microplastics. Although microplastics may be irreversibly released into the marine environment, the severity of environmental and health effects are currently uncertain. Therefore, any restriction would be precautionary. However, the appraisal of precautionary policies is complicated by the uncertainty about the non-market benefits. Therefore, this thesis designs, undertakes, and analyses a Stated Preference survey to estimate the benefits of precautionary restrictions in willingness-to-pay terms. Using both Contingent Valuation tasks and a Choice Experiment, the results indicate that respondents were willing to pay for precautionary restrictions. The hybrid choice model is then used for both methods to show that latent precautionary attitudes positively influence this WTP. Finally, the thesis undertakes an indicative Cost-Benefit Analysis, with distributional weights and sensitivity analysis, to evaluate the value of precautionary restrictions on microplastics.

Contents

List of Figures

List of Tables

Table 1: List of Abbreviations.

Abbreviation	Definition	Abbreviation	Definition
ANA	Attribute-Non-Attendance.	ASC	Alternative-Specific Constant.
BP	Blue-Planet.	BPA	Bisphenol A.
CBA	Cost-Benefit Analysis.	CE	Choice Experiment.
CEA	Cost-Effectiveness Analysis.	C-E	Cosmetics Europe
CL	Conditional Logit.	CTPA	Cosmetics Toiletries and Perfumery Association.
CV	Contingent Valuation.	DBDC	Double-Bound Dichotomous Choice.
DC	Dichotomous-Choice.	DEFRA	Department for Environment, Food and Rural Affairs.
DDT	Dichlorodiphenyltrichloroethane.	ECHA	European Chemicals Agency.
ELC	Environmental Locus of Control.	ES	Ecosystem Services.
GI	Gastro-intestinal.	GHG	Greenhouse Gases.
HDPE	High Density Polyethylene.	HSE	Health and Safety Executive.
ICLV	Integrated Choice Latent Variables.	IIA	Independence of Irrelevant Alternatives.
IID	Independently and Identically Distributed.	IED	Income Elasticity of Demand
KMT	Kaplan-Meier Turnbull.	LCM	Latent-Class Model.
LDPE	Low Density Polyethylene.	LR	Likelihood-Ratio.
MAC	Marginal Abatement Curve.	MBI	Market-Based Instrument.
MCA	Multi-Criteria Analysis.	MD	Marginal Damages.
MEC	Marginal External Cost.	MMT	Millions of Metric Tonnes.
MNL	Multinomial Logit.	MPC	Marginal Private Cost.
MSC	Marginal Social Cost.	MSW	Municipal Solid Waste.
MXL	Mixed Logit.	MWTP	Marginal Willingness-to-Pay.
NEP	New Environmental Paradigm.	N.O.A.A	National Oceanic and Atmospheric Administration.
NPV	Net Present Value.	OV	Option Value.
PAH	Polycyclic Aromatic Hydrocarbon.	PBDE	Polybrominated diphenyl ethers.
PBT	Persistent, Bioaccumulative, Toxic pollutant.	PCB	Polychlorinated biphenyl.
PE	Polyethylene.	PEB	Pro-Environmental Behaviour.
PET	Polyethylene Terephthalate.	PP	Polypropylene.
PS	Polystyrene.	PU	Polyurethane.
PVC	Polyvinyl Chloride.	QOV	Quasi-Option Value.
REACH	Registration, Evaluation, Authorisation and Restriction.	RP	Revealed Preference.
RUM	Random Utility Model.	SBDC	Single-Bound Dichotomous Choice.
SVHC	Substance of Very High Concern.	TA	Think-Aloud.
SP	Stated Preference.	TDI	Tolerable Daily Intake.
TEV	Total Economic Value.	VMT	Virgin Materials Tax.
VOI	Value of Information.	WTA	Willingness-To-Accept.
WTP	Willingness-To-Pay.	WWTP	WasteWater Treatment Plant.

Introducing Microplastics and the Precautionary Principle.

Chapter One Abstract:

This chapter aims to introduce and justify the current policy focus on microplastics. The release of microplastics to the marine environment can potentially have adverse environmental and health effects on both marine and human life. However, as the scientific evidence on their effects is mixed, policymakers may invoke the precautionary principle to justify costly abatement policies. This chapter contextualises this research within the restriction on intentionally-added microplastics proposed by the European Chemicals Agency (ECHA) amidst the uncertainty-irreversibility tradeoff when restricting pollutants.

1.1 Introduction

There is an increasing focus in the environmental sciences and economics literature on the threat to water quality from marine pollution (Vegter et al., 2014). The flow of all marine plastics to the marine environment is estimated at 6.4 million metric tonnes (MMT) (range: 4.7-12.8 MMT) annually - a rate far exceeding the estimated rate of plastic degradation in the ocean (Beaumont et al., 2019; Lebreton et al., 2018; Sudhakar et al., 2007). The stock of plastic in the marine environment stands at approximately 75-150MMT, which degrades slowly and is not practically recoverable (Jambeck et al., 2005; ECHA, 2019). By size, the stock comprises megaplastics (>50cm diameter), macro (5-50cm), meso (0.5-5cm), micro (<0.5cm) and then nanoplastic (1-100 nanometers) (ECHA, 2019; Lebreton et al., 2018; Duis and Coors, 2016). Although there is a range of marine pollutants, including metals and chemicals, this research focuses on the microplastic component of the stock. Duis and Coors (2016) defines microplastics as a synthetic organic polymer weighing around three micrograms and measuring less than 5mm. Lebreton et al. (2018) calculated that the stock of marine microplastics numbered in the trillions. However, the expanse of the marine environment means that the stock of marine microplastics is of low concentration. The large stock and increasing flow of marine microplastics represent an emerging threat to water quality and human health.

A range of deleterious physical and chemical effects have been observed on more than 800 species of marine life that have ingested marine plastics (Mouat, Lozano and Bateson, 2010; Harse, 2011). Although larger plastic items, such as bottles, six-pack drink rings, and carrier bags, can occlude respiratory or digestive tracts, smaller microplastics could translocate into different tissues or leach chemicals when ingested (Duis and Coors, 2016). There is also the possibility for the trophic transfer of microplastics through marine life to eventually affect human health (Lusher, Hollman and Mendoza-Hill, 2017; Bergmann, Gutow and Klages, 2015; ECHA, 2014b). However, Burns and Boxall (2018) urged caution when describing the potential effects of microplastics as many effects are conjecture or have only been observed in unrealistic laboratory conditions. Moreover, Koelmans et al. (2016) reported that the overall ingestion of contaminants was not significantly higher due to the ingestion of microplastics. Finally, current evidence suggests that human ingestion of marine plastic does occur but at an extremely low-level (Thompson et al., 2009; Kosuth, Mason and Wattenberg, 2018). To summarise, there is considerable scientific uncertainty about the severity and existence of potential environmental and health effects of microplastics (Duis and Coors, 2016; Azzarello and Van-Vleet, 1987).

This research investigates the REACH restriction of intentionally-added microplastics proposed by the European Chemicals Agency in 2019. REACH restrictions concern the Registration, Evaluation, Authorisation and Restriction (REACH) of chemicals in the EU (ECHA, 2014a, 2008). As polymers are generally not a substance of very high concern, microplastics have not typically needed the registration or authorisation steps of REACH (Duis and Coors, 2016). However, ECHA (2019) proposed a restriction on the manufacture, sale and use of microplastics given the increasing concentration of microplastics in the aquatic environment. The increasing concentration of microplastics, combined with their persistence, proxies for increasing risk. However, REACH restrictions are typically applied to Persistent, Bioaccumulative and Toxic (PBT) substances, and there is limited evidence on the bioaccumulation and toxicity of microplastics (Koelmans et al., 2016). Given the uncertainty surrounding the environmental and health effects of microplastics, the proposed restriction is inherently precautionary. The precautionary principle argues that the scientific uncertainty around microplastics' long-term environmental and health impacts should not preclude restrictions. Following the precautionary principle would suggest acting to abate the inputs immediately. Alternatively, policymakers may delay a decision until the extent of damages is better known (ECHA, 2019; Interdepartmental Liaison Group, 2002). This thesis estimates the non-market benefits of a precautionary restriction on the release of microplastics.

1.1.1 Structure

This introductory chapter has three sections. The chapter first critically reviews the empirical evidence on the emissions and effects of marine microplastic. Secondly, the theoretical background to the release and precautionary control of micropollutants is reviewed before; finally, the chapter explores the use of Cost-Benefit Analysis (CBA) in the socioeconomic analysis of proposed restrictions.

1.1.2 Contributions to Knowledge.

The primary contribution of this thesis is the unit WTP values for several different scenarios. This contribution is valuable given the extant scarcity of valuations for marine microplastics. Additionally, this research contributes to the relatively scarce empirical literature on precaution in environmental economics and stated preference. Chapters Four and Five contribute a unique application of the hybrid choice model to demonstrate the effect of latent precautionary attitudes on WTP. Finally, Chapter Seven demonstrates how the WTP can be used to calculate an indicative CBA with distributional weights.

1.2 The Microplastic Problem

1.2.1 Sources of Marine Plastic

While microplastics represent only a fraction of the total volume of marine plastic, they are the most numerous category. Indeed, Lebreton, Egger and Slat (2019) estimated the annual number of microplastics released to the marine environment to be in the trillions. Furthermore, microplastics may be both point sources (industrial pre-production pellets and sewage sludge) and non-point sources (littering, abrasion).

One point source of microplastics is pre-production pellets. These pellets are used for plastic production, are typically homogeneous at less than 5mm in a spherical shape, and may enter the ocean during transport, production, as effluent or as accidental loss from a variety of industries and sectors (Pawar et al., 2016; Karlsson et al., 2018; Kershaw et al., 2011; ECHA, 2014b). As they are so easily lost in production, estimates suggest that several billion pre-production pellets are input to the ocean annually (Kershaw et al., 2011). The high concentrations of pellets observed in the North Atlantic, South Atlantic, and Pacific corroborate this estimate (Jambeck et al., 2005; Azzarello and Van-Vleet, 1987; DEFRA, 2017). However, the abatement of pellets' input is complicated by their small and numerous nature, which implies that measures to reduce their loss via improved effluent treatment and capture may not be cost-effective (Kershaw et al., 2011). Although producers incur some financial losses from losing plastic pellets via their water intake being congested by pellets, these are dwarfed by the abatement costs of reducing pellets' concentration in industrial effluent (Karlsson et al., 2018). The benefits of decreasing pellets concentration, lower infection and fatality in marine life cannot be appropriated by firms unilaterally reducing their emissions of pellets. Therefore, there is little incentive for abatement of the input of microplastic pellets (Kershaw et al., 2011; Beaumont et al., 2019).

ECHA (2019) report highlighted one non-point source as intentionally-added microplastics in cosmetics and personal care products (terms used interchangeably here). The justification for focussing on intentionally-added microplastics is that other sources, such as tyre abrasion, are significantly more technically challenging and costly to abate than cosmetics, paints, or detergents, which may be reformulated. The justification for focusing on cosmetics is the previous efforts to restrict microbeads in cosmetics (DEFRA, 2017). If a restriction on microplastics in cosmetics were enforced, fewer microplastics would be released to wastewater.

Many microplastics are released to the terrestrial and aquatic environment from wastewater. Wastewater carries microplastics from a multiplicity of pathways and sectors. These include medicine (covering single-use and in-vitro products), Controlled-Release Fertilisers in agriculture, detergents, paints, cosmetics or abrasion of tyres (Milani et al., 2017; ECHA, 2019). Wastewater flows to WWTP, where it is treated and filtered. Filtered wastewater becomes either sewage sludge which can be dispersed to the terrestrial environment as fertiliser, or is disposed of in the marine environment (Burns and Boxall, 2018). Although WWTP can filter more than 95% of micropollutants, the remaining proportion, primarily micro and nanoplastics, persists in both the sewage sludge and the wastewater (Horton et al., 2020; Murphy et al., 2016; Duis and Coors, 2016). Therefore, WWTPs represent a substantial element of the land-based release of microplastics to the terrestrial and marine environment. Given the multiplicity of wastewater sources, microplastics can be described as a non-point source pollutant that is significantly more challenging to abate given that targeting is not as feasible (Granero-Gomez, 2005).

The marine microplastic problem features increasing and irreversible inputs, uncertainty on the scale and extent of damages, and both point and non-sources. The following section discusses the effects and scale of the problem.

1.2.2 Effects of Marine Microplastic Pollution

This section critically explores the effects of marine microplastic pollution through the lens of the market and non-market effects.

1.2.2.1 Market Effects

There is significant uncertainty on the financial, or more generally market, costs of marine pollution, let alone specifically that from microplastics. Indeed, the most-cited estimate in the literature, McIlgorm, Campbell and Rule (2011), is likely underestimated given the omission of non-market impacts on the marine life and ecosystem (Bergmann, Gutow and Klages, 2015). McIlgorm, Campbell and Rule (2011) suggested overall damages of $1.26bn annually to the Asia-Pacific region composed of approximately $279m in shipping-related damages such as intake of plastic in vessels and equipment, $364m in contaminated and reduced fishing, and $622m in lost marine tourism. An analysis of McIlgorm, Campbell and Rule (2011) methodology suggests the possibility that it underestimates the total damages from marine plastic pollution. Indeed, it likely omits any damages from microplastics specifically. For instance, McIlgorm, Campbell and Rule (2011) assumed that the marine economy was valued at 3% of a country's total

GDP, with the financial damages suffered by the marine economy valued at 0.3% of that value. One critique of this method is that using an average percentage to estimate value ignores variation in the national economies, although it does overcome national reporting differences. A further critique concerns the 0.3% value, which stems from Takehama (1990) reporting the value of damages from marine litter that the Japanese fishing fleet reported in the 1990s. However, since 30 years have passed since that estimate, it will likely be a significant underestimate given increasing plastic production and emissions. Indeed, Mouat, Lozano and Bateson (2010) later noted that the Scottish fishing fleet reported annual damages worth 5% of revenue, which far exceeds the Takehama (1990) estimate. Furthermore, Takehama (1990) considered all marine litter which includes both non-plastics and larger plastics, and so the true value of damages to the fishing industry from marine microplastics is unknown. Specifically, the small scale of microplastics may negate any effect they have on shipping. A final critique is that there are sectoral differences in the impact of marine pollution, and so it may not be appropriate to value the entire damages to the marine economy using only those from the fishing industry (McIlgorm, Campbell and Rule, 2011; Kildow and McIlgorm, 2010; Mouat, Lozano and Bateson, 2010). For example, the tourism sector may suffer reduced visitor numbers given the disamenity associated with increasing concentrations of unsightly marine plastic pollution (Derraik, 2002; UNEP, 2005). Therefore, the current estimate of the market value of marine plastic impacts may be an underestimate.

A further element of uncertainty is the value of financial damages from beach litter. For instance, Leggett et al. (2014) used a travel cost method to report that the damages to tourism in Orange County, USA were such that even a 50% reduction in beach plastics would yield financial benefits to the local area and industry of $70m annually. However, given the popularity of Orange County as a tourist location, Leggett et al. (2014) estimate is not necessarily representative of all beach litter. Mouat, Lozano and Bateson (2010) provided a more indicative estimate who surveyed organisations affected by marine litter and reported an annual cost of reducing beach litter for UK local authorities of £18m each. Additionally, Mouat, Lozano and Bateson (2010) reported that beach litter costs had risen 37% in just ten years with the rise due to increased production and release, a finding robust to measurement period and study area. A further challenge to the validity of the estimated financial impact of beach litter is that only 15% of marine litter is beach litter, and of that, almost none is microplastic (Derraik, 2002; Brouwer et al., 2017). Microplastics are too small to be observable, so they are unlikely to impose a disamenity value as beach litter. To summarise, the market value of microplastic litter on beaches is uncertain.

1.2.2.2 Non-Market Effects

Similarly to the market effects, the value of the non-market effects of microplastic pollution is uncertain. There are two relevant categories of non-market effects; ecosystem services via marine life and human health effects. The marine ecosystem may be affected through changes to provisioning and regulating services, while marine life such as seabirds, molluscs, crustaceans, and fish can be affected through ingestion, bioaccumulation and translocation (Beaumont et al., 2019; Kosuth, Mason and Wattenberg, 2018). Finally, human health may be affected via the ingestion of microplastics through trophic transfer and water quality, although these effects are more uncertain (Koelmans et al., 2016). This section reviews the scientific evidence on the existence, scale, and certainty around each major impact pathway.

1.2.2.2.1 Effects on marine life

Microplastics' effects on marine life stem primarily from the ingestion of microplastics, although larger plastics may also pose a danger to marine life via entanglement. Entanglement in marine pollution is a danger to many marine life species throughout the water column and represents a trade-off between private and social disposal costs. For example, approximately 20% of all seabird fatalities via drowning, asphyxiation or starvation are caused by entanglement in marine plastics (Harse, 2011; Laist, 1997; Derraik, 2002). Indeed, Allsopp et al. (2007) reported that more than 40% of marine species they had studied had shown evidence of being entangled. Additionally, marine species may be entangled in plastics, such as six-pack drinks rings, personal protective equipment, single-use bottles, and non-plastics such as discarded fishing nets called ghost nets (Henderson, 2001; Rakib et al., 2021). For plastics, firms may design multi-pack packaging which has financial value in quantity discounts but is designed in a manner that may entangle marine life, and so a trade-off exists between financial benefits and environmental costs (Azzarello and Van-Vleet, 1987; Hook and Reed, 2018). The trade-off also extends to entanglement in non-plastics whereby the private cost of properly disposing of a ghost net may be significantly higher than littering it in the sea, especially if the social costs of that net entangling marine life are not internalised (Henderson, 2001). Indeed, the social costs of disposing of ghost nets are significant entanglement poses dangers to marine life throughout the water column as 70% of marine litter sinks or floats below the surface (Derraik, 2002). However, the most numerous marine pollution category, microplastics, is too small to entangle marine life but pose other dangers, particularly ingestion and leaching. Therefore, the most commonly observed effect on marine life is not due to microplastics.

The potential effects of seabirds, molluscs, and other marine life ingesting microplastics include asphyxiation, laceration, occlusion of the respiratory and digestive tracts, masking the feeding signal, and potential transport of contaminants (Karlsson et al., 2018; Robards, Piatt and Wohl, 1995; Moser and Lee, 1992; Beaumont et al., 2019; Harse, 2011). Here, the effects are much more likely from microplastics rather than larger plastics. The effect of ingestion can be separated into physical and chemical effects. The physical effects of ingested microplastics are possible inflammation if micro and nano-scale pollutants accumulate in the gastrointestinal tract or translocate to organs. Additionally, microplastics may affect immune function if they translocate to the lymphatic system (Lusher, Hollman and Mendoza-Hill, 2017). Therefore, marine microplastic pollution may present a threat to marine biodiversity (Pawar et al., 2016; Vegter et al., 2014). However, such effects on marine life are rarely observed in the field, with the strongest evidence thus far being unrealistic laboratory conditions or in simulations (Koelmans et al., 2016; Duis and Coors, 2016; Burns and Boxall, 2018). Therefore, the physical dangers of marine life ingesting microplastics are potentially dangerous but currently at a low scale (Lusher, Hollman and Mendoza-Hill, 2017).

There is a range of potential chemical effects from microplastic ingestion. Chemically, microplastics exposed to photo-oxidation, pressure and wind may degrade, fragment and leach additives (Thompson et al., 2009; Lebreton, Egger and Slat, 2019). Observed leachate has included additives such as bisphenol A (BPA), historically banned chemicals including polychlorinated biphenyl (PCB) and dichlorodiphenyltrichloroethane (DDT) and plasticisers like phthalates (Kosuth, Mason and Wattenberg, 2018; ECHA, 2019). Furthermore, microplastics are adept at the adsorption of latent Persistent Bioaccumulative and Toxic (PBT) contaminants such as Polycyclic Aromatic Hydrocarbons (PAH) and Polybrominated diphenyl ethers (PBDE) which persist in the marine environment given a slow decay rate and accumulation through convergent forces in the ocean (ECHA, 2019; Bergmann, Gutow and Klages, 2015; Thompson et al., 2009; Sudhakar et al., 2007; Lebreton et al., 2018). When microplastics adsorb contaminants, they may act as a transport vector for organisms that ingest microplastics. A possible chemical effect of these contaminants is endocrine disruption which may be severe in marine life, especially smaller organisms (Chen et al., 2019). Therefore, the main danger to marine life from microplastics is the possibility of chemical effects from ingestion (Kim, Lee and Yoo, 2019; Lee, 2015).

Despite the range of potentially lethal effects, Thompson et al. (2009) failed to report consistently fatal effects, a finding that was robust to ocean and species. The low level of fatalities may indicate a low concentration in the ocean rather than ingestion not being deleterious (ECHA, 2019). However, a concentration below a no-effect threshold may not persist indefinitely given the observed increase in microplastics. Specifically, both Robards, Piatt and Wohl (1995) and Moser and Lee (1992) reported that the volume of microplastic ingested had risen more than 80% with the frequency of ingestion rising more than 30% during their study period (1970-1980s). Jambeck et al. (2005) highlights that these rises are consistent with rises in plastic production, and given that the stock of marine pollution is increasing and unrecoverable, similar significant increases in the concentration, frequency and volume of ingested microplastics are likely. It is possible to note that ingestion represents the recurring trade-off between financial value and environmental cost in three ways. Firstly, firms may utilise microplastics in cosmetics to add desirable and valuable effects that increase their value and danger given the ability for microplastics to be easily ingested and transport toxic contaminants (ECHA, 2019; Scasny and Zvěřinová, 2014; DEFRA, 2017). Secondly, firms may use additives that produce desirable effects such as flame retardants, plasticisers, and colourings that add private value but may also increasingly resemble prey to marine life or contaminate water quality when plastics degrade the ocean (Azzarello and Van-Vleet, 1987; Lusher, Hollman and Mendoza-Hill, 2017; ECHA, 2014b). Finally, firms may minimise plastic's weight, given that they face private financial obligations calculated on the raw tonnage of plastic placed on the market. However, lighter plastics are more likely to float and, therefore, more likely to degrade and leach contaminants and more likely to be ingested (Waste and Resource Action Programme, 2011; Treasury, 2018; Azzarello and Van-Vleet, 1987; Derraik, 2002; Hammer, Kraak and Parsons, 2012; Sudhakar et al., 2007; Bergmann, Gutow and Klages, 2015). Therefore, the danger to the marine life of ingesting microplastics highlights a trade-off between financial and environmental costs. However, there is substantial uncertainty about the existence, toxicity, and severity of physical and chemical effects on marine life accruing specifically from microplastic ingestion.

1.2.2.2.2 Effects on human life

Regulators, including the UK Health and Safety Executive (HSE) and the European Chemicals Agency (ECHA), have expressed concern over the potential chemical effects of microplastic ingestion on human health (ECHA, 2019; Scasny and Zvěřinová, 2014; Bergmann, Gutow and Klages, 2015; Lusher, Hollman and Mendoza-Hill, 2017; Morrissey, 2019). Microplastics (and, by extension, nanoplastics) are the only relevant category of marine plastics for human health. The most likely vector for microplastic ingestion is seafood although, seafood is typically prepared with the gastrointestinal tract where microplastics accumulate removed, therefore, limiting human exposure (Lusher, Hollman and Mendoza-Hill, 2017; de Wit and Bigaud, 2019). While upwards of 90% of microplastics ingested by humans are excreted, the remaining proportion may lead to potential adverse chemical effects, although this has yet to be observed to be above dangerous concentrations (ECHA, 2019; Lusher, Hollman and Mendoza-Hill, 2017). The potential effects are most likely to be inflammation from an accumulation of microplastics in the gastrointestinal tract. However, there is some conjectured possibility that some nanoplastics may translocate into organs or the lymphatic system to affect immune function (Lusher, Hollman and Mendoza-Hill, 2017; Bergmann, Gutow and Klages, 2015; ECHA, 2014b). Although chemical effects from ingesting contaminated microplastics are also possible, Lusher, Hollman and Mendoza-Hill (2017) believed that as only 4% of a microplastics weight is a contaminant, human exposure is likely to be less than 0.1% of any Tolerable Daily Intake (TDI) of PBTs. Indeed, Thompson et al. (2009) noted that further research on the potential long term human health impacts from microplastic ingestion is necessary to address the current uncertainty. To summarise, ingestion of toxic microplastics has a range of potential physical and chemical impacts, although they have not currently been observed in sufficient concentration to be fatal or deleterious in humans (Lusher, Hollman and Mendoza-Hill, 2017; Kosuth, Mason and Wattenberg, 2018; ECHA, 2014b).

1.2.2.2.3 Effects on ecosystem services

Ecosystem services (ES) provided by the ocean are believed to be worth nearly $50 trillion annually with a 1-5% reduction of that possible from all marine plastic pollution according to estimates (Beaumont et al., 2019). Relevant ES that could be impacted by marine pollution includes provisioning and regulating services. Specifically, the provision of seafood throughout the food chain may be contaminated by marine microplastics if they are ingested at different trophic levels (Lusher, Hollman and Mendoza-Hill, 2017). Indeed, the possibility of trophic transfer not just of microplastics but of their contaminants is currently a conjectured problem, although it may become more likely with increases in microplastic concentrations and emissions. The regulating services provided by the marine environment of water quality can be threatened in two ways by microplastics. Firstly, microplastics may leach and transport contaminants which affect the ability of the marine ecosystem to support marine life (Beaumont et al., 2019; Vegter et al., 2014). Secondly, there is the potential for microplastics to reduce the ability of the marine environment to regulate and sequester carbon (Shen et al., 2020). Specifically, Shen et al. (2020) notes that microplastics are easily ingested by multiple species of plankton, which are necessary elements of the carbon storage potential of the ocean [1]. Finally, McIlgorm, Campbell and Rule (2011) added that cultural ES, such as recreational values, maybe also be affected by marine pollution. However, as microplastics are practically unobservable due to their small scale, they, therefore, may have a weak effect on the provision of cultural ecosystem services (Vegter et al., 2014). Furthermore, the uncertainty around microplastics effect on ES limits the use of the impact pathway approach to impact assessment. Overall, microplastics pose a growing threat to marine ES, although they are a relatively small issue in the context of other threats to ES.

Table 1.1: Summary of possible impacts of marine pollution:

Effect	Description	Effects	Extent	Evidence
Non-market impacts				
Ingestion	Marine life may ingest microplastics.	Asphyxiation inflammation endocrine disruption.	30% of marine species	Thompson et al. (2009) Bergmann, Gutow and Klages (2015)
Entanglement	Larger discarded plastics and non-plastics like ghost nets.	Strangulation occlusion, starvation.	40% of marine species	Henderson (2001)
Leaching	When plastic degrades under sunlight and ocean conditions, it may leach contaminants.	Poisoning, masking of signals.	Unclear	Harse (2011) Thompson et al. (2009) Bergmann, Gutow and Klages (2015)
Damage to ecosystems	Degraded plastic litter can reduce aesthetic and existence value and impair carbon storage.	Reduced provision of regulating/supporting Ecosystem Services.	Annual Value of ES: $49.7 trillion Annual Reduction in ES: 1-5% Annual Reduction Value: $500 - 2500 bn.	Kumar (2012) Beaumont et al. (2019)
Market impacts				
Damage to shipping	Ships can take plastic into the equipment when traversing areas of high concentration.	Damage to equipment reduced function increased repair costs.	~$279mn (£219mn) Asia-Pacific 2010.	McIlgorm, Campbell and Rule (2011)
Damage to fishing	Reduced fishing catch as marine life contaminated by debris.	Loss of earnings cost of sorting catch.	~$364mn (£286mn) Asia-Pacific 2010.	McIlgorm, Campbell and Rule (2011)
Damage to tourism	Marine debris washed ashore dissuades visitors.	Loss of earnings.	~$622mn (£489mn) Asia-Pacific 2010.	McIlgorm, Campbell and Rule (2011)
Clean-up costs	The cost of recovering marine plastic.	Capital and opportunity cost.	Estimated at: ~$18mn (£14mn) cost to UK Local Authorities (2010).	Mouat, Lozano and Bateson (2010) Bergmann, Gutow and Klages (2015)

[1]Shen et al. (2020) noted microplastics are readily ingested by both phytoplankton and zooplankton. Both of these are important elements of the carbon storage potential of the ocean. Therefore, if microplastics reduce the plankton population, then the carbon storage possibility of the marine ecosystem is reduced. However, the carbon storage of the marine ecosystem is influenced by multiple factors, and thus the effect of microplastics specifically cannot easily be isolated or identified. However, as with other conjectured environmental and health effects, the growth in the number of microplastics may increase the possibility of environmental effects in future.

1.2.3 Scale of the Problem

Given the financial and environmental impacts discussed in Section 1.2.2, it is instructive to consider the sources, volume, and distribution of marine microplastic pollution.

1.2.3.1 Pollution Volume

Although microplastics are acknowledged as the most numerous marine pollution category, there is uncertainty over the stock of marine microplastics. The total stock is believed to weigh around 75-150MMT with annual inputs of plastic estimated at 8.4MMT (UNEP, 2005) or 4.7-12.8MMT (Jambeck et al., 2005). Although the inputs represent only 1.70 - 4.65% of annual global plastic production (approximately 275MMT), production is increasing (Lebreton et al., 2018; ECHA, 2019). While Jambeck et al. (2005) estimate is a commonly used estimate in the literature, the rise in production and unique methodology indicate that their estimate may underestimate the current volume, again highlighting the uncertainty. To clarify, Jambeck et al. (2005) calculated the country-level annual generation of waste using aggregated government reports. However, these may be incomplete or using differing methodologies and, most importantly, may omit microplastics disposed of down the drain or washed away. Jambeck et al. (2005) then took 11% of the total waste generation to be plastic, which is comparable with the weight of annual plastic production. The total plastic waste generation is then scaled by the amount of waste generated by coastal populations. The justification for this scaling is that a simple distance effect implies that those closest to the ocean will inevitably dispose of more waste into the sea, although this ignores the role of Wastewater Treatment Plants (WWTP) in filtering microplastics into the environment. Following this scaling, a country-specific proportion is then used to determine the proportion of plastic waste that is 'mismanaged'. Jambeck et al. (2005) suggests that on average 68% of plastic waste is 'mismanaged', which is *"the sum of inadequately managed waste plus 2% littering"* (Jambeck et al., 2005, p. 769). There are several issues with this calculation. Firstly, there appears to be little empirical support for the 2% proportion and nor do they allow for country-level heterogeneity. Secondly, simply scaling the total amount of waste by an arbitrary figure may overestimate littering while omitting microplastics. A final step to their estimation method, Jambeck et al. (2005) took a proportion of the total mismanaged plastic waste estimate. They suggested that this proportion equals the range of a country's annual input of plastic into the ocean. By omitting microplastics and using potentially outdated estimates of littering and at-sea disposal, the input of marine plastic may be different than previously estimated in the literature (Jambeck et al., 2005). However, this estimate, while not specifically referring to microplastics, presents a lagged indicator of microplastic pollution since larger plastics will eventually degrade and fragment into microplastics. As a final comment on estimating the volume or input of microplastics, Lebreton, Egger and Slat (2019) reported that even under conditions of strict abatement, the stock of microplastics was projected to increase significantly. The increase is due to larger plastics breaking down while degrading in the marine environment; ECHA (2019) noted this is similar to the global warming issue whereby carbon stocks decay slowly. Therefore, there is significant uncertainty about the precise volume of microplastics released and existing in the marine environment.

1.2.3.2 Pollution Distribution

Microplastics' distribution can be understood in two ways and is crucial for understanding the potential environmental impacts. Microplastics have been found in almost all oceans and seas, as distant as the Arctic and Mount Everest, from seafood to bottled beer and drinking water (Robards, Piatt and Wohl, 1995; Moser and Lee, 1992; Lebreton, Egger and Slat, 2019; ECHA, 2019; Abate et al., 2020; Koelmans et al., 2016; Burns and Boxall, 2018; Kosuth, Mason and Wattenberg, 2018). Although concentrations may be higher near Wastewater Treatment Plants (WWTP) or industrial areas that use pre-production pellets (Duis and Coors, 2016; Horton et al., 2020; Karlsson et al., 2018), microplastics' distribution within the marine environment varies with proximity to shore and layers of the water column. Initial estimates from Derraik (2002) reported marine plastics to be approximately distributed as 15% floating back to shore, 15% floating at or below the ocean surface, and a further 70% sinking. Although Derraik (2002) did not specifically consider microplastics, these proportions are broadly similar for microplastics as shown by Lebreton, Egger and Slat (2019). The three fates of marine microplastics, floating, sinking or returning to shore, warrant further discussion as they indicate the potential environmental and health impacts.

Starting with the floating percentage, the estimate of just 15% floating is a curious finding given that almost 90% of polyethylene or derivative plastics are buoyant and should, therefore, theoretically float in the marine environment (Waste and Resource Action Programme, 2011; VALPAK, 2017; Sudhakar et al., 2007; Lebreton et al., 2018; Lebreton, Egger and Slat, 2019). This proportion is primarily microplastics emitted but not degraded and larger plastic items that have been 'lightweighted' [2] by manufacturers. Regardless of size, the floating proportion is likely to converge to areas of highly concentrated marine pollution such as the infamous *'Great Pacific Garbage Patch'* (Lebreton et al.,

[2]Lightweighting refers to the practice of reducing the total weight of a plastic product (Røine and Lee, 2006; OECD, 2004).

2018). Weathering effects, photo-oxidation and fragmentation are more pronounced at the surface, which increases the likelihood of chemical leaching with associated social costs on water quality and marine life. Floating marine pollution is more likely to impact shipping and equipment and more likely to be ingested by marine life. Therefore, the proportion of microplastics that floats in the marine environment may have the highest potential for environmental and health effects. Despite 80% of the stock stemming from land-based sources, only a small proportion returns to shore (Hammer, Kraak and Parsons, 2012). This category imposes a cost to the coastal and tourist economy (Leggett et al., 2014; Mouat, Lozano and Bateson, 2010). However, returning to shore makes recovery more cost-effective and feasible, limiting the potential for longer-term damages in the marine environment.

Finally, Derraik (2002) estimated that approximately 70% of all marine pollution would eventually sink to depths throughout the water column where the difficulties of deep-sea exploration limit the understanding of its impacts (Lebreton et al., 2018; Azzarello and Van-Vleet, 1987). However, this proportion, though large, is less relevant to this research as the sinking 70% consists either of non-plastic marine litter such as dumped fishing nets or equipment (Henderson, 2001), or heavier plastics that are less common than their floating counterparts, specifically Polystyrene (PS) or Polyvinyl Chloride (PVC). Although microplastics may eventually lose buoyancy and sink below the surface as they degrade and fragment, this effect is not immediate and may only be slightly below the surface (Sudhakar et al., 2007). Although sinking plastics are less likely to be found in ships intake and thus less likely to cause damages, the effects on marine ecosystems may be more persistent since the rate of degradation decreases with distance from the surface (Sudhakar et al., 2007; Lebreton et al., 2018). The rate of degradation matters as plastics fragment into smaller plastics, which are easier to ingest and thus impose more adverse effects. To summarise, lightweight plastics and microplastics are likely to float at the surface where they are most exposed to degrading factors which increase their potential environmental and health impacts.

1.3 Theoretical and Policy Context

This section discusses some important theoretical and policy context for the release and restriction of microplastics. Firstly, the theoretical links between water and air pollution are explored. Secondly, the theoretical basis for using microplastics is discussed regarding the divergence of marginal private and social cost. Comment is made on the practical implications for the cosmetics sector in particular. Finally, this section reviews the regulatory literature on appropriate options for abatement.

For context, it is worthwhile discussing the notable parallels between microplastics and greenhouse gas emissions highlighted in ECHA (2019). Firstly, both pollutants' stock has a low rate of decay and is practically unrecoverable once emitted. Therefore, releases can be considered irreversible, a property that stresses the abatement of flows rather than stock recovery as a policy focus (Gollier and Treich, 2003). Moreover, in both scenarios, the total stock of pollution increases environmental and health risks rather than the individual flow of pollutants. However, micropollutants' potential risks are less well understood compared to the rich scientific and economic literature on air pollution (Manne et al., 1992; ECHA, 2019; Vegter et al., 2014). Microplastics may be intentionally added to products given desirable properties, while GHG emissions may be a by-product. As such, abating the release of microplastics may require substitution and reformulation of products.

The primary theoretical underpinning for the release of microplastics is the divergence of marginal private and social cost that leads to misallocations of plastic resources. One example of this divergence is that manufacturing firms face incentives to minimise waste costs, which are derived from raw tonnage, and thus lightweight their plastic production (Røine and Lee, 2006; Perchard and Bevington, 2016). However, lightweight plastics are more likely to float and thus be ingested by marine life (Sudhakar et al., 2007; Lebreton, Egger and Slat, 2019). Therefore, floating plastics may impose a high social cost with a low private cost.

More generally, the annual loss of 1-5% of global plastic production to the ocean suggests that the waste management market fails to consistently allocate plastic efficiently (Lebreton et al., 2018; McIlgorm, Campbell and Rule, 2011; Vegter et al., 2014; Oosterhuis, Papyrakis and Boteler, 2014). An efficient allocation features internalisation of the Marginal External Cost (MEC) (Boardman et al., 2017). A nonzero MEC may exist in the presence of externalities, spillover effects on a third party who is not then compensated by the party responsible. A relevant negative externality exists for beach littering or dumping at sea whereby consumers' MPC to doing so is very low, even with the expectation of fines, despite a substantial MSC (OECD, 2004; Mouat, Lozano and Bateson, 2010). A positive externality also exists in recycling, whereby the MSB of recycling, namely in avoided extraction and production costs, is not internalised, and the MPB is less than the MSB. A further example of a nonzero MEC is in the allocation of public goods; or in the case of marine pollution, public bads (Oosterhuis, Papyrakis and Boteler, 2014). Oosterhuis, Papyrakis and Boteler (2014) described marine plastic as a pure public bad given that it is non-excludable. This is because agents who have not contributed to marine pollution may still internalise the damages in the form of higher shipping and fishing prices if firms attempt to pass the damages of marine plastics on to consumers. However, marine pollution damages may be rival as the marine plastic stock is finite, so any ingested microplastic marginally decreases the stock. Therefore, it appears that marine plastic pollution may be characterised as an impure public bad. Currently, however, no market exists to allocate the impure public bad of marine pollution, and so an efficient allocation with an optimal level of marine pollution cannot be achieved (OECD, 2004; Fullerton and Wolverton, 1997; Treasury, 2018). Both Kinnaman, Shinkuma and Yamamoto (2014) and McIlgorm, Campbell and Rule (2011) implied that there might be an optimal level of marine pollution for society, where the Marginal Abatement Costs (MAC) are equal to the Marginal Damages (MD). The MAC of marine pollution is unknown and likely to be steep, given the challenges of recovering plastic across the depth and breadth of the world's oceans (Lebreton et al., 2018). Additionally, as Lebreton, Egger and Slat (2019) estimated the stock of microplastic to number in the billions, the slope of the MD curve is likely to be relatively flat (Lebreton et al., 2018). To summarise, the waste management market may fail to allocate plastic efficiently due to externalities from the divergence of marginal private and social costs.

1.3.1 Policy Instruments

This section discusses the theoretical merits of a tax versus a restriction on microplastics. Previous regulatory action to abate plastic inputs has seen the microplastic beads in cosmetics banned in the UK (DEFRA, 2017). The UK ban on microbeads in cosmetics imposed significant reformulation and implementation costs on producers. This cost may extend to consumers if producers pass along costs; as is easily possible in the cosmetics market, demand is relatively price inelastic (DEFRA, 2017). Although the microbead ban affected only a small number of producers who had not already phased them out, the ban achieved a reduction of 680 tonnes, equivalent to several billion individual microbeads

(DEFRA, 2017). ECHA (2019) estimated that an EU-wide microplastic restriction would lead to a reduction of 3249 tonnes (1453 - 5044t). Although this represents a small proportion, around 0.05%, of total annual global plastic inputs, expressed by the count of microplastics, the reduction is equal to approximately 902bn (399 - 1310bn) microplastics annually using the average weight of a microplastic (ECHA, 2019; Lebreton et al., 2018; Auta, Emenike and Fauziah, 2017). ECHA (2019) has often used the frequency of a pollutant in the environment as a proxy for actual levels of risk and, therefore, the avoided billions of microplastics released to the environment represents a substantial reduction in risk. The proxy is justified in this scenario as microplastics' frequency correlates with the frequency of ingestion and increased dangers from vectoring leached chemicals (Laist, 1997; Moser and Lee, 1992; Robards, Piatt and Wohl, 1995). Therefore, an extension of the UK ban or the UK adoption of the ECHA (2019) proposal for a restriction on intentionally-added microplastics would substantially reduce the volume of microplastics released to the marine environment.

There is a theoretical debate on whether a restriction is an appropriate instrument. For instance, restrictions do not allow least-cost abatement as they impose the same standard on all relevant agents and, therefore, are less efficient than comparable market-based instruments (Baumol et al., 1988). A tax may also be more optimal than a standard or restriction in the context of a flat marginal damages curve as in microplastics (Hoel and Karp, 2002). Despite that, there are three arguments in favour of a restriction. Firstly, restrictions are appropriate for Persistent, Bioaccumulative and Toxic (PBT) pollutants where the optimal emissions may be zero rather than a given market-clearing level (Alberini and Scasny, 2014; DEFRA, 2017). Secondly, restrictions may be superior to Market-Based Instruments (MBI), which do not function well where the microplastics are largely unobservable or measurable in their emissions. Additionally, MBIs also require an accurate estimate of the MEC of emitting pollutants to be efficient, which is not currently possible in this microplastic scenario (Convery, McDonell and Ferreira, 2007). Thirdly, consumers have little control over which products contain microplastics, and so their ability to substitute consumption subject to a MBI is limited. Indeed, as cosmetics' demand is relatively price inelastic and determined partly by non-price factors, such as branding, a tax may pass through producers to consumers with no effect on production or behaviour. In summary, regulatory action to ban microplastic pollutants may be more appropriate than MBIs and are notably effective at abatement.

In practice, the regulatory action to control chemicals would be a REACH restriction. REACH is a system of registering, evaluating, and restricting the production and use of chemicals (ECHA, 2008). Previous REACH restrictions have focused on chemicals or additives that are known with greater certainty to be PBT, very Persistent, very Bioaccumulative (vPvB), or Substances of Very High Concern (SHVC); see the D4/D5 restriction for an example (Duis and Coors, 2016; Environment Agency, 2015). A REACH restriction in the microplastic scenario may be appropriate and advantageous over taxes or MBIs when releases are irreversible (Gollier and Treich, 2003). The precautionary principle suggests that the uncertainty over the potential adverse environmental and health effects of microplastics should not be a barrier to restricting the irreversible release of microplastics (Ha-Duong, 1998; Kuntz-Duriseti, 2004; DEFRA, 2017; Gollier and Treich, 2003). Therefore, in the microplastic context, it appears that the appropriate theoretical policy approach would be a precautionary REACH restriction.

In summary, ECHA (2019) opposed a tax and supported a ban on microplastics for the theoretical reasons of increased effectiveness in the microplastic scenario. While they estimated the costs in their policy impact analysis with certainty, ECHA (2019) failed to estimate the non-market benefits. Non-market benefits are essential determinants of the NPV of the policy and so must be incorporated in the appraisal of any policy (Lavee, 2010).

1.4 Summary

This chapter has characterised the microplastic pollution problem as substantial, increasing, and unrecoverable with potentially adverse marine and human health effects. However, the extent and timing of the damages are uncertain. Microplastics' flow is primarily through WWTP but can be both somewhat point source like pre-production pellets or non-point source such as abrasion. The appropriate policy option appears to be a REACH restriction. However, in the absence of estimates for the benefits of restricting the irreversible release of microplastics, any cost-benefit analysis may be incomplete. Chapter Two of this thesis discusses how to use stated preference methods to monetise the impacts of a precautionary restriction on microplastics use.

Economic Valuation

Chapter Two Abstract:

This chapter critically explores the theoretical and empirical support for using cost-benefit analysis for policy appraisal in the microplastics scenario. Furthermore, this chapter discusses the theoretical background for using Stated Preference methods to value nonmarket benefits for CBA use. Finally, the validity and determinants of individual willingness-to-pay valuations to avoid marine pollution's potential nonmarket impacts are analysed. Overall, this chapter contributes to the literature on the use of SP methods for policy appraisal in the context of water micropollutants.

2.1 Cost-Benefit Analysis

The appraisal of the proposed REACH restriction on microplastics, and more generally any policy on water micropollutants, is incomplete in the absence of estimates for the value of non-market impacts. This chapter considers the theoretical and practical basis for a Cost-Benefit Analysis (CBA) of the microplastic scenario in the context of irreversibility and uncertainty. CBA is adopted in this research against other methods of analysis given that it is inherently a simple process of gathering, monetising, and comparing impacts (Bateman et al., 2002). This simplicity is a bonus compared to other analysis methods, including Multi-Criteria Analysis (MCA), Cost-Effectiveness Analysis (CEA) (Boardman et al., 2017). CEA is worthwhile in contexts where policymakers consider the value of the efficacy of a given policy. Finally, MCA has benefits in tackling several different policy objectives (Atkinson et al., 2018a,b). However, CBA is the most common method for considering the efficiency of resource allocation (DFA, 2006; Atkinson et al., 2018a). In summary, CBA can be used to appraise precautionary abatement policies, although attention must be paid to handling its weaknesses regarding the distribution and uncertainty of impacts. The following section establishes CBA as a method of policy appraisal in greater detail.

2.1.1 Theoretical Foundations

CBA is a policy analysis method that identifies whether a policy is efficient by monetising the value of policy impacts and comparing which plan leads to the highest net benefit (Boardman et al., 2017). Although CBA is concerned with allocating resources at the societal level, it has its theoretical foundations at the individual level. The magnitude of policy impacts can be defined according to their effect on individual utility, with benefits increasing utility and costs decreasing (Atkinson et al., 2018a; Bateman et al., 2002). The value of a change in utility is not defined absolutely but relatively using a single good of comparison, which is typically money given its divisibility and ease of understanding and substitution (Bateman et al., 2002). Changes in utility may be valued at whatever an individual is willing to pay (accept) to exactly offset the change (Bateman et al., 2002; Pearce, 1998). For example, individuals may gain utility from a marine environment with low pollution. Therefore, the benefit of policies that affect the marine environment's quality by abating pollution is valued using individuals Willingness-To-Pay (WTP) for that improvement. Individual WTP valuations can be aggregated to represent the total benefits of a policy (Atkinson et al., 2008). Aggregated benefits can then be compared with estimated total costs, aggregated over the project's lifetime, and then discounted to yield the Net Present Value (NPV) of government intervention. Equation (2.1.1), adopted from Atkinson et al. (2018a), sums the discounted difference between Benefits B and Costs C over each time period t. Policy impacts are discounted, using the discount rate S over the total duration of the policy T.

$$NPV = \sum_{t=0}^{T} \frac{B_t - C_t}{(1+s)^t} \tag{2.1.1}$$

NPV suggests whether introducing the policy is a net benefit or cost to society; where NPV > 0, that is, benefits exceed costs, then CBA suggests that the policy should proceed (Atkinson et al., 2018a; Whitehead and Blomquist, 2006; Bateman et al., 2002; Boardman et al., 2017; DFA, 2006). However, there are several challenges in the literature regarding the validity of NPV and how to calculate it, which are explored in the following section.

2.1.2 Practical Operation

The first three steps of CBA concern the impacts, stakeholders, and effects of a potential policy. Firstly, CBA must specify the attributes of both the status quo and the proposed policy, which in this research include the predicted stock, release, and distribution of marine microplastics under different levels of abatement (Alberini and Scasny, 2014; Van der Meulen et al., 2014). Policy impacts, such as the reduction in microplastic inputs, also need to be predicted over the policy lifetime (Boardman et al., 2017; OECD, 2006). In this scenario, ECHA (2019) believed that a microplastic ban would affect an 85-95% reduction in the annual input of microplastics in Europe, with the majority of the reduction occurring in the first year of the policy. Following predicting the policy effects, another step of CBA is the issue of standing, i.e. whose valuations of the policy are incorporated into the CBA (Boardman et al., 2017). Governments traditionally only consider taxpayers or nationals in their CBA. However, this may not be appropriate for cross-boundary pollutants produced, released, and converged in different spatial areas (OECD, 2006; Vegter et al., 2014; Oosterhuis, Papyrakis and Boteler, 2014). This research considers only the implication of a REACH restriction on the UK, in which case only UK national WTP is relevant.

Policy impacts must be monetised to facilitate the calculation and comparison of the NPV. Individual preferences for the value of policy impacts may be estimated in a CBA using either of two broad approaches, Revealed (RP) or Stated Preferences (SP), usually depending on whether the impact in question is market or non-market (Atkinson et al., 2018a; Boardman et al., 2017). Within RP or SP approaches, there is a family of possible methods. However, the monetisation of impacts is a controversial technique due to the potential omission of intangibles or incommensurables and its reliance on individual estimates (Pearce, 1998). The debate on the validity of monetisation revolves around whether the environment should be valued and, if it should, whether it is valid for self-interested individuals to value it. Firstly, there is the ethical problem of monetising non-market and market goods in similar ways, which, some argue, may debase the environment, and trivialise its intrinsic value (DFA, 2006). Pearce (1998) notes that this critique does not reflect the practical trade-off in policymaking between the opportunity cost of funding conservation or preservation efforts and environmental quality. Furthermore, the valuation of the environment is a necessary element for policy analysis to improve environmental quality (Boardman et al., 2017; Bateman et al., 2002). The second critique of monetisation concerns the reliance on individual preferences for its valuations. While OECD (2006) notes that CBA assumes that individual preferences are worthwhile including, there is some contention on whether it is appropriate to include individual valuations in policy analysis (Pearce, 1998). This critique suggests that individuals are self-interested, and their valuations, thus the magnitude of costs and benefits in a CBA, reflect only that (Pearce, 1998). However, as Pearce (1998) notes, the determinants of individual WTP valuations are more than just self-interest. Specifically, WTP valuations incorporate several influences, including beliefs about the policy being valued and policymakers, motivations, attitudes, and concerns (Kahneman, Knetsch and Thaler, 1990; Convery, McDonell and Ferreira, 2007; Pearce, 1998; Kollmuss and Agyeman, 2002; Kallbekken and Sælen, 2011; Andreoni, 1990). This research elicits WTP, and the determinants of WTP, in a SP survey. Once individual valuations have been elicited, they may be aggregated to represent the annual value to society. In Equation (2.1.1), annual values are aggregated over the lifetime of the project to represent the total costs or benefits of a policy. Therefore, valid estimates are of paramount importance to the outcome of CBA.

The net value may be discounted to reflect the timing of impacts throughout a policy's lifetime. To compare costs and benefits that extend across time, future values may be discounted and expressed as present values (Frederick, Loewenstein and O'Donoghue, 2002; Pearce, 1998). Discounting allows for the comparison of policy impacts throughout a policy lifetime and may be justified given that individuals have been observed to exhibit a strong present bias for immediate values rather than temporally distant ones (Boardman et al., 2017; Atkinson et al., 2018a; HM Treasury, 2018; Dunn, 2012; Frederick, Loewenstein and O'Donoghue, 2002). Present bias may be explained by immediate values being more salient than future ones, which are also less certain (HM Treasury, 2018). To calculate the present value of a policy, costs and benefits must be discounted. The variable S in Equation (2.1.1) is the discount rate, which refers to how strongly immediate values are preferred to future ones. The discount rate used by HM Treasury (2018) (Equation (2.1.2)) follows the classic Ramsey discount rate (Equation (2.1.3)).

$$W_t = \frac{1}{(1+S)^t} \tag{2.1.2}$$

$$S = \rho + \mu\mathcal{G} \tag{2.1.3}$$

In this specification of the discount factor, W is the discount factor, t the time, and S the discount rate, which is composed of firstly ρ the rate of time preference, and secondly a wealth effect in $\mu\mathcal{G}$ which multiplies the μ marginal utility of consumption by the expected growth rate of future real per capita consumption $\mathcal{G}$ (HM Treasury, 2018; Atkinson et al., 2018a). Finally, S may become S_t to reflect time-inconsistent preferences (HM Treasury, 2018). The determinants and calculation of S is the subject of a significant body of literature (Atkinson et al., 2018a). Both academic and government sources suggest that S comprises time preference, the marginal utility of consumption and the expected growth rate of real per capita consumption and may vary with the duration of the project given time-inconsistent preferences (Atkinson et al., 2018a; HM Treasury, 2018; Frederick, Loewenstein and O'Donoghue, 2002). However, there are three critiques to the choice of discount rate S; whether a non-zero discount rate is appropriate, whether holding it constant over time is appropriate and whether holding it constant over different goods is appropriate (OECD, 2006; Atkinson et al., 2018a; DFA, 2006; HM Treasury, 2018). The choice of S complicates the calculation of NPV.

The first issue of using a discount rate is that it may undervalue, or trivialise, the importance of environmental quality, especially in irreversible scenarios such as climate change and marine pollution (Atkinson et al., 2018a; OECD, 2006). A suitable non-zero discount rate may address the undervaluing of the future state of the environment. However, there is a discussion on the appropriate rate to use for different impacts over different periods [3] (Baker, Ruting et al., 2014; Boardman et al., 2017).

A second issue concerns how to discount different impacts over time (Boardman et al., 2017; Pearce, 1998). Impacts that occur in the future may be less salient, and, therefore, individuals may value future impacts at a decreasing rate (Frederick, Loewenstein and O'Donoghue, 2002; Howard, Whitehead and Hochard, 2020). This decreasing rate is also represented in Government official discount rates, which are lower for longer projects, from 3.5% for 30 years of impact to 3.0% for impacts afterwards (HM Treasury, 2018). However, there is substantial empirical evidence that individual discount rates are time-varying; thus, the assumption of exponential discounting where individuals have a constant discount rate is potentially unrealistic (Howard, Whitehead and Hochard, 2020; Sparkman, Lee and Macdonald, 2021; Thaler, 1981). Although Frederick, Loewenstein and O'Donoghue (2002) argued that a hyperbolic function fit better than the exponential approach, Zhuang et al. (2007), and Atkinson et al. (2018a) noted that hyperbolic discounting implies time inconsistency, the observation that past behaviour may not be consistent with future behaviour. Moreover, as this research does not recover information about individual time preferences, the hyperbolic approach is harder to justify. Therefore, this research adopts the exponential discounting approach traditionally used in CBA (Boardman et al., 2017; Atkinson et al., 2018a).

There may also be a difference between the discount rate for monetary goods and environmental, health and life impacts (HM Treasury, 2018). As such, the HM Treasury (2018) guidance advocates a 1.5%, falling to 1.0%, discount rate for health impacts after 30 years of a project which, therefore, weights future impacts highly (HM Treasury, 2018). Although HM Treasury (2018) noted that the low discounting of health impacts might

[3] Atkinson et al. (2018a) explores a scenario where, given positive interest rates and a zero discount rate, each generation lives on subsistence levels of consumption, saving too much for future generations; this repeated impoverishment is unlikely to be politically possible.

also be applied to the environment, the limited evidence for health effects of microplastics suggests that using the lower rate may be misguided. Although Zhuang et al. (2007) reports that discount rates from 0.5% to 15% have been used, this research initially adopts the 3.5% Treasury Green Book discount rate for all costs and benefits. The impacts are assumed to occur within ten years, and thus, the rate does not need to be adjusted. However, this research uses sensitivity analysis to determine the robustness of the CBA to the choice of the discount rate, as consistent with the best-practice in the literature (Luisetti et al., 2011; Logar et al., 2014; ECHA, 2008).

CBA does not necessarily culminate in the calculation of NPV as there is debate on the appropriate decision rule to determine whether a policy should proceed. Historically, the Pareto principle, which suggests that a policy is Pareto-efficient if no one individual would be worse off than the status quo, has been applied to determine whether it is efficient for a policy to proceed (Pearce, 1998). However, a much more pragmatic approach to the determination of efficiency is the Kaldor-Hicks compensation test, where projects are justified if those with 'gains' could compensate 'losers' and all could be no worse off than the status quo (Pearce, 1998). The potential for the redistribution of net gains implies that a policy intervention can be welfare improving; actual compensation occurring is not material as long as it is feasible Atkinson et al. (2018a). This definition of efficiency is most commonly adopted for the decision rule (Bateman et al., 2002). However, it is also one of the focuses for critiques of the CBA method as it does not fully consider the equity and distribution of benefits.

As CBA is primarily concerned with economic efficiency, it may not fully incorporate equity considerations (Pearce, 1998; DFA, 2006; Atkinson et al., 2018a). There are two reasons why CBA may fail to consider the distribution of impacts. Firstly, CBA commonly uses the Kaldor-Hicks criteria to consider the distribution (Baker, Ruting et al., 2014). However, the Kaldor-Hicks rule requires no actual redistribution and is more illustrative than effective (OECD, 2006). Secondly, CBA may be blind to distributional impacts if the measure of benefits, WTP, is correlated with wealth and income, which are distributed unequally in society (Atkinson et al., 2018a). For example, Hökby and Söderqvist (2003) observed that the positive income elasticity of WTP implies that benefits are regressively distributed in society. Generally, if a policy's costs regressively affect low-income areas, such as coastal populations that see their fishing and tourism industries affected by marine plastic pollution (McIlgorm, Campbell and Rule, 2011), there may be pressure to include the distribution of impacts in CBA (HM Treasury, 2018). A possible solution for practitioners is to calculate and apply distributional weights to different groups of stakeholders (Atkinson et al., 2018a). The CBA decision rule can then be reformulated to include distributional weights in that a policy should proceed if the sum of distributionally weighted net benefits is weakly positive (Atkinson et al., 2018a; Boardman et al., 2017).

Assigning distributional weights requires first itemising the incidence of costs and benefits on different stakeholder groups and determining which groups require weighting. However, there is a debate on both the viability and calculation of such distributional weights (OECD, 2006; Atkinson et al., 2018a; DFA, 2006). Distributional weights can be calculated implicitly or explicitly. Implicit weights use sensitivity analysis to determine what weighting would alter the conclusions of a CBA (Loomis, 2010). Alternatively, an explicit weight can be calculated as the ratio of an individual (Y_i) to mean income ($\bar{Y}$) to the power of the elasticity of marginal utility of income (e); this weighting is derived in Atkinson et al. (2018a) using the marginal utility of income. In the explicit method of calculating distributional weights, the weight α_i can vary between 0 - 1 by subgroups such as individual or region. While a zero weight is consistent with standard CBA, a weight equal to 1 is a direct proportion of individual to mean income (Atkinson et al., 2018a; Boardman et al., 2017). This research estimates both types of distributional weights in Chapter Seven to suitably control for the distribution of impacts from selected microplastic policies.

The distribution of impacts suggests that CBA does not exist outside of the political economy of resource allocation. Indeed, CBA is an information-gathering tool and an addition to the political process rather than a substitute for the allocation process due to policymakers' significant role in determining which values to consider and equity weightings (Baker, Ruting et al., 2014). Even where CBA has been used to value a range of impacts from Government policies on natural resources, water quality and chemical hazards, there may still be political challenges to implement policies with significant benefits or costs (Atkinson et al., 2018b; Pearce, 1998; ECHA, 2014b). CBA critiques may instead be viewed as limitations that, if adequately addressed via monetising, discounting, and proper itemising of the costs and benefits for stakeholders, may allow CBA to play a critical role in resource allocation.

As part of the political economy of resource allocation, CBA often incorporates some degree of sensitivity analysis which may be undertaken to compare the degree to which a policy is economically viable given changes in the underlying assumptions (OECD, 2006; Boardman et al., 2017). Sensitivity analysis can be undertaken to allow for variation in the estimated costs and benefits, the appropriate choice of distributional weight, and the discount rate choice. However, CBA may still be characterised by the presence of considerable uncertainty over the incidence, duration and magnitude of costs and benefits (Baker, Ruting et al., 2014; Atkinson et al., 2018a; Boardman et al., 2017). On the issue of uncertainty, Traeger (2014) noted that the standard CBA decision rule of NPV > 0 does not incorporate the value of delaying a project to resolve uncertainty (OECD, 2006). Therefore, NPV omits the potential for costs and benefits to be updated in the future. Although the omission of uncertainty in CBA is a weakness, the following section discusses how it may be handled.

2.1.3 Treatment of Uncertainty

Two key characteristics of the microplastic context are the uncertainty about the irreversible impacts of microplastics. While the uncertainty supports delaying a decision, the irreversible release of microplastics and reduced water quality suggests an immediate precautionary decision. However, the orthodox operation of CBA may ignore both the uncertainty and irreversibility of policy costs and benefits because it ignores the value of delaying a decision (Atkinson et al., 2018a; ECHA, 2019; Traeger, 2014). This irreversibility effect, first recognised by Henry (1974) was encapsulated in the concept of Option Value (OV) and Quasi-Option Value (QOV) by Arrow and Fisher (1974) and Hanemann (1989) (Atkinson et al., 2018a). This section critically explores how OV and QOV relate to the precautionary principle solution to the irreversibility-uncertainty trade-off.

OV is the value of preserving an environment so that future users have the option of using it, and this value exists even if future users never use the environment (Kolstad, 1996). For example, there is a positive OV to preserving the marine environment so that future marine and human life may access its ecosystem services (Beaumont et al., 2019). Preserving the marine environment would require restricting the release of intentionally added microplastics. Restricting microplastics immediately preserves the option to relax any restriction later if the uncertainty is resolved and shows that microplastics pose no adverse human health effects. It is essential to note here that Option Value is distinct from Option Price (OP), as OV includes both OP and expected surplus (Whitehead and Blomquist, 2006). Additionally, it should be noted that OV is a component of an individual's Total Economic Value (TEV) of a good and represents the value of having an option to use the good in future and, therefore, measures a different concept to Quasi-Option Value (QOV) (Boardman et al., 2017; Atkinson et al., 2018a). QOV was originally framed as an extension to OV, although the relatively small literature on QOV has discussed various definitions (Arrow and Fisher, 1974; Henry, 1974).

Generally, QOV measures the difference in opportunity costs between making an immediate but uncertain decision and making a delayed but perfectly informed decision (Atkinson et al., 2018a; ECHA, 2014b; Pearce, 1998; OECD, 2006). More specifically, Ha-Duong (1998) defined QOV as the difference in the expected value of information between a one-shot decision or making decisions about development in many time periods (Ha-Duong, 1998). In this framework of comparing scenarios, Atkinson et al. (2018a) noted that QOV was the difference between an optimal decision and a sub-optimal one made without considering the value of learning during a delay. Traeger (2014) suggested that QOV may also be understood as the OV for learning or, more precisely, the value of preserving an option so that learning may occur to resolve the uncertainty (Traeger, 2014). Mensink and Requate (2005) went further in stating that QOV is the expected value of future information as it is simply the OV for receiving new information and resolving scientific uncertainty. However, the literature has thus far failed to empirically estimate QOV or use it in CBA to address the irreversibility effect [4]. Even if estimated correctly, there is a debate on how best to practically incorporate QOV as a solution to the irreversibility effect in CBA. The first approach, advocated by Boardman et al. (2017); Atkinson et al. (2018a), would be to directly amend the net benefits of a decision. Precisely, this approach would calculate the expected values for no action or abatement and directly incorporate them into the NPV itself rather than used to calculate QOV. However, this approach would then not explicitly illustrate the value of delaying a decision. A second approach furthered by Traeger (2014) would amend the CBA decision rule to include QOV explicitly. Traeger (2014) demonstrated that the CBA decision rule could be reformulated such that a policy is viable where NPV $>$ QOV and the value of acting immediately exceeds the gains to waiting for more-complete information. Traeger (2014) further argues that the value of learning is always positive, so QOV should negatively influence NPV as it argues against a current decision. In practice, however, policymakers may not be aware of the appropriate incorporation of a concept that has not yet been empirically estimated and have instead often acted according to the precautionary principle to address the issues of uncertainty and irreversibility in CBA.

Both QOV and the precautionary principle argue that, in the presence of uncertainty, the appropriate policy response is preservation, especially in the context of irreversible

[4] One example is the appraisal of the UK 2018 plastic microbead ban, which did not estimate benefits of either restricting the irreversible loss of plastics or the benefits of delaying a decision to resolve the uncertainty (DEFRA, 2017).

changes to the environment if not preserved. In this context, the precautionary principle argues that the absence of full scientific uncertainty about the environmental and health effects of a pollutant should not be a barrier to pre-emptive, precautionary restrictions of pollution before the true extent of the damages is revealed (DEFRA, 2018, 2017; Beaumont et al., 2019; Vegter et al., 2014; Interdepartmental Liaison Group, 2002). The precautionary principle may be defined as:

"Where there are threats of serious or irreversible environmental damage, lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation." Rio Declaration 2013 (Interdepartmental Liaison Group, 2002).

This approach is appropriate where the pollution inputs are irreversible (ECHA, 2014b; Interdepartmental Liaison Group, 2002). Indeed, Gollier and Treich (2003), later supported by Traeger (2014), noted that precautionary abatement before benefits are known with certainty may be optimal. Precautionary abatement in this context can be defined as acting to abate the release of microplastics before the scientific uncertainty is resolved (Kuntz-Duriseti, 2004). The precautionary principle has been used where the CBA decision rule of NPV >0 does not incorporate the irreversibility effect (Traeger, 2014; Ha-Duong, 1998; Kuntz-Duriseti, 2004). For example, regulators can trade-off uncertainty for irreversibility by choosing whether to immediately abate plastic inputs given present uncertainty or delay until more-complete information is available, while the stock of marine microplastics irreversibly increases. These possibilities can be understood using either a one-shot or sequential decision-making process (Ha-Duong, 1998). The one-shot decision collapses to standard CBA as policymakers consider only the expected costs and benefits and decide policy for all periods (Ha-Duong, 1998; Atkinson et al., 2018a). In the alternative sequential model, policymakers may decide to defer a decision until research resolves the uncertainty, and they may then abate or not as appropriate. The precautionary principle suggests that there is a value to an immediate restriction to address irreversibility. This research estimates the values of both a precautionary restriction and a delay to resolve uncertainty. The difference in NPV between the two scenarios can then indicate how policymakers should tackle the irreversibility effect in the CBA of microplastic policy.

2.2 Eliciting Willingness To Pay

The value of changes in the provision of non-market goods are only valued at what an individual is willing to forgo to achieve them; expressed via either Willingness-to-pay (WTP) or willingness-to-accept (WTA) depending on whether the change is a cost or benefit to individuals (Fujiwara and Campbell, 2011; Atkinson et al., 2018a). Although ECHA (2008) noted that WTA could also feasibly be estimated, WTP is more commonly used in the REACH context. WTP can be estimated using a range of techniques summarised in Table 2.1 and the Section 2.2.1 discusses which of these are appropriate to elicit individual WTP to avoid the non-market impacts of marine plastic in this research.

Table 2.1: Selected plausible valuation methods:

Method	Description	Examples	Advantages	Disadvantages
Revealed Preference				
Travel Cost	Examines how expense and frequency of visits change with attributes.	Valuing the impact of beach litter on tourism in Orange County USA (Leggett et al., 2014).	Based on observed market data.	Not applicable where non-use value is relevant to the analysis.
Hedonic Pricing	Examines how individuals change their consumption of a good given attribute changes.	Commonly used for housing in areas of higher environmental risks (Atkinson et al., 2018a). May also be relevant to estimate a wage premia for workers in an area of higher pollution.	Observes actual behaviour and explores how individuals trade-off housing attributes	Cannot separately estimate non-use value.
Stated Preference				
Contingent Valuation	Asking respondents to state their willingness-to-pay, contingent on background factors.	Has been used to estimate Total Economic Value, non-use value or WTP for changes in pollution levels.	Can estimate TEV and allows respondents to explicitly state their maximum WTP.	May be prone to hypothetical bias while valuations may be sensitive to design effects.
Choice Modelling	Allow respondents to indicate their preferred choice when presented with multiple alternatives that differ only by attribute's levels.	Brouwer et al. (2017) used a CE to estimate the value of beach litter. Alberini and Scasny (2014) used a CE to elicit attribute-specific WTP for reductions in chemical risks.	Estimates attribute-specific WTP, which may be appropriate for multi-dimensional policymaking problems.	A trade-off exists between task complexity and practicality and CEs may be challenging to complete and analyse.

While impacts can only be monetised using either RP or SP methods, there are two other valuation approaches to note for completeness. Firstly, the subjective wellbeing approach in Fujiwara and Campbell (2011); HM Treasury (2018) may be used to understand how a policy change affects wellbeing. Although Fujiwara and Campbell (2011) notes that this approach is free of the theoretical assumptions required for stated preference valuation, there are additional issues in measuring the effect of non-market goods on life satisfaction. Future research may, however, be interested in understanding how uncertainty about microplastics affects wellbeing. A second increasingly popular method is the Natural Approach to monetising ES (Beaumont et al., 2019; Atkinson et al., 2018b,a; DEFRA, 2020) [5]. In this approach, natural capital provides valuable ES (Atkinson et al., 2018b; DEFRA, 2020). Beaumont et al. (2019) attempted to describe how the ES provided by the marine environment's natural capital are affected by marine plastic. Although their estimate, global damages of $500-2500bn annually, indicates the adverse effect of plastic on marine ES, it far exceeds any previous estimate of the damages from marine plastic and is not specific to microplastics. However, it is not clear whether this approach is relevant for this research given the challenges to accurately estimating the local effect on the marine ecosystem from microplastics. One challenge is the scientific uncertainty about the impact pathway and marginal damages from microplastics (Vegter et al., 2014; ECHA, 2019; Duis and Coors, 2016). A second is the spatial distribution of microplastics; Lebreton, Egger and Slat (2019) demonstrated that once released, microplastics can easily transport across national boundaries and thus, valuing the UK-specific benefits of a restriction on their release is complex. If the impacts could be understood in terms of diminished natural capital, they may be valued in reducing carbon sequestration or loss of biodiversity. Currently, no paper exists which has done this at the national level in the context of a REACH restriction and, therefore, this research favours the more established SP methods for use in CBA.

2.2.1 Revealed Versus Stated Preferences

The RP approach is based on observed behaviour where individual preferences are revealed through market prices (Bateman et al., 2002; Boardman et al., 2017). Market behaviour may reveal non-market values as individuals may be willing to pay for the non-consumptive use of a coastal location for recreation (Atkinson et al., 2018a). There are two primary RP methods; travel cost and hedonic pricing. The travel cost method (TCM) examines changes in the number of trips given changes in an area's attributes. Research using the travel cost method indicates that individuals are willing to pay less to visit beach areas with higher concentrations of litter (Leggett et al., 2014). The TCM can estimate the benefit of litter reduction in such areas by multiplying the increased number of trips by trip value. Similarly, the Hedonic Pricing (HP) method evaluates house prices when an attribute of the house price, say local pollution levels, change (Boardman et al.,

[5] Additional thanks to audience comments at the DEFRA Environmental Seminar Series for suggesting this.

2017; Atkinson et al., 2018a). HP approaches to environmental valuation have been evident primarily, but not exclusively, in the ecosystem services valuation literature; (Kumar, 2012; Łaszkiewicz, Czembrowski and Kronenberg, 2019; Anstine, 2000). To summarise, both main RP approaches have been able to estimate non-market costs, such as the benefits to pollution reduction, using observed market behaviour (Leggett et al., 2014).

However, RP methods are not appropriate for this research as they cannot value non-use value as it is not observed in market behaviour. Bateman et al. (2002) notes that non-use values, such as the existence or bequest value of the ocean, can only be elicited using SP methods as they are not realised in the market. Moreover, if markets do not exist or fail, then the non-market impacts' monetisation is only possible with SP methods (Bateman et al., 2002; Boardman et al., 2017). While future research could use RP methods to estimate the marine environment's use-value, SP methods are appropriate where the benefits include non-use value.

2.2.2 Stated Preference Methods

This section briefly establishes the theoretical background for stated preference (SP) methods before exploring their critiques. The fianl design for the CV and CE tasks can be found in Section 2.2.2.1. To briefly review the welfare economics basis, SP methods estimate the Hicksian Compensating Surplus as a measure of welfare (Atkinson et al., 2018a). This measure is notably different from equivalent variation or Marshallian measures and can be defined as:

"The change in income, paid or received, that will leave the individual in his initial welfare position after a change in the provision of the good or service" (Atkinson et al., 2018a, p.88).

Note here that the provision refers to the non-market good of the marine environment, which is altered by the release of marine microplastics. The change in welfare owing to a change in non-market goods can then be estimated using either compensating or equivalent variation, often noted as WTP or WTA (Johnston et al., 2017; Fujiwara and Campbell, 2011). Further discussion of the foundations of WTP measures as a welfare measure are available in Bateman et al. (2002); Boardman et al. (2017). To summarise, individuals' utility is assumed to be a function of market and non-market goods. When the provision of the non-market goods is altered, the effect on individual welfare can be measured in the monetary different necessary to restore the individual to the prior utility level. The measure of this welfare change is WTP, which can be estimated using both CV and CE methods.

2.2.2.1 Contingent Valuation

Contingent Valuation (CV) is a commonly-used SP method where respondents state their individual WTP valuations for non-market valuation problems (Atkinson et al., 2018a; Bateman et al., 1995; Boardman et al., 2017; Mitchell and Carson, 2013; Carson, Flores and Meade, 2001). Elicited WTP represents an individuals TEV rather than attribute-specific valuations (Mitchell and Carson, 2013; Bateman et al., 1995). However, Atkinson et al. (2018a) argued that respondents might face difficulties in disentangling different categories of use and non-use of TEV. As such, respondents may value the TEV of an ecosystem higher than the sum of its parts given the interconnected nature of ecosystem provision (Beaumont et al., 2019; Kumar, 2012). TEV simplifies both responses and aggregation (Hoyos, 2010; Boardman et al., 2017). CV WTP is elicited using a specific payment question, the valid design of which is an area of substantial debate (Mitchell and Carson, 2013; Atkinson et al., 2018a). The validity of CV WTP is an area of such significant debate that the NO.A.A. blue-ribbon panel of economists convened to issue a report on the optimal design of CV questions to ensure valid valuations (Arrow et al., 1993; Murphy et al., 2005). The NOAA panel report was followed by a significant amount of research on optimal question design that could fill an entire second report, as in Bateman et al. (1995) and Johnston et al. (2017). The following section synthesises the best-practice guidance from the extensive literature to design a CV question that can estimate WTP for reductions in microplastics release.

2.2.2.2 Choice Experiments

In CEs, individuals choose between alternatives that vary only by the levels of different attributes (Ryan, Gerard and Amaya-Amaya, 2007; Clark et al., 2014). The theoretical justification for valuing the attributes of a good rather than the good itself is derived from Lancaster (1966) characteristic theory of economic value, which suggests that individual utility from consuming a good is a composite of utilities for the attributes of that good. Lancaster (1966) suggested that an attribute is relevant if its omission would substantially change consumers preferences, examples might be the cost, frequency, or severity of an alternative. A set of relevant attributes forms an alternative, and respondents must choose their preferred alternative from a choice set of mutually exclusive alternatives (Hoyos, 2010; Ryan, Gerard and Amaya-Amaya, 2007; Hauber, Fairchild and Johnson, 2013; Lancaster, 1966). There is a debate in the literature on how each alternative should be described to respondents (Hoyos, 2010). There are three main methods whereby respondents indicate their preferred alternative. These are contingent ranking, where individuals rank alternatives against each other; contingent rating, where individuals assign a semantic or numerical rating to each alternative; and CEs, where respondents only indicate their preferred alternative and do not impose any ranking on their preferences (Competition Commission, 2010). While using a numeric or semantic scale to assign weightings and preferences between alternatives allows respondents to indicate the strength of their preferences, respondents may understand the ranks differently, thus reducing understanding (Atkinson et al., 2018a). Furthermore, it is not clear how ranks may then be represented in the utility framework, whereas choosing alternatives is consistent with the random utility model described below (Atkinson et al., 2018a). Alternatively, CEs allows researchers to infer respondents substitution patterns between attributes such as increased product prices for a reduction in health risks (Atkinson et al., 2018a; Clark et al., 2014; Scasny and Zvěřinová, 2014). Given that the proposed REACH restriction would require the reformulation of cosmetic products, attribute-specific WTP is relevant to this research, and, therefore, a CE is appropriate.

2.2.2.3 CV Versus CE Methods

While both CE and CV methods can estimate welfare measures, it is instructive to compare the two. CV may be preferred when a single value for the TEV is required for policymaking as CE instead elicits attribute-specific marginal WTP (Atkinson et al., 2018a; Lancsar and Louviere, 2008). Furthermore, CV explicitly states WTP, whereas CE implicitly calculates WTP. Although CE gains more information per respondent and allows for a slightly smaller sample size, the complexity - optimality trade-off in the CE design complicates responses and, therefore, CV may be preferred for ease of response (Hoyos, 2010). However, Bateman et al. (2002) noted that many of the same critiques of CV being sensitive to design effects also applied to CE. Indeed, the types of validity checks used in SP research are relevant for both approaches and are estimated in this research for each type of data (Johnston et al., 2017). Although there are weaknesses common to both CE and CV methods, including both can capture different WTP measurements and test the convergent validity of the WTP estimates (Diamond and Hausman, 1994; Carson, Flores and Meade, 2001; Johnston et al., 2017; Arrow et al., 1993). Overall, this research includes both CE and CVM tasks to elicit several different WTP values.

2.2.3 Critiques of Stated Preference

This research used a SP survey to estimate the non-market benefits in WTP terms of the proposed REACH restriction on intentionally added microplastics. Therefore, it is worthwhile briefly commenting on critiques of WTP values. For instance, it has been suggested that individuals valuations are not reflective of their perception of the TEV of a good, but rather subject to scope, embedding and social-desirability effects (Diamond and Hausman, 1994). Diamond and Hausman (1994) argued that WTP under these effects is, therefore, arbitrary rather than accurately and specifically valuing the good in question.

Lew and Wallmo (2011) explores the difference between scope tests, which measure changes in WTP according to a change in one component of the utility function, and embedding tests, which measure differences in WTP according to changes in multiple components of utility. The embedding effect suggests that valuations are sensitive to whether the good is individual or embedded as a package, with an example being respondents valuing the clean-up of one lake similarly to the clean-up of five lakes, including that one lake (Hausman, 2012). An embedding effect in this research would be evidenced if respondents valuations for one ocean were similar for global impacts. The similar scope effect suggests that respondents' valuations are not sensitive to the scope of the good being valued (Hausman, 2012). An example of the scope effect is the scenario in Diamond and Hausman (1994) where respondents valued the loss of 2000, 20000 and 200,000 birds similarly. There are two challenges to Hausman (2012) critiques. Beforehand, it is essential to note that Hausman (2012) was motivated by the use of the CVM in litigation of the Exxon-Valdez disaster (Mitchell and Carson, 2013; Carson, Flores and Meade, 2001) [6]. Firstly, the mitigation of scope and embedding effects were discussed by the NOAA panel and updated in Johnston et al. (2017), which developed techniques to ensure the validity of WTP valuations from the CVM (Arrow et al., 1993; Fujiwara and Campbell, 2011; Mitchell and Carson, 2013; Carson, Flores and Meade, 2001; Bateman et al., 2002).

Regarding social-desirability bias, the advent of internet-based sampling may reduce the social-desirability element of surveys (Bateman et al., 2002). Indeed, Lindhjem and Navrud (2011) evaluated the validity of face-to-face interviews versus internet sampling

[6] Alongside the references provided, I also very briefly spoke to Professor Richard Carson at the 2019 LEEP Institute Conference about Hausman's critiques, and he specifically mentioned the Exxon-Valdez legislation motivation.

and given the absence of social desirability effects, decreased cost, and negligible changes in other factors, internet sampling appeared to be sufficiently accurate sampling methods.

A necessary condition for valid CV questions is incentive-compatibility (Bateman et al., 1995; Day et al., 2012). Incentive-compatibility, described in Mitchell and Carson (2013), and related to SP surveys in Johnston et al. (2017), is where a respondent's dominant strategy is to reveal their preferences, and thus valuations, truthfully. The truthful revelation of preferences is essential to minimise hypothetical bias on valuations (Cummings and Taylor, 1999). A necessary but not sufficient condition for truthful revelation is believing the participation to be consequential[7]. Indeed, Brouwer et al. (2017) argued that making respondents believe their valuations to be 'consequential' was crucial to making valuations incentive-compatible. There is, therefore, a link between incentive compatibility, perceived consequentiality, and hypothetical bias in CV questions.

Hypothetical bias arises when individuals are asked to provide valuations of hypothetical scenarios and can be minimised but not eliminated (Arrow et al., 1993; Hausman, 2012; Aadland and Caplan, 2003). Pearce (1998) argued that hypothetical bias amounted to individuals attempting to estimate their warm-glow utility from valuing an environmental good rather than reliable and precise valuations (Kahneman, Knetsch and Thaler, 1990; Diamond and Hausman, 1994; Hausman, 2012; Murphy et al., 2005). SP methods are uniquely vulnerable to hypothetical bias as respondents must state their valuations in a hypothetical context rather than actually paying for an item on the market. In contrast, RP methods observe behaviour in a real market where choices are incentive-compatible as they are consequential. The CV literature has designed treatments and question formats to minimise hypothetical bias. This research introduces certainty statements to evaluate hypothetical bias (Blomquist, Blumenschein and Johannesson, 2009; Loomis, 2014). Certainty statements ask respondents to state how certain they are that their valuation is realistic, consequential, and accurate. Such statements minimise the effect of hypothetical bias on valuations with a minimal penalty on survey length and complexity (Blomquist, Blumenschein and Johannesson, 2009). For example, respondents could be asked whether they are 'Unsure', 'Quite Sure', or 'Very Sure' about their responses. In practice, the least sure respondents exhibit the highest degree of hypothetical bias with greater certainty leading to more accurate valuations (Blomquist, Blumenschein and Johannesson, 2009). Therefore, certainty statements may minimise hypothetical bias in the CV questions.

[7] A respondent believing that they will have to pay is another condition for incentive compatibility.

2.3 Determinants Of Willingness To Pay

This section critically hypotheses which factors influence the magnitude of individual WTP in the SP survey. These factors can then be included in the survey to understand the individual-level influences of preferences and WTP. There are two broad categories of factors; sociodemographic variables such as age, gender and income, and attitudinal variables such as knowledge and concern about microplastics. This section explores the theoretical and empirical justification for each covariate included in the SP survey.

2.3.1 Plastics Preferences.

Before evaluating the broad range of variables that may influence WTP, it is worthwhile briefly reviewing the literature on preferences and WTP for reductions in marine plastic. Thus far, no work, to the best of the author's knowledge, has estimated WTP to reduce microplastics, so this review is confined to the growing body of work considering marine plastics. The notable place to start is Abate et al. (2020) who elicited WTP for a proposal in Norway to reduce marine plastics in Arctic ice. Their result of median WTP being \$642 per household per year suggests a strong preference for reductions in plastic pollution. Notably, the effect of involvement in environmental charities on support for plastic reduction was statistically significant. Similarly, Hynes et al. (2020) used a CE to demonstrate that exposure to the Blue-Planet II documentary influenced preferences regarding the marine environment. However, the effect on preferences was not then translated into a statistically significant difference in WTP. This result may be due to the timing of the research or the well-known gap between attitudes and behaviour (Kollmuss and Agyeman, 2002). Finally, Deng et al. (2020) used face-to-face surveys in China to specifically evaluate public knowledge and preferences regarding microplastics. They did not elicit WTP and was not in a European context as the previous work. While, Deng et al. (2020) observed that microplastic-specific knowledge is generally low, they did note that those familiar with microplastics were much more likely to be willing to support measures to reduce their release. To summarise, respondents' are generally opposed to microplastics if they are made aware of them, although there is limited evidence on how preferences translate to WTP.

2.3.2 Socioeconomic Determinants

This section describes the possible hypotheses about the effect of socioeconomic variables on the magnitude of an individual WTP valuation (Bateman et al., 2002; Boardman et al., 2017; Pearce, 1998). Only so many hypotheses may be tested without increasing task complexity and reducing the power of explanatory models. Therefore, a SP survey instrument must seek only those indicators that have been empirically observed to influence WTP valuations. Fransson and Garling (1999) conducted a meta-analysis of such determinants of WTP and reported upon five main influences; age, gender, location, class and political ideology. Latter studies have increasingly added income and attitudinal questions (Atkinson et al., 2018a). The following section discusses how these and other socioeconomic factors are hypothesised to determine the magnitude of respondent WTP.

The effect of age on WTP is uncertain. Fransson and Garling (1999) argued that a negative effect could plausibly exist if younger age groups have greater environmental concern, which is positively correlated to WTP. There is some support for the hypothesis of greater environmental concern and awareness in younger age groups (Kollmuss and Agyeman, 2002; Li et al., 2019; Fransson and Garling, 1999). Moreover, Fransson and Garling (1999) observed a positive correlation between concern and WTP for environmental quality. However, the magnitude and statistical significance of that correlation are disputed (Best and Kneip, 2011; Spash, 2006). Moreover, older respondents typically have higher wealth and income, which are strongly related to the magnitude of WTP, so the overall sign of age on WTP is unclear. This research includes age, income and environmental concern questions to test whether age is correlated with WTP.

The effect of gender on WTP and PEB is also ambiguous; female respondents may exhibit environmental concern but for different reasons than male respondents (Fransson and Garling, 1999; Kollmuss and Agyeman, 2002; Li et al., 2019; Best and Kneip, 2011). Therefore, this research appends a gender question to the survey instrument to test the hypothesis that gender differences in environmental concern translate into WTP.

Income effects on WTP are common in the literature as environmental quality may be assumed to be a normal good. The income effect suggests that individual WTP rises with income purely as individuals possess more wealth, and their marginal propensity to spend may increase (Bateman et al., 2002; Boardman et al., 2017). As such, the absolute value of WTP may increase, but the proportion of income or wealth could be less (Atkinson et al., 2018a). Although the precise magnitude of the elasticity is an area of debate in the literature, Tyllianakis and Skuras (2016) meta-analysis confirmed that WTP is income-elastic. The income effect may also affect the incidence of costs and benefits. Specifically, higher-income groups may express an absolutely higher WTP simply as a function of their greater wealth rather than their exposure to high concentrations of marine pollution (DEFRA, 2007; Kildow and McIlgorm, 2010; Oosterhuis, Papyrakis and

Boteler, 2014). Given that house and travel prices are lower for higher pollution areas, lower-income groups may be more exposed to environmental effect. However, their lower budget constraint restricts the expression of this in WTP. Therefore, income can distort the reported WTP and must be accounted for in the survey design.

To better understand income effects, this research also asks respondents for their education and employment. Respondents are asked to report their employment status given a clear relationship with income and Thalmann (2004) finding that more secure employment increased environmental concern. Asking about respondents level of education has empirical support with Fransson and Garling (1999) supporting the hypothesis that education influences environmental concern and Aadland and Caplan (2003) reporting that education influences WTP via income effects [8]. A final covariate of income is a question about whether respondents' income was affected by the coronavirus pandemic, although the question did not determine the direction of change. Further motivation and interpretation is provided for this question in later chapters but suffice to say that the pandemic affected disposable income and thus influenced WTP through the income effect. Overall, this research includes income and determinants of income to understand income effects on WTP.

The difference in valuations between lower and higher-income groups may also be related to their spatial location, i.e. a distance-decay effect (Fransson and Garling, 1999). A distance-decay effect suggests that those with greater exposure and salience of pollution's effects may value its reduction more highly than those spatially distant from it (Bateman et al., 2002). This research asked respondents to report approximately how far they lived from the coast and then used that measure of distance to evaluate distance-decay. Respondent-level postcodes were not available for a more precise calculation of distance from the coast although should be gathered in future research to evaluate spatial autocorrelation and clustering of preferences. Although distance-decay is common in the SP literature, the unobservable nature of microplastics may negate any possible distance-decay effect. Furthermore, the marine plastic problem has already been established as having some non-localised effects such as loss of option and non-use value and potential health impacts from the transmission of microplastics and leachate through the food chain (Beaumont et al., 2019; Auta, Emenike and Fauziah, 2017; ECHA, 2014b). To summarise, this research is, therefore, interested in testing existence and direction of distance-decay withiin the context of microplastic pollution.

[8] Although professional qualifications were not included in the education categories, there was sufficient data to determine the proportion of the sample who had attended higher education.

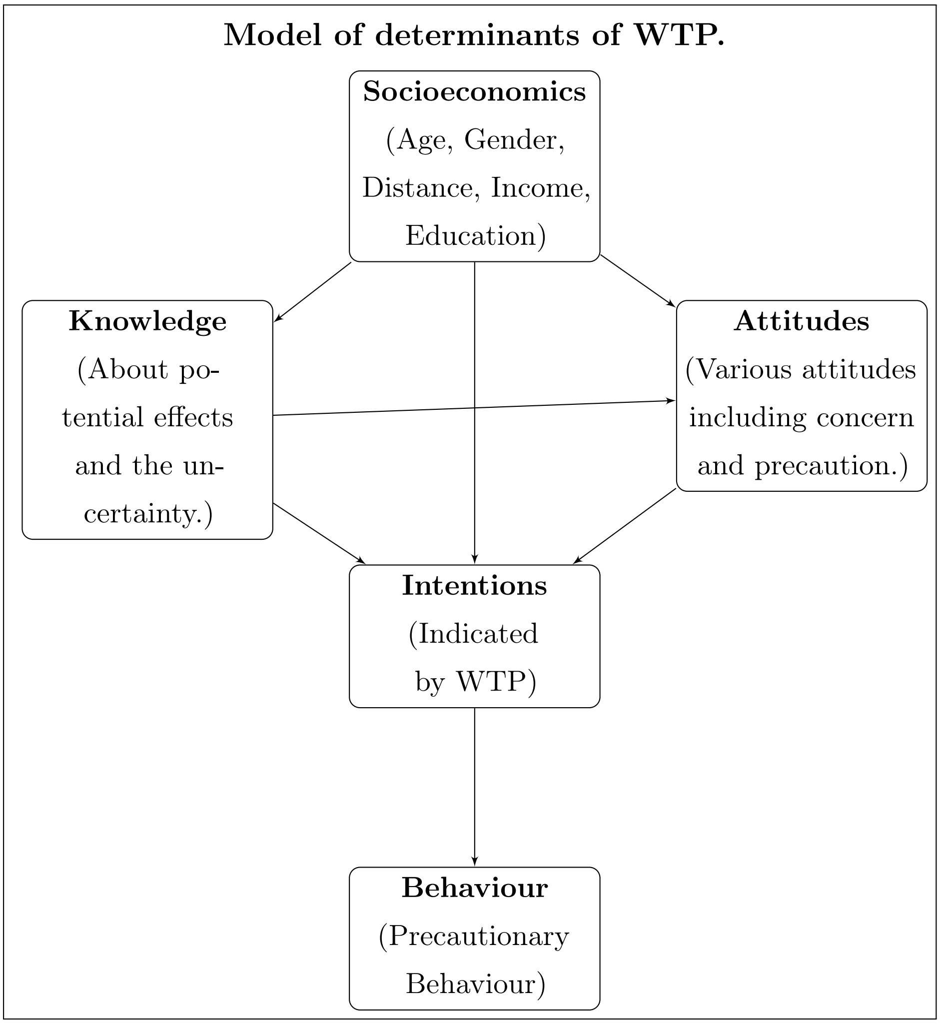
2.3.3 Attitudinal Determinants

There is a substantial body of interdisciplinary research on the determinants of WTP for environmental causes, and this section discusses which should be included in the SP survey design (Fransson and Garling, 1999; Kollmuss and Agyeman, 2002; Kallbekken and Sælen, 2011; Spash, 2006; Trivedi, Patel and Savalia, 2015; Li et al., 2019; Faccioli et al., 2020). Figure 2.1, adapted from Kollmuss and Agyeman (2002), reports a general interpretation of how each factor influences WTP. Although this is not designed to replace the richer and more realistic Pro-Environmental Behaviour (PEB) models, it illustrates the link between different survey questions and WTP. The PEB in this research may be interpreted as buying cosmetic products that have been reformulated to substitute out microplastics. The socioeconomic determinants discussed in Section 2.3.2 are represented in this model as influencing WTP directly and indirectly through environmental factors. One general conclusion is that the relationship between environmental beliefs and WTP is modulated by two personality-based determinants: knowledge and concern. This section discusses how to measure the link between these two determinants and WTP.

The original linear model of knowledge - attitudes - behaviour hypothesised that increasing individuals knowledge of both consequences and alternatives to environmentally damaging behaviour might alter behaviour and thus WTP (Kollmuss and Agyeman, 2002; Trivedi, Patel and Savalia, 2015). In the context of Figure 2.1, WTP can be taken as an indicator of behavioural intentions, although there is a difference between intentions and observed behaviour (Faccioli et al., 2020). For example, individuals who do not know the impacts of marine microplastic pollution are unlikely to value those impacts highly (Kollmuss and Agyeman, 2002; Trivedi, Patel and Savalia, 2015; Kallbekken and Aasen, 2010; Spash, 2006). Although the early literature believed that increasing knowledge by raising awareness of an issue may change behaviour and WTP, later work indicates that knowledge acts more indirectly to influence attitudes. However, this model is too simplistic and has been largely rejected, given the significant empirical evidence that merely providing knowledge to increase awareness does not then strongly influence behaviour and thus WTP. The interested reader is directed to the theory of reasoned action and later developments charted in Kollmuss and Agyeman (2002).

One reason for the weak transmission of knowledge to behaviour could be that respondents' knowledge concerns only general rather than microplastic-specific effects. For instance, Deng et al. (2020) found a generally low level of public knowledge about microplastics, a finding sensitive to gender, age, education and income. The low level

Figure 2.1: Simple Model of determinants of WTP.



of knowledge implies a lower WTP, but their study did not consider this extension. As Deng et al. (2020) found a low-level of specific knowledge, respondents should be informed about the science and uncertainty about microplastics to provide informed and more valid estimates (Johnston et al., 2017). In this research, two knowledge questions are used to test the effect of information provision and test the finding that knowledge is a poor predictor of WTP given other determinants (Kollmuss and Agyeman, 2002). Specifically, respondents are initially asked about their current knowledge level, then provided information before being asked to self-report their level of knowledge about microplastics at the end of the survey. The objective of this design is to understand better the link between knowledge of water micropollutants and WTP. To summarise, this research evaluates how knowledge about uncertain potential effects influences WTP for precautionary restrictions.

One widely reported salient influence on knowledge about microplastics has been media coverage of the marine plastic problem (Forrest, 2018; Hook and Reed, 2018). Media coverage, most notably the *Blue-Planet II* BBC programme, has focused on the damages from marine plastic on marine life, particularly on fatalities by entanglement in discarded single-use products or ingestion of a fatal quantity of plastic (The Economist, 2019; Forrest, 2018; Hook and Reed, 2018; Environmental Audit Committee, 2018; Green Alliance, 2018; Hynes et al., 2020). Once individuals are exposed to provocative or emotional images, they may increase their WTP valuations as they believe there to be a greater benefit to actions congruent with the protection of the marine environment (Fransson and Garling, 1999; Kollmuss and Agyeman, 2002; Kallbekken, Kroll and Cherry, 2011; Bateman et al., 2002; Nixon and Saphores, 2007). However, it is not clear whether the Blue-Planet effect on awareness then translates into greater WTP (Hynes et al., 2020). Moreover, the interaction between increased knowledge of marine pollution and attitudes to microplastics restrictions is not currently clear. Specifically, while media coverage may affect attitudes, it is unclear how attitudes then translate into WTP (Kollmuss and Agyeman, 2002; Fransson and Garling, 1999). Indeed, the total effect of media coverage on WTP valuations may peak after viewing the descriptive content but fall over time and have a negligible effect on valuations (The Economist, 2019). It may also be possible that the effect of knowledge on WTP may be influenced by whether knowledge comes from media viewership or level of education. Therefore, a survey question on media coverage of the marine plastic problem is included to test the effect of the source of knowledge on WTP.

Alongside knowledge, a significant determinant of WTP is environmental attitudes. However, there is a difference between general attitudes and specific attitudes to different pollutants and impacts. For example, strongly anthropocentric individuals may only report high WTP if an environmental problem has the potential to affect them, or to a lesser extent, society. In contrast, ecocentric individuals may report high WTP for environmental problems of low risk to humans but a higher risk to the environment (Fransson and Garling, 1999; Kollmuss and Agyeman, 2002). Attitudes may also be affected by personal values and societal norms, although few are for the marine environment or micropollutants (Schwartz, 1977; Abbott, Nandeibam and O'Shea, 2013). Finally, WTP may be more strongly influenced by specific attitudes, such as concern about the effects of microplastics, rather than more general attitudes such as the concern for the ocean (Kollmuss and Agyeman, 2002; Fransson and Garling, 1999; Spash, 2006; Cooper, Poe and Bateman, 2004; Dunlap and D. Van Liere, 2008; Abate et al., 2020; Laroche, Bergeron and Barbaro-Forleo, 2001). Assessing specific attitudes allows a stronger indication of specific behaviours and WTP (Fransson and Garling, 1999). This research assesses a specific attitude of environmental concern and accordingly adds three indicator questions. The questions assess respondents specific attitudes regarding the risks from microplastics to themselves both currently and in the future, and finally, the extent to which they believe microplastics currently pose a threat to the marine environment. It is hypothesised that greater concern, specifically about microplastics, has a strong positive effect on WTP. Using three different attitudinal indicators reveals differences in types of concern. Although the three indicators use the common Likert scale format, the specific items have not been validated or used before in the literature. This contrasts with the more commonly used scales discussed in Fransson and Garling (1999) including the New Environmental Paradigm (NEP) scale (Dunlap and D. Van Liere, 2008; Kotchen and Reiling, 2000). While the NEP has empirical support, it is also much longer, more complex, and is not microplastic-specific. Therefore, it is not an appropriate indicator of concern about microplastics for this research.

Respondents are also asked whether they have been involved, via membership or donation, with environmental charities. Charity membership is evidence of respondents acting on their concerns, and thus, involved respondents are expected to report higher WTP (Kollmuss and Agyeman, 2002). Secondly, both Laroche, Bergeron and Barbaro-Forleo (2001) and Trivedi, Patel and Savalia (2015) reported that respondent WTP for more environmentally-friendly products was, in part, influenced by Environmental Locus of Control (ELC). ELC links to consequentiality as externally located individuals believe control over actions is external to them and that their actions are inconsequential, suggesting a low WTP (Trivedi, Patel and Savalia, 2015; Kollmuss and Agyeman, 2002).

However, internally located individuals internalise their market power and are more likely to believe actions are consequential and thus may be WTP for changes in environmental quality (Trivedi, Patel and Savalia, 2015; Vossler and Watson, 2013). Trivedi, Patel and Savalia (2015) finds evidence to support a positive link between ELC and WTP, while Laroche, Bergeron and Barbaro-Forleo (2001) finds that this extends to WTP for environmentally-friendly products. Therefore, this research includes questions about experts and stakeholders to test respondents degree of ELC. Although there is scarce economics literature on ELC, it appears to be one of many determinants of environmental attitudes (Trivedi, Patel and Savalia, 2015). However, the strength of the link between environmental concern and knowledge and WTP is mixed. Therefore, this research includes several indicators of environmental knowledge and concern in the survey design. Figure 2.1 is by no means exhaustive but summarises how each major group of survey questions contributes to WTP determinants.

2.3.4 Survey Questions

Table 2.2 reports all the socioeconomic and attitudinal questions included in the survey given the theoretical and empirical evidence discussed in this section. While age, gender, income have all been studied and shown to weakly influence the magnitude of valuations, others such as specific knowledge on microplastics and degree of environmental concern have uncertain effects on WTP. Therefore, debriefing questions on each relevant determinant are incorporated in the survey design. The following chapter designs and pre-tests the survey.

2.4 Summary

This chapter has reviewed the theoretical and empirical literature on the use of different SP methods to estimate individual WTP for non-market policy impacts. non-market values can be estimated using either CV or CE approaches, and this research adopts both. The following chapter practically designs the rest of the SP survey focusing on the valid and reliable elicitation of WTP.

Table 2.2: Variable Summary Table.

Variable	Coding	Expectation	Min.	Median	Mean	Max.
ID	Respondent response ID runs 1-670.	None.	1.0	335.5	335.5	670
Timing	Survey completion length in seconds.	Lower WTP for speeders.	121.000	393.000	448.737	1765.000
Order	1 = Q7 First, 2 = Q6 First	Significant ordering effect	0.000	1.000	0.543	1.000
Q1Gender	Female = 0, Male =1	Gender differences but direction uncertain	0.000	0.000	0.473	2.000
Q2Age	18-25 = 0, 26-39 = 1, 40-55 = 2, 56-70 = 3, 70+ = 4	Decreased knowledge with age but higher income and thus WTP	21.500	47.500	42.891	71.000
Q3Distance	0-2miles = 1, 3-10miles = 2, 11-20miles = 3 21-49miles = 4, 50miles+ = 5	Distance-Decay effect	1.000	35.000	29.482	50.000
Q4Trips	0trips = 0, 1-2 trips = 1, 3-5 trips = 2, 6+trips = 3	Positive relationship to WTP	0.000	1.000	1.634	3.000
Q5Knowledge	No knowledge = 1, Little = 2, Average = 3 Good = 4, Strong = 5	Positive relationship to WTP	1.000	3.000	2.818	5.000
Q6ResearchResponse	0 = No, 1 = Yes	N/A	0.000	1.000	0.5104	1.000
Q6ResearchCertainty	Unsure = 0, Quite sure = 1, Very sure = 2	Decreased WTP with certainty	0.000	1.000	1.378	2.000
Q7TreatmentResponse	0 = No, 1 = Yes	N/A	0.000	1.000	0.645	1.000
Q7TreatmentCertainty	Unsure = 0, Quite sure = 1, Very sure = 2	Decreased WTP with certainty	0.000	2.000	1.437	2.000
Q7TreatmentUpperResponse	0 = No, 1 = Yes	N/A	0.000	1.000	0.618	1.000
Q7TreatmentLowerResponse	0 = No, 1 = Yes	N/A	0.000	0.000	0.399	1.000
Q8DominatedTest	0 = A, 1 = B	Used to truncate the sample	0.000	0.000	0.287	1.000
Q9-12 Choices	Levels coded as in tables.	N/A	0.000	1.000	0.571	1.000
Q12CECertainty	Unsure = 0, Quite = 1, Very = 2	Decreased WTP with certainty	0.000	1.000	1.391	2.000
Q13 Threat to Self	Likert scale 1-5	Increasing WTP with concern	1.000	3.000	3.422	5.000
Q14 Threat to Future	Likert scale 1-5		1.000	4.000	3.743	5.000
Q15 Threat to Environment	Likert scale 1-5		1.000	4.000	4.012	5.000
Q16 Blue-Planet	None = 0, Some=1, All =2	Positive relationship with WTP	0.000	1.000	0.866	2.000
Q17Responsibility_Firms	0 = No, 1 = Responsible	Theory mixed	0.000	1.000	0.761	1.000
Q17Responsibility_Consumers	0 = No, 1 = Responsible		0.000	1.000	0.573	1.000
Q17Responsibility_Government	0 = No, 1 = Responsible		0.000	1.000	0.703	1.000
Q17Responsibility_LocalAuthority	0 = No, 1 = Responsible		0.000	0.000	0.402	1.000
Q18Charity	No = 0, Yes = 1	Positive relationship with WTP	0.000	0.000	0.404	2.000
Q19Knowledge	No knowledge = 1, Little = 2, Average = 3 Good = 4, Strong = 5	Positive relationship with WTP	1.000	3.000	3.001	5.000
Q20Consequentiality	No = 0, Don't Know = 1, Yes = 2	Used for truncation	0.000	1.000	1.137	2.000
Q21Experts	Likert Scale 1 - 5	Theory mixed	1.000	4.000	3.596	5.000
Q22Education	Secondary = 1, Further = 2, Bachelor = 3, Postgrad = 4	Positive relationship with WTP	0.000	2.000	2.404	4.000
Q23Employment	Prefer not to say = 0, NEET =1 Retired= 2, Student= 3 Part-time = 4, Self-employed = 5 Full-time=6	Positive relationship with WTP	0.000	6.000	4.460	6.000
Q24A Coronavirus	No = 0, Yes = 1	Theory mixed	0.000	1.000	0.533	2.000
Q24Income	£0-500 = 0, £501-1000= 1 £1001-1500 = 2, £1501-2000= 3 £2001-2500 = 4, £2501-3000 = 5 £3001-4000= 6, £5000+ = 7 Prefer not to say = 8 Or low/high income dummy approach.	Positive relationship with WTP	250.000	1750.000	2193.657	5000.000
Q25Survey	1-10 scale	Used for truncation	1.000	9.000	8.597	10.000

Survey Implementation.

Chapter Three Abstract:

This chapter designs a valid and reliable stated preference survey to value the benefits of microplastic abatement policies. Firstly, the theoretical background for using SP methods, notably CEs and CV, to elicit WTP is discussed. Secondly, the determinants of WTP are explored. Finally, a rigorous pre-testing process is undertaken. Overall, this chapter contributes to the literature on the development of SP methods for use in the water pollution field in the context of irreversibility and uncertainty.

3.1 Design of the Valuation Tasks.

This section reviews the theoretical and empirical literature with regards to the appropriate specification of the CV and CE tasks.

3.1.1 Designing CV questions

The CV question design must choose an incentive-compatible format to minimise hypothetical bias (Arrow et al., 1993). While many formats exist, payment cards, payment ladders, binary choice, dichotomous choice, the empirical literature increasingly supports only Dichotomous Choice (DC) formats (Arrow et al., 1993; Johnston et al., 2017). The most common DC format is Single-Bounded DC (SBDC) which asks a binary yes/no question similar to the referenda format recommended by Arrow et al. (1993). The SBDC format mitigates anchoring and ordering effects as it is incentive-compatible; respondents only face one binary choice and cannot update their choice (Johnston et al., 2017; Cummings and Taylor, 1999). Anchoring effects suggest that respondents anchor subsequent valuations on the first valuation task they perform in a survey. Order effects suggest that the ordering of questions leads to different magnitudes of valuations (Day et al., 2012). Both effects violate the assumptions of independent valuations (Bateman et al., 1995). The presence of such effects in CV studies has been well documented in the literature and has led to a fall in the popularity of the payment ladder and other DC formats for CV questions (Johnston et al., 2017). However, one weakness of the SBDC format is that it limits how much information is gained from respondents (Kjær et al., 2006). Accordingly, other DC formats have attempted to balance the amount of information received while maintaining incentive compatibility. Examples included One and a Half Bound DC (OOHBDC), which may be as consistent as SBDC, Double-Bounded DC formats (DBDC) which may be as efficient as SBDC, Multiple Bounded DC (MBDC) and Polychotomous Choice (PC) in Kjær et al. (2006); Hanemann (1984); ECHA (2014a); Alberini, Boyle and Welsh (2003); Foster and Mourato (2003) respectively. The following section explores each question format in greater detail.

The advantage of using the DBDC format is that the follow-up bound enables WTP to be estimated more precisely. Follow-up questions may be more efficient but may also be vulnerable to anchoring and ordering effects (Choi and Lee, 2018; Day et al., 2012). Specifically, Mitchell and Carson (2013) observed that responses to the two different questions did not correspond to the same underlying distribution. The literature is, therefore, moving away from the DBDC format in favour of SBDC. SBDC is efficient and incentive-compatible, albeit with some loss of precision (Johnston et al., 2017). Given this trade-off, this research presented the first bound of the DBDC individually so that respondents treated it as a SBDC question, and it may, therefore, be incentive-compatible. The second bound was then presented to gather more information on respondents, and no option to update their previous valuations is allowed - a pragmatic approach to CVM elicitation that balances incentive compatibility and information gathering. To summarise, this research adopts both the SBDC and DBDC formats and includes the cheap-talk treatment and consequentiality-reminders to minimise hypothetical bias. The final question text is reproduced in Section 3.2.4.

3.1.2 Designing a CE

This section discusses the literature on CE design in the context of water pollution (Alberini and Scasny, 2014; ECHA, 2014b).

3.1.2.1 Alternatives, Attributes and Levels.

The first step to designing a CE is choosing the alternatives, attributes and levels (Tinelli, 2019). This research used two alternatives, labelled ‘Option A’ and ‘Option B’, which corresponded to the status quo and the proposed restriction, respectively. A status quo alternative was included as an opt-out option consistent with a majority of the applied literature as discussed in Hooper (2013) and consistent with welfare theory as discussed by Bateman et al. (2002). While Clark et al. (2014) notes that the literature commonly features more than two alternatives, this research chooses to use only one non-status quo option for simplicity. As such, the CE only asks respondents to choose between the status quo or a restriction. An Alternative-Specific Constant (ASC) can be included in the econometric analysis when alternatives are labelled, although it must be defined against one of the alternatives (Hoyos, 2010; Train, 2009). Each alternative had three attributes called 'product performance' and 'release of microplastics', each taking three levels and the 'price' attribute having four levels[9]. Including more attributes makes a scenario more realistic but also increases task complexity which is an example of the task plausibility - optimality trade-off explored by Hoyos (2010). To decide the ideal number of attributes and levels and their description, this research used an pre-testing process involving literature, expert consultation, interviews and pilot studies described in Section 3.2. To summarise, this research designed a CE with two alternatives, three attributes and three levels with an example choice card presented in Figure 3.2 in Section 3.2.4.

3.1.2.2 Experimental Design

Once attributes and levels are selected, an experimental design to present them must be chosen. The experimental design is crucial for managing task complexity. For example, in a *full-factorial* design there is a maximum of L^A choices. Using L for the three levels (4 for the price parameter) and A for the three attributes, 27 possible choice tasks in this research (Hoyos, 2010; Clark et al., 2014; Hooper, 2013). As this number may be excessive for respondents, a *fractional-factorial* design to significantly reduce the number of choice tasks may be advisable. Generally, the literature is increasingly moving from a full-factorial to a *fractional-factorial* approach for two reasons; efficiency and task-complexity. Firstly, a fractional-factorial design can be 100% efficient, which minimises the standard errors of the parameters and, therefore, produces more precise estimates (Ryan, Gerard and Amaya-Amaya, 2007; Hoyos, 2010). Secondly, while full-factorial designs present respondents with a large number of alternatives, there is a clear trade-off between gathering complete information and making the task manageable for respondents; an example of the task plausibility - optimality trade-off in CE design (Atkinson et al., 2018a; Hoyos, 2010; Clark et al., 2014). Therefore, this research adopted a fractional-factorial experimental design.

Precisely, this research used an Orthogonal Main Effects Plan (OMEP) design provided using IBM SPSS Statistics 26 for the CE. Orthogonality is a necessary element of the experimental design to ensure unbiased estimates as it implies that attribute levels appeared with equal frequency (Lancsar and Louviere, 2008). Lancsar and Louviere (2008) further noted that orthogonal designs imply the existence of a strictly additive indirect utility function, and this implication is referred to when analysing the CE results. A main effects design, also variously referred to as a Resolution Three design, means

[9]Originally, there was a fourth attribute called 'Ingestion', but this was dropped for fears of correlation with the 'release' attribute, which would violate the orthogonality design (Lancsar and Louviere, 2008).

that only the main marginal effects of attributes on utility can be estimated, although interaction effects cannot (Bateman et al., 2002). Interaction effects determine the extent to which behaviour is connected with variations in the combinations of different offered attributes and are only a concern where they are a priori expected to be a relevant design concern (Bateman et al., 1995). The OMEP design in this research yielded 16 possible choice tasks. The tasks were blocked into four sets so respondents would face only four choices plus one dominated-scenario task to test their rationality and understanding of the CE. A CE design with three attributes and four levels leading to five choice tasks is consistent with Clark et al. (2014) survey of CE design literature. An example choice card from the OMEP design is presented in Figure 3.2, and note that the tasks presented to respondents varied only in the attributes' levels.

3.2 Design of the Survey

This chapter aims to explore and justify the eventual design of the stated preference survey. The distribution of the final survey design to 670 nationally representative adults in the UK in April 2020 was supported by funding from the Environment Agency (EA) and conducted by DJS Research. The CE experimental design was created using IBM SPSS Statistics 26. The survey text was created in Microsoft Word to allow comments from multiple parties before being sent to DJS who hosted it in their bespoke online tool. The survey's marketing was generic containing only contained the approximate length of time to complete amount and a URL. Respondents' gained credits for their participation. The survey's pre-testing took place from November 2019 to March 2020 and consisted of three elements; expert consultation, interviews, and a small pilot survey. This chapter reviews the contribution of these three stages to the final design, focusing on the validity of responses.

3.2.1 Expert consultation

The design process continuously consulted experts, including, among others, economists, policymakers, eco-toxicologists and cosmetic industry specialists [10]. Experts' were first asked to comment on questions relevant to their area of expertise (for instance, stated preference experts discussed CV questions) before they were asked to give general comments on remaining questions for completeness. The primary focus of expert consultation concerned three specific areas of the survey, the descriptions of microplastics, the description of the CE, and the CV format. Firstly, experts contributed to the text and editing of the descriptions of microplastics. The information aimed to balance various experts' diverse views while limiting survey complexity and completion length. The final version of the information provided is available in Section 3.2.5.2, while Section 6.2.2.2 evaluates the effect of this information on WTP. Secondly, the CE section also underwent significant changes to the number of attributes and levels given expert review. Finally, expert consultation recommended changing the payment ladder format to the Dichotomous Choice (DC) format given superior incentive compatibility (Johnston et al., 2017). The changes from the first to the final draft survey are further discussed in subsection 3.2.4.

[10] My sincere thanks to all those who contributed to reading any of the 45 draft survey versions. Special thanks to participants and supervisors at the University of Bath, staff at the University of Exeter, where I visited in January 2020 for help with pre-testing, and individuals from the CTPA, HSE and the EA.

3.2.2 Interviews

The second part of the pre-testing process included ten one-to-one semi-structured interviews. The purpose of the interviews was to reveal respondents comprehension and understanding of the survey. Interviews were used as a cost-effective alternative to focus groups, and the interviews were standardised using a common set of questions across the researchers. The interviews used the 'Think-Aloud' (T-A) method, which asks respondents to verbalise their thoughts when completing the survey (Cheraghi-Sohi et al., 2007). Respondents are asked to describe their thought process and understanding of the survey, which can be used to evaluate whether respondents are conforming to rational choice theory as assumed in the econometric analysis of SP surveys (McFadden et al., 1973; Lancsar and Louviere, 2008). Phillips (2014) discussed how the T-A approach had been previously used in healthcare to pre-test CEs with the implication that respondents may verbalise their thoughts regarding Attribute-Non-Attendance (ANA), payment and policy consequentiality, scope-sensitivity and survey understanding. However, Cheraghi-Sohi et al. (2007) noted that T-A's effective use required training which was not present in this research given the relatively short pre-testing period. T-A was used in the ten 1-1 semi-structured interviews for pre-testing the survey. The respondents were a convenience sample of personal acquaintances, so social desirability bias cannot be eliminated from the responses nor can the un-representative nature of this sample be ignored. Table 3.1 reports the five core questions used in all the interviews alongside standard T-A guidance. The questions were devised first using previous survey design experience and aimed to evaluate the comprehension of the information provided and choices made. The total changes from the pre-testing to the final survey are detailed in subsection 3.2.4. To summarise, ten semi-structured interviews used the T-A approach to evaluate respondents comprehension and responses to the survey.

Table 3.1: The common questions used in the semi-structured pre-testing interviews.

Number	Question
1	Is the information easy enough to understand or is it too technical?
2	Do the pictures/graphs make sense?
3	Do you think that the numbers in this question are realistic?
4	What made you choose that option?
5	What, if anything, would you change about this section?

3.2.3 Pilot survey

The final stage of the pre-testing process involved a small pilot survey. Using an early draft of the survey and potential respondents from the sample frame, a Google Forms link was completed by 54 non-representative respondents. Given methodological limitations of the pilot, the focus now turns to how it informed the final version.

3.2.4 Changes from the pilot

The main changes from the pilot concerned the CE and CV methods. Starting with the two CVM questions, pilot Q5 was dropped, and Q6 was split into two different questions. The first new CV question elicited WTP for research into microplastics. The second new CV question elicited WTP for enhanced filtering of microplastics at Wastewater Treatment Plants (WWTP). There are two benefits to using these two scenarios. Firstly, the benefits of two different policy options can now be estimated more precisely. The benefit to respondents of Q6 is resolving the uncertainty about the effects of microplastics. The benefit to respondents of Q7 is a resolution of the irreversible release of microplastics. Secondly, the two scenarios are the two options in the QOV framework; one estimates the value of delaying a decision to facilitate learning while another estimates the value of immediate precautionary restrictions. However, QOV would require the scenarios to differ in only whether learning occurs. Future research may amend the two scenarios to differ along only one dimension, such as research and reductions versus just reductions in microplastic release, to estimate Quasi-Option Value (QOV). In this research, however, the difference in the values from the final survey's two CV questions can be interpreted as a premium for precautionary abatement. More generally, it estimates the value of tackling irreversibility over uncertainty. To summarise, this research estimates the premium for the precautionary abatement of microplastics as a practical contribution to the CBA of microplastic policy and establishes a framework to empirically estimate QOV in future work.

Further changes to the CV questions included amending the payment vehicle, question format, and bids number. Additional water bills were used instead of additional income tax upon the advice of experts who suggested respondents may be opposed to income taxation increases. The CV format was again dichotomous choice but single-bound for Q6 and double-bound for Q7. The use of the DBDC approach means that the first bound of Q7 is directly comparable to Q6, while the second bound gains greater insight to the distribution of Q7 WTP. The number of bid levels was increased to six randomly varying bids for both questions. The bid levels were taken from the pre-test and average annual water bills in the UK to increase question credibility (Logar et al., 2014). The use of water bills may increase respondent beliefs about payment consequentiality, although this research only assessed policy consequentiality. Finally, the order of Q6 and Q7 was randomly varied to explore the existence and significance of ordering effects from answering a research or investment question first. To summarise, the scenario, payment vehicle, format and bid levels of the CVM questions were changed to increase the credibility of the scenario and the precision of the WTP. For completeness, the agreed text for the two questions is reported below, with discussion available in Sections 5.3 and 5.4 respectively.

Question Six:

"One possible policy option would be to fund research into the long-term environmental and health effects of microplastics in the environment.

The research would definitely resolve the scientific uncertainty about any possible effects, though it would have no effect on the amount of microplastics currently entering the environment from wastewater sewerage.

An increase in your water bills would cover only the cost of this research. Any follow up action, depending on the research findings, would be funded separately. Would your household be willing to pay £X per year in extra water bills specifically for such research?"

Question 7:

"Suppose that the UK was going to introduce a policy that would stop microplastics from wastewater sewerage entering the environment now, before waiting for the results of the research discussed in the previous question.

This policy would pay to upgrade wastewater treatment plants filtering systems so that they would capture all the microplastics in sewerage wastewater heading to the environment.

An increase in your water bills would be used to pay for the cost of this investment. Would your household be willing to pay £X per year in extra water bills to implement this policy?"

The final CE design is presented in Figure 3.2. Changes from the pilot CE included changing the number of attributes and levels. Specifically, the ingestion attribute was dropped as there was a worry that respondents would treat the ingestion and accumulation attributes as correlated. Moreover, the number of levels was held at three for the release and performance attributes but increased to four for the price attribute to better understand scope sensitivity. Given changes in the number of attributes and levels, respondents were asked to complete four, rather than three, tasks that increased survey complexity and completion length. The CE scenario was similar to the pilot using sun cream as an example product. Suncream was an ideal example product given that producers must maintain the same level of protection, say Factor50, regardless of their composition. Therefore, any reformulation without microplastics would only affect the weight, durability and feel of the product. However, other products were also mentioned with suncream to indicate the extent of the proposed ECHA restriction. Overall, the CE was redesigned to improve the scenario's credibility.

Table 3.2: Example CE:

	Option A	Option B
Reduction in the effectiveness of the personal care product.	0%	5, 10, 50%
Percentage reduction in the release of microplastics from cosmetics.	0%	10, 40, 90%
Increase in product price.	£0	£0.5, 1, 2.50, 5
I prefer:		

Final changes from the pilot due to the pre-testing included adding controls for the order and block of tasks respondents were presented. Furthermore, the attitudinal questions were amended to remove the generic and complex New-Environmental Paradigm scale favouring three Likert scales that assessed respondents' concern about microplastics. Finally, text responses were added to allow for analysis of protest votes. To conclude, the thorough pre-testing process of expert consultation, interviews and the pilot survey led to a more credible and accurate survey design although some limitations persist due to the unique challenge of valuing microplastics.

3.2.5 Undertaking the survey

The final version of the survey incorporated feedback from the experts, interviews, and pilot survey to produce a valid survey design. The following section discusses the practical undertaking and initial analysis of the final survey design.

3.2.5.1 Sampling

The sample used for the SP survey is of critical importance for the validity of the WTP. This section discusses the theoretical background underpinning the sampling strategy used in this research. Gathering a sample of a size sufficient enough to likely lead to statistically significant estimates is key for the elicitation of WTP (Ryan, Gerard and Amaya-Amaya, 2007; Bateman et al., 2002; Atkinson et al., 2018a; Boardman et al., 2017). In sampling theory, it is first necessary to define the sample population, units, frame, and strategy used in the research design (Ben-Akiva, Lerman and Lerman, 1985; Bateman et al., 2002; Ryan, Gerard and Amaya-Amaya, 2007; Hensher, Rose and Greene, 2005). The sample is simply a subset of the population. Hooper (2013), citing Bateman et al. (2002), discusses how the relevant population can be divided into use and non-use populations depending on their relation to the goods being valued. In this research, the user population of the marine environment is likely to be large. This is due to the different categories of use, including stakeholders in the marine economy who make direct use of the marine environment in both consumptive (fishing industry) and non-consumptive (shipping and tourism industries) (Kildow and McIlgorm, 2010; Mouat, Lozano and Bateson, 2010). Given the option of coastal and marine tourism, there is also a significant option use to the marine environment (Oosterhuis, Papyrakis and Boteler, 2014). There may also be a non-use population who value the marine environment's existence but do not directly make use of it (Bateman et al., 2002). Therefore, the use and non-use populations are likely to be large in the context of marine microplastic abatement. The population may be narrowed down geographically to the area where the abatement is targeted, but microplastics are easily spatially dispersed and, therefore, even narrowing down this population is challenging (Ben-Akiva, Lerman and Lerman, 1985; Bateman et al., 2002; Beaumont et al., 2019). A sample frame, the list of mutually exclusive units that constitute a population, maybe more feasible to construct and is commonly either the individual or the household (Hensher, Rose and Greene, 2005; Ryan, Gerard and Amaya-Amaya, 2007; Bateman et al., 2002). However, the most critical sampling decisions concern calculating the minimum necessary sample size and determining an appropriate sampling method.

The minimum necessary sample size for a CE is an area of significant debate and again presents a trade-off between practicality and optimality (Bateman et al., 2002). The required sample size increases with both the desired degree of precision and size of the relevant population (Hensher, Rose and Greene, 2005; Bateman et al., 2002). Furthermore, a larger sample may increase the likelihood of obtaining statistically significant parameter estimates (Ryan, Gerard and Amaya-Amaya, 2007; Ben-Akiva, Lerman and Lerman, 1985). However, there are diminishing returns to increasing sample size as sample administration and recruitment costs increase. Therefore, the precision of estimates and cost of the survey must be traded-off (Bateman et al., 2002). Large sample size may also lead to large subsample sizes, implying that any inference from the subsamples may be statistically significant (Bateman et al., 2002). Indeed, insufficient subsample size has often been a critique of inference from subsamples in CVM research (Mitchell and

Carson, 2013; Carson, Flores and Meade, 2001). A larger subsample size may not be strictly necessary if the amount of information gained per respondent is large - as in choice modelling approaches which yield more information on respondent substitution patterns and valuations per attribute (Bateman et al., 2002). However, for the sake of task complexity and possible positive correlations between individual responses, there is still no perfect trade-off where a reduced but richer sample is appropriate (Bateman et al., 2002). Indeed, both Bateman et al. (2002) and Orme (2010) comment that gathering 1,000 pieces of information from one respondent presents less information about the population than collecting one piece of information from 1,000 respondents. To relate the trade-off between information and sample size, Hooper (2013) used a formula from Orme (2010) to suggest a required sample size for choice models.

$$\frac{nta}{l} > 500 \tag{3.2.1}$$

The formula, adopted from Hooper (2013) and Orme (2010), has sample size n, number of choice tasks t, number of alternatives a, highest number of levels for an attribute when considering main effects l. However, Orme (2010) urged caution in that the given 500 was a de minimis level, and researchers should aim for 1000 instead. Regardless of the minimum threshold, however, this formula shows that the appropriate sample size for choice modelling is dependent on the CE design. To calculate the appropriate sample size in this research, Orme (2010) rule can be solved for n given the four tasks, two alternatives, and a maximum of four levels: the de minimis level of 500 is reached with a sample of 250, and the preferred 1000 threshold is possible with a sample of 500. However, a CV question is also included in the survey design, which generally requires a larger sample size where Bateman et al. (2002) recommends samples in excess of 500. Therefore, a sample size of over 500 complete responses should suffice for this research. Although some of the subsamples approach this lower bound, the final sample of 670 comfortably exceeds this.

Regarding the sampling method, there are both probability and non-probability approaches, although Bateman et al. (2002) criticises non-probability approaches as potentially biased and inappropriate unless for pilot studies. Indeed, the literature favours probability methods such as random and stratified random sampling (Ben-Akiva, Lerman and Lerman, 1985; Hensher, Rose and Greene, 2005; Ryan, Gerard and Amaya-Amaya, 2007; Bateman et al., 2002). Random sampling can be a pragmatic and convenient choice but may not minimise variance in the estimates if certain sample strata have heterogeneous variance (Ryan, Gerard and Amaya-Amaya, 2007). Therefore, a stratified random sampling strategy may be preferred as it may minimise variance by oversampling some strata and undersampling others (Ben-Akiva, Lerman and Lerman, 1985). Stratified sampling can be used to achieve subsample sizes that are more likely to lead to statistically significant estimates for subsamples of interest (Ben-Akiva, Lerman and Lerman, 1985). Relevant subsamples that could be targeted include those who live proximal to the coast, split-samples when testing ordering, and subsamples to ensure a nationally representative sample (Ben-Akiva, Lerman and Lerman, 1985). While stratified sampling has historically been of high cost due to telephone or mail surveys, newer internet-based sampling methods may make stratified sampling strategy and associated minimum variance samples and large subsamples a lower-cost alternative (Bateman et al., 2002; Atkinson et al., 2018a; Ben-Akiva, Lerman and Lerman, 1985). Therefore, while trade-offs between practicality and cost versus optimal design and sample size exist, it appears that a sample size specified by Orme (2010) rule, constructed using both use and non-use populations as the sample frame, and then sampled using stratified sampling, is an appropriate sampling strategy to administer in this research. Practically, DJS Research LTD recruited an online sample of 670 nationally representative UK adults. The sample did not use explicit quotas but aimed to be representative of the UK adult population along gender, age, and income lines.

3.2.5.2 Information Provision

This section discusses the information provided to respondents given the pre-testing process. The final versions are in Figures 3.1 - 3.4 with the main change from the pilot being the formatting of the information from a word document to an online survey format. It should, however, be noted, that the four pages of information could have been more extensive to fully acquaint respondents' with the valuation context.

Figure 3.1: Full survey first page of information provided after Q5 and before the CV questions.

Microplastics are small plastic particles, up to 5mm in diameter. Microplastics are some of the most commonly found types of plastic in the environment. The majority of microplastics in the environment come from larger plastics, such as packaging, that have broken down.

Some microplastics in the environment come from products, such as fertilisers, tyres, and personal care products that once used, may then be washed via sewage to the sea. As sewage sludge may be applied as fertiliser, some microplastics will stay in the environment and not reach the sea.

Microplastics released to the environment cannot realistically be removed and may persist there for many thousands of years. A small amount of microplastics may be present in water and seafood, which is consumed by humans and animals. The potential for adverse effects is a cause of concern. However, it is not currently possible to determine the long-term impact of exposure on the environment and human and animal health.

The survey results will be useful for future microplastic policies so we would like you to answer all questions as realistically and accurately as you can.

The first information (Figure 3.1) provided respondents set out some basic information about microplastics and their effects and has been critically reviewed by a team of economists, industry experts, toxicologists, policymakers, and respondents. The second page of information (Figure 3.2) was necessary to provide respondents with appropriate context for the private-good valuation exercise in the CE and concerned microplastics from cosmetics specifically. The information provided was clarified and evaluated by industry experts. The third page (Figure 3.3) described the CE attributes in greater detail and can report high content validity given the extensive piloting and expert review (Rakotonarivo, Schaafsma and Hockley, 2016). The final page (Figure 3.4) was an example CE used to instruct respondents on the CE format. The information's validity and accuracy were enhanced by collaboration with the CTPA and EA. To summarise, the information provided to respondents was designed to increase their knowledge and familiarity with microplastics; such an aim is commonplace in the survey design literature with examples in Adamowicz et al. (2011); Logar et al. (2014); Brouwer et al. (2017).

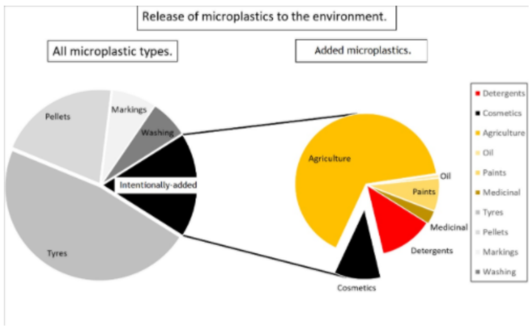
Figure 3.2: Full survey second page of information provided after the CV before the CE.

In this section we are interested in an alternative policy that would deal with the production of microplastics which are added to commonly used products. You are being asked about this as it is a different approach to controlling microplastics than those policies mentioned before.

Please note:

- Some types of microplastics added to personal care products, such as scrubs and exfoliators, were banned in the UK in 2018 as they were found to enter the environment. However, other types of microplastics added to personal care products have not been banned as there is limited evidence about their effects as discussed earlier in the survey.
- Although microplastics come from many sources, in this section we focus on those specifically added to personal care products, such as, toothpaste, shower gel, sunscreen and deodorant, as they are those most commonly used by consumers, see the following graph for context:

Microplastics by type: This chart represents the proportion of microplastics entering the environment by type. We are specifically interested in cosmetics as other policies exist for the other categories. Source: https://echa.europa.eu/documents/10162/12414bc7-6bb2-17e7-c9ec-652a20fa43fc



Example microplastics:
Microplastics in products such as sunscreen and toothpaste are tiny, in the micrometer size range, and visible only under the microscope. Source: https://www.saci-cfpa.com/site/upload/fiches/82597200447d539cc7d54e.pdf

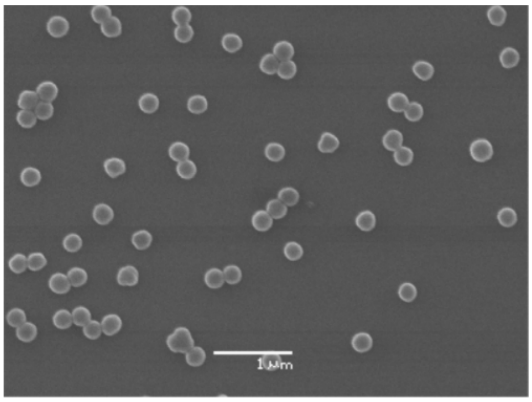


Figure 3.3: Full survey third page of information provided.

This section uses a different question format where you will be presented two options; A and B, which are described in terms of 3 characteristics:

- **Product Performance**: How effective personal care products are with and without microplastics.
  - Without microplastics, personal care products would feel different or run out more quickly. e.g. sunscreen without microplastics may be heavier or greasier to apply
  - The values presented are the estimated change in effectiveness between 0% change (no change) and 90% (significant change).
- **Release**: How many microplastics from personal care products are annually released to the environment.
  - Approximately 500 tons of microplastics from personal care products are estimated to be released to the environment annually from the UK.
  - The values presented are the percentage reduction in the tonnage of microplastics coming from personal care products that may end up in the environment.
- **Price**: How costly personal care products are with and without microplastics.
  - Without microplastics, producers must find alternative, more expensive substitutes.
  - The values presented are the estimated increase in the price of a personal care product, such as an average bottle of SPF50 sunscreen if more expensive substitutes are used.

These characteristics will take different values for each option. We then ask you to carefully select which option you prefer – there is no right or wrong answer.
Please Remember: As the existence and extent of environmental and health effects from microplastics are uncertain, paying more for a personal care product without microplastics is a *precautionary* choice, i.e. it guards against the possibility of any potential adverse effects on environment and health.

Figure 3.4: Full survey fourth page of information provided.

The next section presents options A and B - please choose whichever you prefer, there is no right or wrong answer.

You will be shown a table like this:

Example Table	**A**	**B**
Reduction in the performance of the personal care product.	0%	50%
Percentage reduction in the release of microplastics from personal care product.	0%	100%
Increase in product price.	£0	£1

You will then be asked which option you prefer.

Option A represents current real levels.
- No change in price or quality.
- Some possibility of environmental and health effects.

Option B represents a proposed level.
- The Government would ban microplastics from being added to commonly used personal care products (toothpaste, shampoo, sunscreen, etc).
- Products of lower quality would be more expensive.
- There would be a reduction in the likelihood of possible environmental and health impacts, although the existence and extent of these effects is uncertain in any case.
- You would have less money but would reduce the amount of microplastics going to the environment as a precaution against any potentially harmful effects.

We are only interested in the situation you prefer.

3.3 Survey Analysis

This chapter concludes by describing, and analysing the sample to facilitate later chapters of econometric analysis. The core issues addressed in this section are the collection of the survey data and then initial cleaning and truncation performed on the sample. Section 8.1 in the Appendix considers the truncation of the sample.

3.3.1 Data Collection

Following the pretesting process, the survey instrument was ready for distribution. The Environment Agency project funding was used to hire DJS Research LTD who were tasked with disseminating the survey to a nationally-representative of UK adults with the following requirements:

Requirements:

1) Randomly vary bid level for all the CVM questions:
In the CV literature, the bid levels are randomly varied to elicit more information on the distribution of WTP in the sample (Bateman et al., 2002). This research used eight bid levels for each question which is consistent with the empirical literature (Scasny and Zvěřinová, 2014; Zambrano-Monserrate and Ruano, 2020). The amounts are reported below and were chosen using the pretest process. Note that the bid levels for Q6 and Q7 are identical. Only the DBDC component uses different bid levels to evaluate the difference between the SB and DB approaches. Q6: {£5, £10, £20, £40, £60, £80, £90, £100 }
Q7 (first question): {£5, £10, £20, £40, £60, £80, £90, £100}
Q7B (upper-bound): {£10, £20, £40, £80, £120, £160, £180, £200 }
Q7C (lower-bound): {£2.50, £5, £10, £20, £30, £40, £45, £50 }

2) Randomly vary CVM order:
The effect of question ordering on WTP has been commonly studied in the SP literature; see Day et al. (2012) for a discussion of potential ordering effects in CVM studies and Kjær et al. (2006) for CEs. To test ordering effects in this design, respondents were randomly allocated to the 'consecutive' order, answering question six (Q6, research) and then question seven (Q7, treatment) or the 'reversed' order Q7 then Q6. The subsamples were relatively balanced; N= 364 (55%) for the consecutive order and N=306 (45%) for the reversed order.

3) Randomly assign respondents to block 1-2-3-4 in the DCE:
The CE was designed using an OMEP fractional-factorial design which lead to 16 total choice tasks. These were blocked into four blocks of four to manage the task-complexity for respondents (Hooper, 2013). Respondents were then randomly assigned to either block 1, 2, 3, 4 for each of the four choice tasks. Table 8.10 reports how many respondents were in each block.

4) Time responses:
Survey completion length has been used in the literature, especially in CEs, to gauge respondent understanding with 'speeders' (completing the survey unrealistically quickly) and slow respondents being removed from the sample in ECHA (2014b, 2016).

5) Representative random sampling:
Section 3.2.5.1 established that the sample frame must be representative of the national population, which were the target of the proposed restrictions. Table 3.3 indicates that the sample was broadly representative of the UK adult population measured by age, gender, income and education.

The sample of 670 was collected over two weeks in April 2020 [11], funded by the Environment Agency. Given that the respondent IDs ran to 1028, a crude sample response rate of 65% can be calculated (670/1028)*100. As the data collection was online and during the 'lockdown' period, the response rate may have been greater as respondents were required to stay home. The remainder of this section now describes the sample and data characteristics. Firstly, Table 3.3 details how the sample is sufficiently representative of the UK Adult population across a range of categories. Table 2.2 in Appendix One then reports how each variable was coded for the analysis, the a priori theoretical expectations, and some summary statistics about each variable.

[11] Section 6.2.1 analyse the possible effects of collecting data during the pandemic.

Table 3.3: Full sample characteristics:

Category	**Sample**	**Population**
Gender	Male: 46% Female: 53%	Male: 49% Female: 51%
Age	Mean: 42 years old	Mean: 38 years old
Trips to the coast	Annually: 1.6	Annual coastal trips: ∼4 [1]
Charity involvement	Donated: 33% Not: 63%	Data from the Charities Aid Foundation (2019) suggests that more than 60% of people are involved with charities. However, environmental charities make up fewer than 4% of total charitable donations.
Highest Education	A level or equivalent: 50.75% Graduate or more: 49.25%	A level or equivalent: 40.4% Graduate or more: 42%
Employment	Prefer not to say = 2.68% NEET [2] = 11.34% Retired = 7.76% Student = 4.47% Part-time = 14.95% Self-employed = 6.85% Full-time = 51%	NEET: 3.7% Student: 3.5% Part-time: 10.4% [3] Self-employed: 15.1% Full-time: 36.9%
Gross monthly income [4]	Mean: £2193	Mean:[5]£2340
Order	Order 0: 364 Order 1: 306	The split-samples are slightly unbalanced

[1] Natural England Report: http://publications.naturalengland.org.uk/file/5257280994410496

[2] NEET: Not in Employment, Education, or Training.

[3] Office of National Statistics:
https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/employmentintheuk/march2020

[4] Gross monthly income was used as it is the figure that respondents were most familiar with, although gross annual may have been more comprehensive. This figure is calculated when removing ‘prefer not to say’ responses and before using random imputation. The missing values are imputed using a random sampler from the HMISC R package. This is a robust and pragmatic approach to maintaining sample size with missing values.

[5] Office of National Statistics:
https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/annualsurveyofhoursandearnings/2019

3.3.2 Protest Analysis

This section details the types and occurrences of protest votes in the sample based on feedback to the Q6 (WTP for research) and Q7 (WTP for treatment) CV scenarios. There is an empirical debate on identifying true protests, and often the choice is subjective (Johnston et al., 2017). The analyst must discern which responses are against the scenario or the payment vehicle and which are genuine zero WTP whereby respondents are already utility maximising and would not value any change from the status quo (Atkinson et al., 2012; ECHA, 2016; Badura et al., 2019; Rakotonarivo, Schaafsma and Hockley, 2016; Zambrano-Monserrate and Ruano, 2020). While some studies discard protest zero WTP as they skew the distribution (ECHA, 2014b), others argue that excluding protests then biases sample WTP (Brouwer and Martín-Ortega, 2012). Although Brouwer and Martín-Ortega (2012) argue that protest votes in CV studies can be handled using the Heckman sample selection approach, Johnston et al. (2017) notes that this has not been widely applied in the CE literature. For completeness, this research reports WTP from both the full and truncated sample to illustrate whether excluding protesters significantly influence WTP.

In this research, protest votes were identified by examining the text responses follow-up questions following questions 6 (WTP for research), 7 (WTP for investment), 8 (dominated task), and 25 (survey understanding). Table 8.1 shows a highly significant Mann-Whitney test of statistical difference in mean fitted WTP between protesters and other respondents. This statistical difference holds across both CE and CV WTP except for Q6, which reported no statistically significant difference in means due to protest votes. This is a curious result, given that most protests were identified in the text responses to Q6. It could be that respondents still reported their WTP but noted their protests or reported different WTP but did not report any protests. However, it should be noted that protest votes are the truncation rule most open to interpretation as protesting was inferred from the text responses.

A tabulation of the protest responses is available in Figure 8.5 in the Appendix. Although multiple motivations were noted, they can primarily be broken down into four reasons. Firstly, 'cost' reasons if the bid level is greater than individual WTP, 'use' reasons for respondents objecting to the use of money for research or for the scenario, 'protests' for those objecting to contributing, the payment vehicle or the scenario. Finally, the survey company included a 'Don't Know' option as a default, and some respondents used that option. Only the 'principle' and 'use' protests were excluded as the other reasons do not necessarily represent irrational preferences. Although there were 90 protesters in total, 59 of these were excluded by the other truncation rules. Therefore, the net difference of excluding protesters was 31 respondents or 4.63% of the sample.

Finally, Figures 3.5 and 3.6 report the difference in WTP between protesters and other respondents. The result is a clear and statistically significant difference in WTP across each SP task, especially for the CE. One weakness here is that the bar charts group all protesters together and do not use question-specific protests, although many protesters had the same issue with each question. To summarise, the protesters reported different WTP across each task and, therefore, there is merit to their exclusion.

Figure 3.5: CE Protest Analysis.

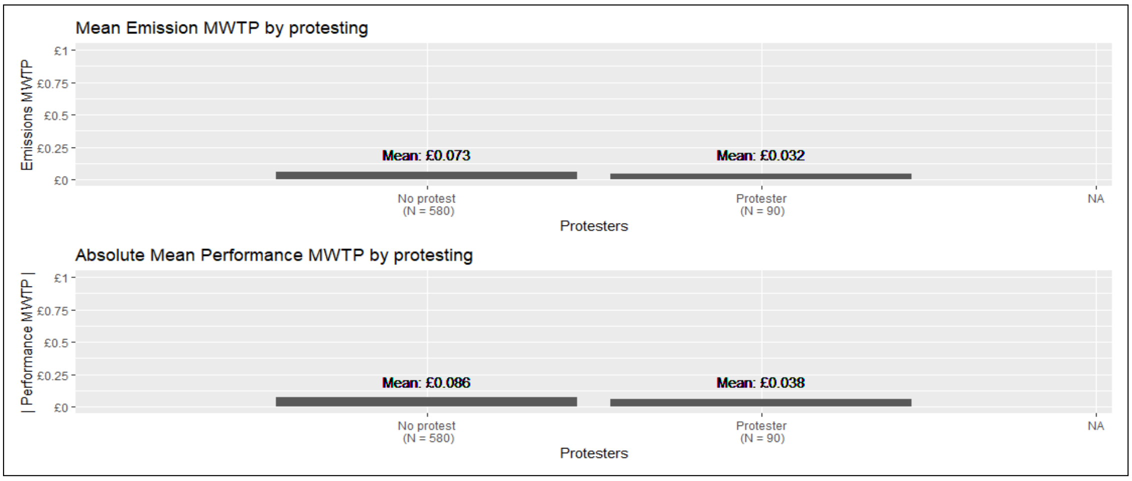


Figure 3.6: CV Protest Analysis.

3.4 Summary

This chapter has designed, piloted, conducted, and analysed a SP survey appropriate for eliciting the non-market benefits of a REACH restriction on intentionally added microplastics in the UK. The pilot survey yielded a range of changes for the final survey. The final section of this chapter has reported the data collection, evaluation and truncation process in detail. The following chapters detail the econometric modelling of the survey data using the full sample of 670 [12].

[12]Replication files are available on request and at: `https://github.com/pmpk20/PhDPilotSurvey`

Econometric Modelling of Choice Experiment Survey Data.

Chapter Four Abstract:

This chapter undertakes the econometric analysis of the CE data. Consistent with the literature, the data is first analysed using the simpler conditional (CL) and multinomial (MNL) logits. However, the restrictive assumptions underpinning these models motivates a more complex treatment of respondent heterogeneity. Two alternative treatments are trialled; the Mixed Logit (MXL), which models heterogeneity at the respondent level, and the Latent-Class Model (LCM), which models heterogeneity at the class level. Finally, a hybrid Mixed Logit also referred to as the Integrated Choice-Latent Variables (ICLV) model, is estimated to show that latent precautionary attitudes may drive respondent heterogeneity. Overall, this chapter contributes to the discrete choice econometrics literature by extending the use of hybrid choice models. The analysis was conducted using R version 4.1.1 in Rstudio. with the Apollo library (Hess and Palma, 2019).

4.1 Choice Experiments

To understand respondents precautionary behaviour, the CE data can be analysed using the Random Utility Model (RUM) (McFadden et al., 1973; Hanemann, 1984; Clark et al., 2014; Hauber, Fairchild and Johnson, 2013). In the RUM (Equation (4.1.1)), the utility U of individual i conditional on alternative j is U_{ij} with deterministic component $\mathcal{V}_{ij}$ and stochastic component ε_{ij};

$$U_{ij} = \mathcal{V}_{ij}(\beta \mathcal{X'}_{ij}) + \varepsilon_{ij} \tag{4.1.1}$$

The deterministic or observed component is a function of $\mathcal{X'}_{ij}$, a vector of attributes for alternative j, and β, estimable coefficients that represents the effect of attributes on choice probabilities. In this research, the elements of $\mathcal{X'}_{ij}$ are the three attributes, 'price', 'performance', and 'emissions'.

$$\mathcal{V}_{ij} = \beta \mathcal{X'}_{ij} \tag{4.1.2}$$

Although utility is unobserved and unobservable, the RUM assumes that individuals will only select an alternative if and only if its utility is greater than any other alternative in the choice set (Ryan, Gerard and Amaya-Amaya, 2007). The probability of a respondent choosing a given alternative, that is $Y_{ij} = 1$, depends on the probability that the utility of that alternative is higher than other alternatives $k \neq j, \forall j = 1, k, \cdots, J$ as in Equation (4.1.3) adapted from (Ryan, Gerard and Amaya-Amaya, 2007).

$$Y_{ij} = \begin{cases} 1 & if \;\; \mu_{ij} > u_{ik} \\ 0 & \text{Otherwise} \end{cases} \tag{4.1.3}$$

$$\begin{aligned} P(Y=1) &= P(\mathcal{V}_{ij} + \varepsilon_{ij} > \mathcal{V}_{ik} + \varepsilon_{ik}) \\ P(Y=1) &= P(\mathcal{V}_{ij} - \mathcal{V}_{ik} > \varepsilon_{ik} - \varepsilon_{ij}) \end{aligned} \tag{4.1.4}$$

Shalizi (2012) noted that the choice probabilities can be logistic transformed:

$$log \frac{P(Y=1)}{1 - P(Y=1)} \tag{4.1.5}$$

Train (2009) notes that the probabilities in equation 4.1.4 can then be assessed as:

$$P_{ij} = \frac{\mathrm{e}^{(uV_{ij})}}{\sum_j^J \mathrm{e}^{(uV_{ik})}} = \frac{\mathrm{e}^{(\beta \mathcal{X'}_{ij})}}{\sum_j^J \mathrm{e}^{(\beta \mathcal{X'}_{ik})}} \tag{4.1.6}$$

The marginal WTP (noted MWTP) for non-monetary attributes, indicated here by subscript a, is the ratio of the coefficients for the non-monetary and monetary parameters:

$$MWTP = -\frac{\beta_a}{\beta_{Price}} \tag{4.1.7}$$

The primary aim for analysing the CE data is to elicit WTP as a measure of the benefits of precautionary restrictions on microplastics. Model-specific MWTP can be calculated in Equation (4.1.7) by dividing the non-monetary attribute of interest coefficient by the monetary attribute coefficient. However, this approach may be flawed when parameters are allowed to be randomly distributed; specifically, dividing two random coefficients implies that the WTP is itself random. Hole (2006) discussed three different methods to precisely estimate the MWTP; the delta method, the Krinsky-Robb (K-R) parametric bootstrap and, nonparametric bootstrapping. Although accurate and commonly used, the delta method assumes that MWTP is normally distributed and may not be relevant for the CE data (Train and Weeks, 2005). As the K-R method also requires distributional assumptions, this research opts for the nonparametric bootstrap approach, although this is more computationally-intensive (Hole, 2006). To summarise, this research bootstraps MWTP from each estimated logit model and then uses the unit values as a measure of the benefits of restrictions on intentionally added microplastics.

The most common starting point of analysis is the Conditional Logit (CL) and Multinomial Logit (MNL) models from the logit family of models (Clark et al., 2014; Ryan, Gerard and Amaya-Amaya, 2007; Train, 2009). Hoffman and Duncan (1988) distinguishes the two by arguing that the CL is a function of attributes only while the MNL is a function of both attributes and respondent characteristics. Although Train (2009) states that the MNL applies only to scenarios with more than two alternatives, Weng et al. (2020) review of the literature indicates that the term 'MNL' is often used even for designs with only two alternatives. Although there are only two alternatives in the CE design, this research refers to the MNL, rather than technically appropriate binary logit, for consistency with the literature.

4.2 Multinomial Logit

4.2.1 Theory

This section discusses the theoretical derivation and properties of the MNL. The general econometric specification of the MNL is as follows, adapted from Lancsar and Louviere (2008); Train (2009); Ryan, Gerard and Amaya-Amaya (2007). In Equation (4.2.2) the utility (u) of individual i choosing alternative j is composed of indirect utility V and a stochastic error term independent and identically distributed type one extreme value (Hoyos, 2010). The indirect utility Equation (4.2.3) is composed of an alternative-specific constant (ASC) α_j, the vector of CE attributes X_{ij} which vary over respondent and alternative, and respondent characteristics Z_i which vary over individuals but not over choice alternatives. The CE attributes in this research are the Price, Performance, and Emissions attributes from the CE design. The parameters β and γ remain to be estimated. The expression is often simplified to just the β and a vector X, which contains socioeconomic variables and a constant. The indirect utility for each option uses the utility-difference approach, where only differences in utility matter, to calculate respondents' choice probabilities as in Equation (4.2.4). The logit probabilities are then transformed into log-likelihoods, in Equation (4.2.5), which are then maximised.

Utility function:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{4.2.2}$$

Indirect utility:

$$V_{ij} = \alpha_j + \beta X_{ij} + \gamma Z_i \tag{4.2.3}$$

Choice probability P for individual i and alternative j:

$$P_{in} = P(Y_i = 1) = P(V_{ij} - V_{ik} > e_{ik} - e_{ij}) = \frac{\mathrm{e}^{\mu(\alpha_k + \beta X_{ik} + \gamma Z_i)}}{\sum_{j=1}^{J} \mathrm{e}^{\mu(\alpha_j + \beta X_{ij} + \gamma Z_i)}} \tag{4.2.4}$$

Log-likelihood:

$$LL = \sum_{j=1}^{J} \sum_{i} \mathcal{P}_{ij} \left[\beta \mathcal{X'}_{ij} - ln \left(\sum_{i} \mathrm{e}^{(\beta \mathcal{X'}_{ij})} \right) \right] \tag{4.2.5}$$

There are two contentious assumptions necessary for the MNL to yield consistent parameter estimates: Independence of Irrelevant Alternatives (IIA) and constant error variance (Train, 2009). The IIA assumption arises as the errors ε_{ij} can include both unobserved components and preference heterogeneity (Lancsar and Louviere, 2008) [13]. Unobserved determinants can be modelled using the stochastic term in the RUM, which is assumed to be Independently and Identically Distributed (i.i.d) around the extreme value Gumbel distribution which implies IIA (Ryan, Gerard and Amaya-Amaya, 2007). If IIA holds, the relative probabilities of two alternatives being chosen do not change when other alternatives are added or subtracted in the choice set (Hoyos, 2010). However, this may not be realistic where alternatives may vary only slightly in their levels (Ryan, Gerard and Amaya-Amaya, 2007).

The second MNL assumption, constant error variance, may also be unrealistic as it ignores respondent heterogeneity. Specifically, the error variance parameter scales individual utility to reflect variance in the unobserved element of the utility function (Lancsar and Louviere, 2008; Ryan, Gerard and Amaya-Amaya, 2007). Assuming that the scale parameter is constant imposes unrealistic homogeneity of unobserved components. In equation 4.1.6 the scale parameter u that is inversely proportional to the variance of the error distribution. As only the product ($u\ \beta_{ij}$) of the heterogeneity can be observed, the MNL typically assumes u to be a constant equal to one to allow estimation of the β (Ryan, Gerard and Amaya-Amaya, 2007; Atkinson et al., 2018a). Although MNL necessitates the assumption of u=1 for a constant variance of individual scale parameters, Ryan, Gerard and Amaya-Amaya (2007) argues that this assumption of homoskedasticity can be relaxed to allow for heterogeneity in the taste parameter, which is more realistic. In summary, the unrealistic and restrictive assumptions for the MNL favour more flexible models. However, it is common in the literature to fit an MNL first and report how WTP and goodness-of-fit adjust when relaxing the restrictive assumptions (Clark et al., 2014).

[13] Unobserved components arise as any survey lengthy enough to gather data on all possible sources of heterogeneity would likely be too long to complete; further evidence of a trade-off between plausibility and optimality in design (Hoyos, 2010; Ryan, Gerard and Amaya-Amaya, 2007)

4.2.2 Conditional Logit

This research estimates three different MNL specifications to indicate respondents' behaviour in the CE and calculate a benchmark MWTP value for more realistic models. The CL model, essentially an attributes-only MNL, does not interact the ASC with any variables. Therefore, only the sign, significance and magnitude of the CE attributes are relevant for inference about respondent's behaviour. The results are reported in Table 4.1. This strategy of first estimating a CL before more complex models to address respondent heterogeneity has been employed before in Bennett and Adamowicz (2001); Foster and Mourato (2002); Adamowicz et al. (2011).

In the CL model (Table 4.1), the significant positive parameter of the ASC suggests that ceteris paribus, respondents preferred the non-status quo alternative: Option B (Brouwer et al., 2017). Each attribute is also highly statistically significant, implying that each had a strong influence on respondent choices. The negative coefficient for the monetary attribute is consistent with the literature (Train, 2009), and the comparatively large magnitude suggests that respondents were primarily motivated by the price of each alternative. For the non-monetary attributes, product performance changes have the expected negative sign; respondents are more likely to choose the status quo when reductions are larger. Alternatively, the emissions attribute has a positive sign suggesting that respondents were more likely to choose Option B when fewer microplastics were released. Finally, MWTP can be calculated from the attribute coefficients and is reported in the bottom panel of Table 4.1. This MWTP can be used to benchmark the results from more realistic and complex models. To return to the estimation of the value of precautionary restrictions, the CL reports that the performance MWTP is negative, implying willingness-to-accept (WTA) reductions in product performance. The emissions MWTP is positive but of smaller absolute magnitude than that for performance changes, and thus product performance may be more important to respondents than the use of microplastics. This finding is further supported by the coefficient for the performance attribute being of a larger magnitude. Therefore, the CL indicates that respondents had a preference for product performance compared to reducing the release of microplastics. However, the CL is of limited relevance as it omits socioeconomic factors that may influence behaviour and is vulnerable to violations of the IIA assumption.

Table 4.1: Conditional logit model (N = 670).

Coefficient	**Estimate**	**Robust.std.err.**	**Robust.p-val(0)**
ASC_B	0.668***	0.092	0.000
β_{Price}	-0.210***	0.023	0.000
$\beta_{Performance}$	-0.009***	0.002	0.000
$\beta_{Emission}$	0.008***	0.001	0.000
Estimation Statistics			
AIC:	3539.16	Log-Likelihood:	-1765.6
McFadden R^2:	0.035	Likelihood ratio test:	Chi.Sq = 130.05 (p.v = 0.000)
WTP			
Performance MWTP	-0.043	Emission MWTP	0.038

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

4.2.3 Multinomial Results

The MNL is a marginally more realistic model than the CL as it includes respondent's characteristics. The specification for the MNL estimated in this research is reported in Equations (4.2.3), (4.2.3), (4.2.3). The indirect utility function is specified for the two CE options, A and B. The dependent variable for the MNL and all other CE models was the binary observed choice of respondents in the CE; zero if they chose Option A or one if they chose Option B. Each indirect utility function includes the three CE attributes; price, performance, emissions. One ASC is included between two equations to create utility differences. The ASC for option B was interacted with all the relevant socioeconomic variables available in the survey.

$$V_{iA} = ASC_A + \beta_{Performance} * Performance_A + \beta_{Emission} * Emission_A + \beta_{Price} * Price_A + \varepsilon_{ij} \tag{4.2.6}$$

$$V_{iB} = ASC_B + \beta_{Performance} * Performance_B + \beta_{Emission} * Emission_B + \beta_{Price} * Price_B + \varepsilon_{ij} \tag{4.2.7}$$

$$\begin{aligned} ASC_B = ASC_B &+ \beta_{Order} * Order + \beta_{Task} * Task + \\ &\beta_{Gender} * Q1Gender + \beta_{Age} * Age + \\ &\beta_{Distance} * Distance + \beta_{Trips} * Trips + \\ &\beta_{Q12Certainty} * Q12Certainty + \beta_{BP} * BP + \\ &\beta_{Charity} * Charity + \beta_{Cons} * Consequentiality + \\ &\beta_{Experts} * Experts + \beta_{Education} * Education + \\ &\beta_{Income} * IncomeDummy + \beta_{Q25Understanding} * Q25Understanding \end{aligned} \tag{4.2.8}$$

This section comments on two notable features of the specification; the inclusion of income and the exclusion of attitudes. There are multiple approaches to interacting the ASC with income levels. This research elicits self-reported gross monthly income in eight brackets. Table 8.13 in the Appendix reports a model that linearly includes the level of income following Adamowicz et al. (2011); Beharry-Borg and Scarpa (2010); Chen and Cho (2019). However, Beharry-Borg and Scarpa (2010) reported no income effect, and Adamowicz et al. (2011) also included a square term to evaluate non-linearity. An alternative approach successfully used in Faccioli et al. (2020); Sandorf, Persson and Broberg (2020); Buckell, Hensher and Hess (2021) is to include income as a dummy of being a 'low-income' or 'high-income' household, defined as being below or above the sample median income, respectively. This approach is thematically similar to the concept of distributional weights used in CBA and indicates systematic differences in choices between high and low-income groups. Finally, an alternative approach, exhibited by Brouwer et al. (2017), is to include the levels of income in natural log form to represent income effects more realistically, although Abate et al. (2020) note that this approach was unsuccessful at representing income effects in their work. This research reports the dummy approach in-text with income levels in the Appendix.

Although attitudinal indicators were observed, they were not used as linear predictors. Linearly including attitudinal scales raises the possibility of measurement issues in the models as scales only indicate a latent unobserved attitude (Hess and Beharry-Borg, 2012; Faccioli et al., 2020; Vij and Walker, 2016). The measurement issue may confound the identification of the parameters and thus inflate welfare estimates. An alternative approach would use the indicators in latent variable models to indicate latent environmental attitudes; see Section 4.3.3 for an alternative treatment for the effect of attitudinal indicators on WTP.

Table 4.2 reports the MNL estimated using the full sample and including all covariates interacted with the ASC. For robustness, Table 8.32 in the Appendix estimates the same model but on the truncated sample (N=670 vs N=304) to illustrate differences in preferences by sample. All three CE attributes were highly significant at the 1% level with signs and magnitudes consistent with a-priori expectations. This finding corroborates the CL model in suggesting that respondents had a preference for product's performance rather than release of microplastics, a result that casts doubt on the value of precautionary restrictions on the use of microplastics in the cosmetics sector. The ASC was also statistically significant, indicating some status quo bias (Adamowicz et al., 2011). As the ASC's standard errors are relatively large, there is heterogeneity in the sample's amount of status quo bias. This evidence of preference heterogeneity may motivate the estimation of an alternative model, which allows for more flexible choice behaviour (Bennett and Adamowicz, 2001; Train, 2009).

The weakly significant and negative dummy on income (β_{Income}) suggests that above-median income households were slightly more likely to choose the status quo, consistent with Faccioli et al. (2020). Therefore, the benefits of a restriction may be distributed progressively if lower-income households reported higher WTP. The relatively large effect contrasts to the much smaller effect when using gross monthly income levels, although that approach is highly significant in both the full and truncated sample. With regards to choice behaviour, the choice task dummy (β_{Task}) was not statistically significant, which confirms that the random allocation of respondents to blocks did not affect choices. However, the question-order dummy (β_{Order}), as motivated by Kjær et al. (2006), is statistically significant and positive with a relatively large magnitude, which indicates that the CV questions' order influenced later choices in the CE. Therefore, this research suggests that the order of tasks prior to the CE also influences behaviour; this contrasts with the SP literature that has primarily focused on the order of the CE attributes or tasks, (Kjær et al., 2006; Day et al., 2012; Day and Prades, 2010; Logar et al., 2014). Future work could randomise the CE and CV sections' order to control for this possible ordering effect.

Other respondent-specific factors are the truncation variables of certainty, consequentiality, and understanding. Consistent with Czajkowski et al. (2017), consequentiality ($\beta_{Consequentiality}$) had a large positive effect on choosing the alternative option. As the respondents believing participation to be inconsequential were excluded in this sample, the large effect refers to a respondent moving from 'Don't Know' to 'Yes' that participation being consequential. Perceived consequentiality, therefore, results in greater support for precautionary restrictions. The certainty variable ($\beta_{Q12CECertainty}$) similarly measured the effect of a respondent moving from 'Quite Sure' to 'Very Sure'. Although the effect was not statistically significant at even the 10% level, the negative sign is consistent with Dekker et al. (2016) who suggest that greater certainty may increase status quo bias and thus decrease support for precautionary reformulations of cosmetics. Finally, the socioeconomic controls of gender, age, distance, trips, charity involvement, and education were not statistically significant. While each control has been previously used in the literature, most were also not significant even in the full sample, suggesting that there may be some collinearity that masks each variable's effect. The CL model avoids this collinearity issue by excluding all socioeconomic variables, although this suggests an omitted variable bias. To summarise, the MNL reports statistically significant coefficients for the CE attributes as consistent with the literature. However, there was a minimal qualitative difference in including controls on the MWTP.

The validity of the MNL can be evaluated using a Likelihood-Ratio (LR) test, which compares the MNL with all covariates against a constant-only model. The results of an LR test in Table 4.2 suggest that the MNL with all covariates is superior to the constant-only model. The more powerful Hausman-McFadden test of the IIA assumption is not possible as it requires dropping one alternative and this design had only two alternatives (Hausman and McFadden, 1981). Compared to the CL, the AIC and log-likelihood are improvements while the difference in MWTP is minimal. To summarise, the MNL can benchmark MWTP from more complex and realistic models that relax the restrictive assumptions of IIA and constant error variance necessary for the MNL (Ryan, Gerard and Amaya-Amaya, 2007).

Table 4.2: MNL model with all covariates (N = 670).

Coefficient	Estimate	Bootstrap.std.err.	Bootstrap.p-val(0)
β_{ASC}	-0.886	0.323	0.006***
β_{Price}	-0.221	0.024	0.000***
$\beta_{Performance}$	-0.010	0.002	0.000***
$\beta_{Emission}$	0.008	0.001	0.000***
β_{Order}	0.012	0.083	0.887
β_{Task}	-0.043	0.037	0.244
$\beta_{Q1Gender}$	0.078	0.085	0.361
β_{Q2Age}	0.001	0.003	0.738
$\beta_{Q3Distance}$	0.000	0.002	0.984
$\beta_{Q4Trips}$	0.096	0.047	0.042**
$\beta_{Q12CECertainty}$	-0.151	0.073	0.038**
β_{Q16BP}	0.012	0.065	0.857
$\beta_{Q18Charity}$	0.034	0.077	0.659
$\beta_{Q20Consequentiality}$	0.370	0.060	0.000***
$\beta_{Q21Experts}$	0.250	0.052	0.000***
$\beta_{Q22Education}$	0.003	0.041	0.937
$\beta_{Q24Income}$	0.000	0.000	0.002***
$\beta_{Q25Understanding}$	0.015	0.026	0.571
Estimation Statistics			
AIC:	3428.74	Log-Likelihood:	-1694
McFadden R^2:	0.07	Likelihood ratio test:	Chi.Sq = 272.47 (p.v = 0.000)
WTP			
Performance MWTP	-0.045	Emission MWTP	0.036

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

4.3 Modelling respondent heterogeneity

A missing element from the MNL analysis is the possibility of heterogeneity in preferences for precautionary reformulations of cosmetics. Indeed, the MNL assumptions of IIA and constant error variance do not allow for unobserved preference heterogeneity (Adamowicz et al., 2011). To better understand preference heterogeneity, this section estimates and compares three alternatives to the MNL. Firstly, a Mixed Logit (MXL) in Section 4.3.1 incorporates heterogeneity by allowing preferences to be randomly distributed continuously at the respondent level. Secondly, Latent-Class Models (LCM) in Section 4.3.2 instead assume a discrete distribution whereby preferences vary at the class-level (Bujosa, Riera and Hicks, 2010; Dillingham, 2016; Beharry-Borg and Scarpa, 2010; Chen and Cho, 2019). Finally, this research estimates an Integrated Choice-Latent Variables model (ICLV) in Section 4.3.3, a specific type of hybrid choice model. The ICLV suggests that respondent heterogeneity is driven by their latent attitudes (Czajkowski et al., 2017). The ICLV in this research augments the standard MXL with latent variables and thus may also be termed a Hybrid-MXL (Czajkowski et al., 2017). The motivation for estimating three common alternatives to the MNL is to allow for more realistic models of choice behaviour. Respondent heterogeneity is critical for understanding the distribution of WTP for precautionary restrictions. Although Faccioli et al. (2020) compares welfare estimates using the MXL and Hybrid-MXL, and Adamowicz et al. (2011) compares the effect of incorporating heterogeneity using the MXL or the LCM, there is little evidence comparing all three models against the MNL. This section estimates the three models using the CE data to determine the appropriate treatment of respondent heterogeneity in this research.

4.3.1 Mixed Logit

4.3.1.1 Theory

The MXL includes unobserved preference heterogeneity at the individual level by relaxing the IIA and scale parameter assumptions of the MNL (Bujosa, Riera and Hicks, 2010; Train, 2009; Hoyos, 2010; Hausman and McFadden, 1981). As this research is more interested in the distribution of preferences for restrictions, a random-parameter MXL is more appropriate than the formally equivalent error-components specification, which investigates possible correlations between the two alternatives (Train and Weeks, 2005; Beharry-Borg and Scarpa, 2010). Additionally, the random-parameters approach is more commonly used in the literature (Clark et al., 2014; Hoyos, 2010). A general specification of the MXL is reported in Equations (4.3.1) through (4.3.5) which are adapted from

Train (2009).

Utility:

$$U_{ij} = \beta_i X_{ij} + \mathrm{e}_{ij} \tag{4.3.1}$$

The choice probabilities use weights from the density $f(\beta|\theta)$ to calculate a weighted average of the logit probabilities; hence the integral (Ryan, Gerard and Amaya-Amaya, 2007). The density depends on the distribution chosen by the researcher; a discrete distribution leads to the LCM while a binary zero or one leads to a CL model (Dillingham, 2016). Train (2009) provides an example of the normal distribution leading to the density $\phi(\beta|\mu,\sigma)$, with estimable parameters μ the mean and σ the variance; therefore, MXL results often present the mean and standard deviation of the parameters for interpretation.

$$P_{ij} = \int L_{ij}(\beta) f(\beta|\theta) d\beta \tag{4.3.2}$$

The $L_{ij}(\beta)$ component is the standard MNL probability but evaluated at a specific β:

$$L_{ij}(\beta) = \frac{\mathrm{e}^{\beta X_{ij}}}{\sum\limits_{j=1}^{J} \mathrm{e}^{\beta X_{ik}}} \tag{4.3.3}$$

Train and Weeks (2005) notes that as the MXL does not have a closed-form solution, it must be solved via simulation. Train (2009) derives the probabilities to facilitate simulation to solve the MXL (Equation (4.3.4)) where r $(= 1, \cdots$ R) is simply the random draws from the distribution. The number and type of draws are a decision of the researcher. The use of simulation leads to a Simulated Log-Likelihood (SLL) in Equation (4.3.5) which includes the simulated probabilities and an indicator function d_{ij} equal one if alternative j is chosen by individual i, and zero if not.

Simulated probabilities:

$$P_{ij} = \frac{1}{R}\sum_{r=1}^{R} L_{ij}(\beta^r) \tag{4.3.4}$$

Simulated Log-Likelihood:

$$SLL = \sum_{j=1}^{J}\sum_{i=1}^{I} d_{ij} ln P_{ij} \tag{4.3.5}$$

The choice of the distribution of the random parameters, usually normal, uniform, triangular, or lognormal, can be supported using both econometric and economic theory (Adamowicz et al., 2011; Hoyos, 2010). An econometric approach to revealing the appropriate distribution would use an iterative process with LR tests to report superior models, although this approach may be computationally-intensive (Clark et al., 2014). An economic approach limits the choices based on prior hypotheses. For instance, as few respondents are expected to hold a positive price parameter, the normal distribution with support on both sides of zero is not appropriate. Furthermore, there is debate on the number and type of draws used to simulate from the distributions; see Bhat (2001) and Scarpa and Alberini (2005) for a theoretical discussion. The most commonly used are Halton draws, although Hess and Palma (2019) note that other types are more appropriate with a higher number of alternatives. Finally, an iterative process to determine the appropriate number of draws is undertaken and reported in the Appendix as consistent with the literature (Scarpa and Alberini, 2005; Adamowicz et al., 2011). To summarise, MXL is an increasingly popular choice for modelling respondent heterogeneity in the literature given advances in computing power for simulation and the relaxation of otherwise restrictive assumptions about substitution patterns and unobserved heterogeneity (Train, 2009; Clark et al., 2014; Hoyos, 2010; Ryan, Gerard and Amaya-Amaya, 2007).

4.3.1.2 Application

The final specification, following a specification search to choose the appropriate distribution and draws, is stated in Equations (4.3.6) to (4.3.8). There are two key differences from the MNL. Firstly, the three CE attributes are assumed here to be randomly distributed; an example being the negative lognormally distributed price parameter in Equation (4.3.8). The lognormal specification has support only on one side of zero. A negative lognormal was adopted for the price attributes, which a priori can be expected to have a negative sign. A normal distribution was adopted for both non-monetary attributes to allow positive and negative preferences. This design is similar to Faccioli et al. (2020) who favoured the normal distribution for their non-monetary attributes. Although lognormal distributions led to behaviourally implausible results in Beharry-Borg and Scarpa (2010), a negative lognormal for the price parameter has empirical support in Howard, Whitehead and Hochard (2020); Train and Weeks (2005); Ghosh, Maitra and Das (2013). Finally, it should be noted that a MXL with correlations between alternatives or between unobserved components over time can be estimated. However, neither is appropriate to this specific CE design as only observations for one period of time between two alternatives, one the status quo, are available. Overall, while the flexibility of the MXL necessitates a specification search, this research presents the final adopted specification in text.

A second notable difference from the MNL is that the indirect utility functions in (4.3.6) and (4.3.7) are multiplied by the monetary attribute and thus being estimated in WTP-space. Estimating in WTP-space allows attribute MRS to be directly interpretable as WTP and is common in the MXL literature (Train and Weeks, 2005; Johnston et al., 2017; Scarpa and Alberini, 2005), although Bujosa, Riera and Hicks (2010) notes that the alternative preference-space approach may be superior in limited cases. Therefore, the mean of the attribute coefficients can be read as WTP. Alongside the mean, the standard deviation is also estimated and can be interpreted as the amount of heterogeneity around the mean (Faccioli et al., 2020). The standard deviations refer to the distribution of each of the random parameters. Elsewhere, the socioeconomic variables were again interacted with the non-zero ASC, similarly to the MNL. Although Johnston et al. (2017) noted that further interaction terms between the attributes and the socioeconomic variables could be considered, there is no strong justification for diverging from the traditional interaction of socioeconomic variables and the ASC as this explains differences in status quo bias by respondent-specific characteristics.

$$V_{iA} = ASC_A + \beta_{Price} * (Price_A + \beta_{Performance} * Performance_A + \beta_{Emission} * Emission_A) \tag{4.3.6}$$

$$V_{iB} = ASC_B + \beta_{Price} * (Price_B + \beta_{Performance} * Performance_B + \beta_{Emission} * Emission_B) \tag{4.3.7}$$

$$\beta_{Price_i} = -exp^{(\mu_{log(\beta_{Price})} + \sigma_{log(\beta_{Price})} * \xi_{Price,i})} \tag{4.3.8}$$

4.3.1.3 Results

Table 4.3 reports the results of a MXL using 1000 Halton draws, estimated in WTP-space with all covariates and three randomly distributed attributes. The price parameter is assumed to be negative lognormally distributed while the two non-monetary attributes were normally distributed. Each attribute's mean and standard deviation is highly significant, suggesting that respondents had heterogeneous preferences and were all sensitive to changes in attribute levels. The means can be interpreted as MWTP. Contrary to the MNL, the WTA for a marginal change in product performance is now lower in absolute magnitude than the WTP for a marginal reduction in the emissions of microplastics. This change suggests that the random-parameters approach to including preference heterogeneity is critical for determination of welfare measures. The standard deviations' significance suggests that the MXL is an improvement on the MNL as it represents the high degree of heterogeneity evident. The ASC is larger than that from the MNL but still not statistically significant, although the large standard errors and the negative sign again suggest heterogeneity around the sample's degree of status quo bias.

Table 4.3: MXL model in WTP-space with a full sample (N = 670).

Coefficient	Estimate	Bootstrap.std.err.	Bootstrap.p-val(0)
ASC_B	-1.150*	0.712	0.050
μ_{Price}	-0.761***	0.164	0.000
σ_{Price}	1.905***	0.532	0.000
$\mu_{Performance}$	-4.349***	0.037	0.000
$\sigma_{Performance}$	-2.852***	0.064	0.000
$\mu_{Emission}$	3.738***	0.018	0.000
$\sigma_{Emission}$	-3.138***	0.099	0.000
$\beta_{Q1Gender}$	-0.036	0.229	0.342
β_{Q2Age}	0.022**	0.014	0.019
$\beta_{Q3Distance}$	-0.003	0.009	0.191
$\beta_{Q4Trips}$	-0.105	0.205	0.244
$\beta_{Q12CECertainty}$	-0.149	0.240	0.231
β_{Q15BP}	0.029	0.221	0.437
$\beta_{Q18Charity}$	-0.234	0.255	0.129
$\beta_{Q20Consequentiality}$	0.613***	0.164	0.000
$\beta_{Q21Experts}$	0.387***	0.148	0.000
$\beta_{Q22Education}$	-0.047	0.180	0.358
$\beta_{IncomeDummy}$	-0.000***	0.000	0.007
$\beta_{Q25Understanding}$	-0.042	0.072	0.254
β_{Order}	0.013	0.255	0.476
β_{Task}	-0.059	0.063	0.114
Estimation Statistics			
Estimation Method	BFGS	LL (start)	-1753.231
Convergence	Successful	LL (final, whole model)	-1480.455
Number Individuals	670	AIC	2974.91
Observations	2680	BIC	3281.03
Adjusted R^2	0.203	Iterations	69
WTP			
Emissions	0.028	Performance	-0.0467

The MXL covariates indicate how the survey questions influenced choice behaviour and can be compared with those from the MNL. The MWTP for emissions is again lower than that for performance, although the magnitudes are consistent between specifications. The difference between the MNL and MXL WTP suggests that accounting for individual-level heterogeneity can alter welfare estimates. This driven is driven by substantial individual-level heterogeneity as evidenced by the highly significant and large standard deviations for all three attributes (Train, 2009).

There are some other notable differences between the MNL and MXL. Both the task dummy (β_{Task}) and the question order dummy (β_{Order}) are not significant in the MXL; suggesting that the CV questions' order did not influence the CE behaviour. Elsewhere, the income dummy ($\beta_{IncomeDummy}$) was statistically significant in the MXL with the expected negative sign. However, the magnitude was extremely small, robust to measuring income in levels and consistent with (Hess and Beharry-Borg, 2012) and Buckell, Hensher and Hess (2021). A possible mechanism is that other covariates' inclusion masks the relatively weak effect of income on choices; although truncated-sample model in the Appendix is also not statistically significant. Similarly to the MNL, many socioeconomic controls were not statistically significant even at the 10% level. Although gender (β_{Gender}) was not statistically significant, the negative sign is consistent with the literature finding that male respondents have weaker environmental attitudes (Faccioli et al., 2020; Abate et al., 2020). Moreover, the weak significance and small magnitude of age (β_{Age}) may be explained by the empirical evidence suggesting that age effects can be either positive, owing to higher income, or negative, owing to weaker environmental attitudes (Fransson and Garling, 1999; Kollmuss and Agyeman, 2002). Among the highly significant variables is the consequentiality variable ($\beta_{Consequentiality}$), where 'consequential' and 'Don't Know' respondents again have statistically different preferences. This effect is consistent both with the MNL and the literature (Czajkowski et al., 2017; Vossler and Watson, 2013). Furthermore, the MXL supports the MNL finding that there is no statistically different effect on preferences from different certainty levels. Finally, the distance and trips variables may not be significant as there is unlikely to be a distance-decay effect for unobservable pollutants. To conclude, the relaxation of the restrictive assumptions of the MNL in the MXL leads marginally altered MWTP. Although the MXL involved a specification search specifying the number and types of draws, and the appropriate distribution, one approach not tried was using a discrete rather than continuous distribution. Section 4.3.2 now attempts this in the form of Latent-Class analysis.

4.3.2 Latent-Class Model

An alternative approach to understanding and modelling the heterogeneity in respondent's preferences is the Latent-Class Model (LCM) (Adamowicz et al., 2011). In the LCM, respondents are probabilistically allocated to a series of latent classes (Beharry-Borg and Scarpa, 2010). Preferences are homogeneous within classes but vary between classes (Bujosa, Riera and Hicks, 2010). There are two noteworthy differences between the MXL and LCM. Firstly, socioeconomic variables in the MXL influence deterministic or preference heterogeneity, while in the LCM, they are used to determine class allocation. Secondly, the MXL assumes between-individual heterogeneity, while the LCM assumes between-class heterogeneity in preferences. Although the LCM can introduce within-class heterogeneity using a class-specific MXL, the central premise of the LCM is to model random parameters using a discrete distribution while the MXL uses continuous distributions. Although a continuous distribution may allow a broader interpretation of preference heterogeneity, the LCM has been used where population segments with relatively homogeneous preferences can be expected, such as marketing and transport (Adamowicz et al., 2011; Bujosa, Riera and Hicks, 2010; Dillingham, 2016). Indeed, Clark et al. (2014) noted that the LCM is a popular choice for researchers given that, unlike the MXL, it does not require explicit distributional assumptions and can be solved without simulation. To summarise, the LCM uses a class-allocation model driven by socioeconomic variables to probabilistically allocate respondents to the classes and choices in the CE are then conditional on class membership (Dillingham, 2016). This research first derives the LCM before using an iterative process to indicate how many discrete classes of preferences regarding precautionary restrictions exist. This section discusses the socioeconomic characteristics and fitted MWTP for each class to better understand the preferences of different latent classes. Finally, comment is made on whether the MXL or LCM presents a more realistic understanding of heterogeneous preferences in this research.

4.3.2.1 Theory

In the LCM, the probability of respondents' choices is conditional on class membership where the probability of individual i choosing alternative j (j = 1, $\cdots$, J), is conditional on class membership c; see Equation (4.3.10). The class-allocation model in Equation (4.3.9) is a function of socioeconomic variables D_i that allocates individual i (i = 1, $\cdots$, I) to class c (c = 1, $\cdots$, C) with probability $Prob_{ic} = \pi_{ic}$ (Hess and Daly, 2014; Bujosa, Riera and Hicks, 2010). The sum of class probabilities is equal to one: $0 < \pi_{ic} < 1$, $\sum\limits_{c=1}^{C} \pi_{ic} = 1$

and is a function of both class-specific coefficients (θ) and socioeconomic variables (β). Unconditional probability can be calculated in Equation (4.3.11) as can a log-likelihood function in Equation (4.3.12). Bujosa, Riera and Hicks (2010) reports that the log-likelihood is simply a weighted average of the class-specific log-likelihoods which use $y_{ia} = 1$ if and only if individual i chooses alternative j otherwise $y_{ij} = 0$. It should be noted here that given the logit specification, the LCM can be estimated using maximum likelihood and does not require simulation unlike MXL. Once estimated, both class-specific and sample MWTP can be reported as in Equation (4.3.13) and Equation (4.3.14) respectively. Sample WTP requires the use of $\widehat{W_c}$ class-specific weights which are typically the proportion of the sample allocated to each class. The following are adapted from Bujosa, Riera and Hicks (2010); Chen and Cho (2019):

Class-allocation:

$$\pi_{ic} = \frac{e^{\theta_c D_i}}{\sum\limits_{c=1}^{C} e^{\theta_c D_i}} \tag{4.3.9}$$

Choices conditional on class:

$$\pi_{ij|c} = \frac{e^{\beta_{ic} X_{ia}}}{\sum\limits_{j=1}^{J} e^{\beta_{ic} X_{ij}}} \tag{4.3.10}$$

Unconditional probability of i choosing:

$$\pi_{ij} = \sum_{c=1}^{C} \pi_{ic} \pi_{ij|c} \tag{4.3.11}$$

Log-Likelihood:

$$LL = \sum_{i=1}^{I} ln \left[\sum_{c=1}^{C} \pi_{ic} \left(\prod_{j=1}^{J} \left(\pi_{ij|c}\right)^{y_{ij}} \right) \right] \tag{4.3.12}$$

Class marginal WTP for non-monetary attribute a:

$$\widehat{MWTP}_{ac} = -\frac{\widehat{\beta}_a}{\widehat{\beta}_{price,c}} \tag{4.3.13}$$

Sample WTP:

$$WTP_a = \sum_{c=1}^{C} \widehat{wtp}_{ac} \widehat{W}_c \tag{4.3.14}$$

4.3.2.2 Application

A specification search was undertaken to determine how many discrete classes of preferences towards precautionary restrictions existed in the sample. The search varied the number of classes, the within-class model, and the number of socioeconomic variables in the class-allocation model to determine the optimal specification. An iterative process of estimating an increasing number of classes until the optimal fit is observed is necessary as the true number of classes in the data is unobserved (Chen and Cho, 2019). Although three classes are more common, higher numbers have been tested in the literature (Beharry-Borg and Scarpa, 2010; Chen and Cho, 2019). While details of the two, three, and four class specifications are available in the Appendix (Table 8.20), three classes appeared to be the optimal number. Secondly, the within-class probabilities can be treated using either the MNL or MXL. The majority of the literature uses a MNL where the assumption of preference homogeneity is congruent with the LCM's implication of within-class homogeneity. However, there is increasing use of the MXL to allow for heterogeneous preferences within classes (Bujosa, Riera and Hicks, 2010; Logar, Brouwer and Campbell, 2020). Although this research estimates both approaches, the MWTP was most plausible when using a MNL and assuming homogenous preferences within classes. Finally, the specification search had to determine how best to include socioeconomic variables which probabilistically allocate respondents to latent classes. The optimal model included no socioeconomic variables, although summary statistics of the socioeconomic characteristics of each class can be estimated post-hoc (Adamowicz et al., 2011). To summarise, a specification search was necessary to understand how respondents' preferences were distributed.

Table 8.20 in the Appendix presents 16 different possible specifications. This research adopts the 3-class model with the MNL class model and no socioeconomic characteristics. The choice is motivated by comparing MWTP, class-shares, goodness-of-fit criteria and LR tests to determine which is optimal. Eight of the 16 models use the full sample, and of these, two are dropped for singular Hessian matrices (specifications 12 and 13), and three others are dropped for implausible class-allocation (specifications 14, 15, 16). Of the remaining three (specifications 9, 10, 11), specification 11 is a slight improvement, but the third class is minimal, so class allocations are implausible. Between the final two, a Likelihood-ratio test in Table 8.19 in the Appendix reports that specification 10 with three classes, no socioeconomic variables and uses an MNL within-classes, is optimal. The results are presented in Table 4.4.

Table 4.4: 3-class LCM (N = 670).

Variable	Estimate	Robust.std.err.	Robust.p-val(0)
ASC_2	0.522***	0.182	0.004
$\beta_{Price,Class1}$	-4.777*	2.509	0.057
$\beta_{Price,Class2}$	-0.653***	0.193	0.001
$\beta_{Price,Class3}$	-0.307***	0.046	0.000
$\beta_{Performance,Class1}$	0.084**	0.041	0.042
$\beta_{Performance,Class2}$	0.04***	0.010	0.000
$\beta_{Performance,Class3}$	0.012***	0.004	0.001
$\beta_{Emission,Class1}$	0.001	0.019	0.976
$\beta_{Emission,Class2}$	0.392***	0.088	0.000
$\beta_{Emission,Class3}$	0.009***	0.002	0.000
δ_{Class2}	0.784***	0.177	0.000
δ_{Class3}	1.012***	0.172	0.000
Estimation Statistics			
Estimation method	bfgs	LL(start)	-1857.634
Convergence	Successful	LL(final, whole model)	-1476.23
Number of individuals	670	AIC	2976.46
Number of observations	2680	BIC	3047.18
Adj.Rho-square (0)	N/A	Iterations	89
WTP			
Performance	Class1: -0.017	Class2: -0.068	Class3: -0.038
Emission	Class1: 0.001	Class2: 0.600	Class3: -0.029

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

4.3.2.3 Results

A notable feature of the LCM results is the between-class heterogeneity in the attribute parameters' sign and magnitude. This class-specific heterogeneity is consistent with the literature and supports the use of the more complex MXL and LCM models over the MNL, which assumed that preferences were homogeneous (Bujosa, Riera and Hicks, 2010; Logar, Brouwer and Campbell, 2020). Only the Class2 performance attribute, larger in absolute magnitude than the other classes, had the expected sign with the emissions and price attributes not consistent with the CL, MNL, and MXL. Overall, the LCM results elucidate the difference in results when treating unobserved heterogeneity at either the individual or class levels.

A further notable feature of the estimation in Table 4.4 is that the ASC was statistically significant and positive, unlike the negative sign in the MNL and MXL. This finding suggests that the LCM reports a status quo bias unobserved in other models (Beharry-Borg and Scarpa, 2010; Adamowicz et al., 2011). Another parameter that used the utility-difference approach was δ, alternatively noted as the intercept or constant of the class-allocation model in the literature (Chen and Cho, 2019; Bujosa, Riera and Hicks, 2010; Adamowicz et al., 2011). The negative signs suggest that most respondents were probabilistically allocated to the first class. Furthermore, the large magnitude of the constant for Class2 δ_2 indicates that respondents were least likely to be allocated to the second class; this is consistent with it being the smallest class. The class shares are reported in Table 4.5 and support the inference from the δ parameters. Further inference from the LCM is possible by fitting socioeconomic characteristics to each class following Adamowicz et al. (2011) post-hoc approach. These results are provided in Table 4.5 to evaluate each class's characteristics. This final post-hoc step is necessary to understand the distribution of respondent's preferences for precautionary abatement of microplastics through reformulating cosmetics.

The motivation for using the LCM is to understand the distribution and sources of unobserved preference heterogeneity. While the MXL assumes a continuous distribution of preferences at the individual level, the LCM instead assumes a discrete distribution where preferences are heterogeneous between classes. However, the CE attributes' statistically significant standard deviations in the MXL indicate that there may be substantial individual-level preference heterogeneity. The LCM attempts to model this preference heterogeneity between classes and assumes that preferences are relatively homogenous within classes. The sources of between-class heterogeneity can be evaluated using a post-hoc approach inspired by Adamowicz et al. (2011), and Chen and Cho (2019) where summary statistics for each class can be produced by probabilistically allocating respondents to their most likely class. Therefore, socioeconomic characteristics can be used to identify sources of preference heterogeneity and evaluate class-specific welfare impacts (Bujosa, Riera and Hicks, 2010; Dillingham, 2016). For consistency, the summary statistics are the same as those reported in the full sample summary statistics in Table 3.3. However, class allocation is only probabilistic, with no socioeconomic characteristics used in the adopted specification. Therefore, the exact composition of each class may be imprecise. However, as a purely indicative exercise, Table 4.5 reports summary statistics fitted from each class to understand the sources of between-class preference heterogeneity.

Table 4.5: 3-class LCM class-allocation.

Category	**Class1**	**Class2**	**Class3**
Share	52.30%	16.32%	31.38%
Performance MWTP	-0.042	-0.374	-0.066
Emission MWTP	0.024	0.600	0.496
Gender	Male: 44% Female: 56%	Male: 43% Female: 57%	Male: 47% Female: 53%
Age	44.43	45.73	45.34
Distance	31.13	27.66	26.51
Charity involvement	31%	22%	38%
Education	A level or equivalent: 53% Graduate or more: 47%	A level or equivalent: 51% Graduate or more: 49%	A level or equivalent: 45% Graduate or more: 55%
Employment	Prefer not to say = 0.82% NEET = 5.74% Retired = 12.30% Student = 4.10% Part-time = 16.39% Self-employed = 4.92% Full-time = 55.70%	Prefer not to say = 3.45% NEET = 24.13% Retired = 8.62% Student = 1.72% Part-time = 6.90% Self-employed = 3.45% Full-time = 51.72%	Prefer not to say = 2.86% NEET = 15.24% Retired = 7.62% Student = 4.76% Part-time = 10.48% Self-employed = 5.71% Full-time = 53.33%
Mean Gross monthly income	£2260	£2297	£2228
Environmental Concern	Q13: 3.31 Q14: 3.66 Q15: 4.07	Q13: 3.41 Q14: 3.57 Q15: 3.69	Q13: 3.70 Q14: 4.06 Q15: 4.29
Knowledge	Q5: 2.84 Q19: 3.07	Q5: 2.69 Q19: 2.74	Q5: 3.00 Q19: 3.29

Table 4.5 reports class-specific shares and MWTP. The majority of the sample is in classes one (52.30%) and three (31.38%) with MWTP comparable in sign and magnitude to the MNL and MXL; small differences in MWTP between the LCM and MXL have been observed before (Adamowicz et al., 2011; Beharry-Borg and Scarpa, 2010). However, a notable minority of the sample in Class2 (16.32%; about one in six respondents) reported MWTP an order of magnitude larger than before, possibly driven by their higher income as their environmental attitudes and knowledge were comparable to the other classes. By contrast, Class3 appear to be the most concerned and knowledgeable about microplastics given it was the only one to report a majority of graduates and reported the highest charity involvement despite reporting the lowest mean income (Chen and Cho, 2019). Furthermore, Class3 reports a much larger WTP than Class1, and the ratio of the two attributes is consistent with the MXL rather than the MNL; the emissions attribute is larger than that for performance. Overall, the post-hoc analysis of class-specific socioeconomic factors can indicate how between-class heterogeneity is driven by differences in socioeconomic characteristics, influencing class-specific WTP.

To summarise, the primary advantage of the LCM is that it demonstrates how preferences, strongly for or against the status quo, for example, vary between latent classes of respondents, which would not otherwise be apparent in the MXL (Chen and Cho, 2019; Dillingham, 2016). However, the LCM may be inferior to the MXL for modelling preference heterogeneity for two reasons. Firstly, the MXL appeared to fit the sample data better as there was lower AIC and LL and higher adjusted R^2; these relative improvements in fitting the data are discussed further in Section 4.4. Secondly, the insignificance of some latent classes and the statistically significant standard deviations in the MXL suggest that heterogeneity is best represented at the individual rather than class level. The alternative treatment of heterogeneity leads to more plausible MWTP, which is central to estimating the value of precautionary restrictions on microplastics.

4.3.3 Integrated Choice and Latent Variables Model

This chapter started by estimating the common but restrictive MNL and then relaxed the assumptions to incorporate respondent heterogeneity at the individual (MXL) and class levels (LCM). However, an omission from all these models are environmental attitudes. This research observed three attitudinal indicators; see Table 4.6. These indicators should be included in the analysis as attitudes are commonly found to be strong determinants of individuals intentions, and to a lesser extent, behaviour (Kollmuss and Agyeman, 2002; Bateman et al., 2002). However, they have thus far been excluded given that Hess and Beharry-Borg (2012), supported by Vij and Walker (2016), noted the potential for measurement and endogeneity issues. Specifically, an endogeneity issue arises where attitudes may be jointly determined with utility by an unobserved factor. Furthermore, there is the potential for measurement error, given that indicators imperfectly observe attitudes. Given these twin issues, Ben-Akiva et al. (2002) recommended 'hybrid choice' models that incorporate attitudes using latent variables. A hybrid choice model combines traditional discrete choice models, such as the MXL in Faccioli et al. (2020), with models explaining latent variables (Hess and Beharry-Borg, 2012). One specific example of a hybrid choice model is the Integrated-Choice Latent Variables (ICLV) model estimated in Buckell, Hensher and Hess (2021). This research now derives and defends the ICLV approach to understanding how latent precautionary attitudes influenced respondents' CE behaviour.

Table 4.6: Summary of attitudinal indicators.

Question	1	2	3	4	5	Mean
Q13) Please indicate the degree to which you think that microplastic pollution currently presents a threat to yourself.	4.78%	8.21%	43.28%	27.46%	16.27%	3.42
Q14) Please indicate the degree to which you think that microplastic pollution will in the future present a threat to yourself.	2.99%	5.52%	30.45%	36.27%	24.78%	3.74
Q15) Please indicate the degree to which you think microplastic pollution currently presents a threat to the environment.	1.79%	4.48%	22.99%	32.24%	38.51%	4.01

4.3.3.1 Theory

A growing body of literature has attempted to integrate choice models with latent variable models to understand better the determinants of WTP (Ben-Akiva et al., 2002). Latent attitudes are typically measured by Likert scales, which Hess and Beharry-Borg (2012) argued may be subject to measurement error if respondents' differently interpret the item and its' levels. Vij and Walker (2016) noted that responses to Likert scales might be endogenously determined with utility, and thus it may be erroneous to include them directly in the choice model (Hess and Beharry-Borg, 2012; Vij and Walker, 2016). Alternatively, the ICLV approach can be used to include latent attitudes. One relevant example is Abate et al. (2020) groundbreaking paper, which used the ICLV model to analyse the effect of concern on WTP for reductions in Arctic marine plastic. However, their use of the ICLV was limited in that they did not recover WTP and instead calculated it using the standard probit approach. Prior to this, the ICLV, or more generally hybrid choice models, had been primarily used with CE data (Czajkowski et al., 2017; Hess and Beharry-Borg, 2012; Faccioli et al., 2020). The ICLV can be adopted to estimate the effect of many types of latent variables, including attitudes (Vij and Walker, 2016), beliefs about the survey (Hess and Beharry-Borg, 2012), decision uncertainty (Dekker et al., 2016), or environmental concern (Abate et al., 2020). The main advantage of the ICLV is a correction for omitted variables by identifying structural relationships between observed and unobserved (latent) variables (Vij and Walker, 2016). As the ICLV can identify structural relationships between the latent and observable variables, this reduces parameter estimate variance and may improve the model's prediction accuracy (Hess and Beharry-Borg, 2012; Vij and Walker, 2016). However, this comes with the disadvantage of increased computation and estimation time as the model is not usually estimated sequentially. This research estimates an ICLV model data using the three attitudinal indicators included in the survey. To reiterate, the aim is to evaluate how the benefits of restrictions change when accounting for latent attitudes.

Figure 4.1: ICLV Structure adopted from Ben-Akiva et al. (2002).

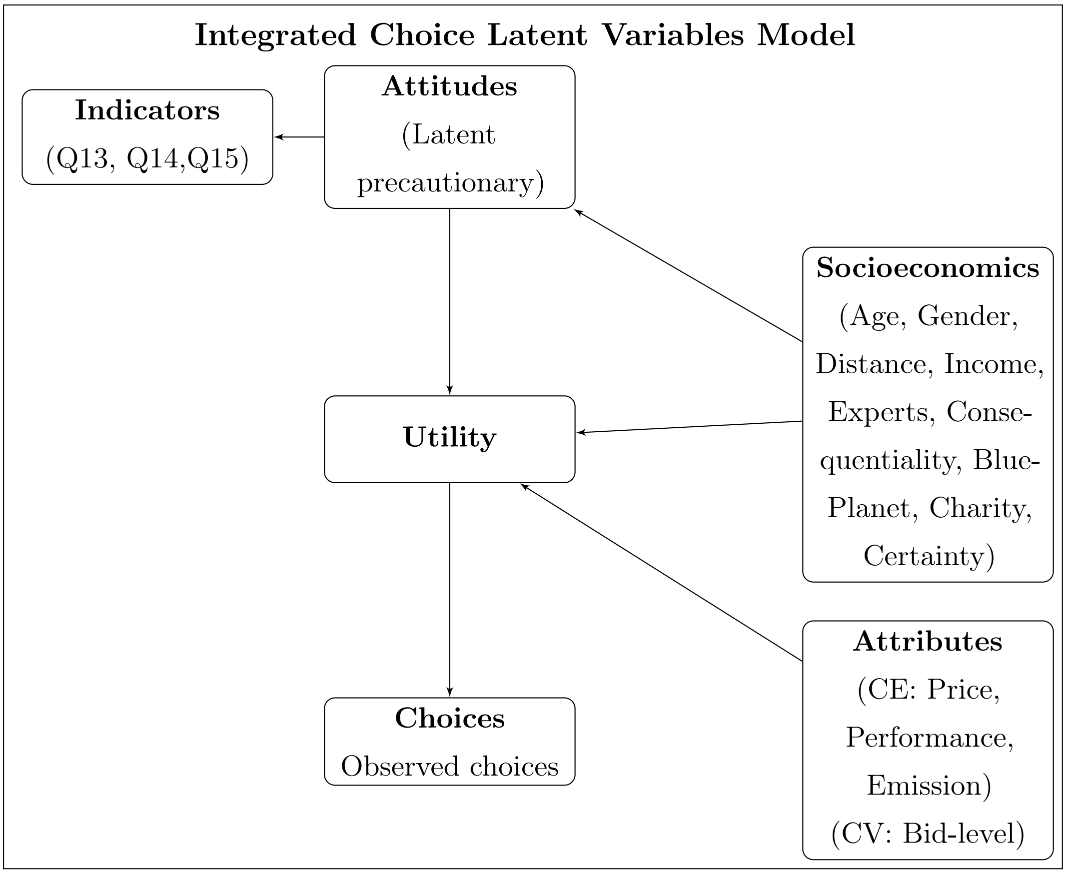


Figure 4.1 indicates how the ICLV combines three elements to determine utility and thus predict choices; a discrete choice model such as the MXL used for the CE, a measurement equation that links latent variables to indicators, and finally, structural equations which estimate the effect of covariates on latent variables these are then combined in a likelihood function (Ben-Akiva et al., 2002; Vij and Walker, 2016; Czajkowski et al., 2017; Hess and Beharry-Borg, 2012; Ben-Akiva et al., 2002). The choice model in Equation (4.3.15) is respondent i and alternative j specific. Utility is assumed to a function of the CE attributes X_i and the latent attitude α_i. Similarly to the MXL, the parameter β represents the effect of attributes on utility. The parameter λ represents the effect of latent attitudes on utility.

Choice Model:

$$U_{i,j} = \beta X_i + \lambda \alpha_i + \varepsilon_i \tag{4.3.15}$$

The Structural Equation (4.3.16) shows that respondents' latent attitudes α_i are a function of socioeconomic characteristics Z_i and error term η. The γ parameter indicates the effect of different socioeconomic factors on precaution. Using socioeconomic variables to influence the latent attitude represents a departure from the MXL and LCM where respondent's characteristics determine choices or class allocation, respectively (Beharry-Borg and Scarpa, 2010). The error is normally distributed with mean zero and standard deviation σ_α which Hess and Beharry-Borg (2012) denotes $g(\eta)$ (Hess and Beharry-Borg, 2012; Hess and Palma, 2019). Ben-Akiva et al. (2002) noted that there is thus one structural equation per latent variable.

Structural Equation:

$$\alpha_i = \gamma Z_i + \eta_i \tag{4.3.16}$$

As the latent variable is not directly observed, a Measurement Equation (4.3.17) is used to link unobserved latent variables to observed responses to attitudinal questions. The measurement equation contains δ_{I_k} as an indicator-specific constant, ζ as the estimated effect of the latent variable on the indicator and v as a normally distributed error. The measurement equation is typically an ordered probit or logit when attitudinal scales are used, such as the three Likert scales in questions 13-15 of this research (Faccioli et al., 2020). The three components are then simultaneously estimated using the full-information log-likelihood in Equation (4.3.18) (Vij and Walker, 2016).

Measurement Equation:

$$I_{nk} = \delta_{I_k} + \zeta_{I_k} \cdot \alpha_n + v_{kn} \tag{4.3.17}$$

Finally, the three equations can be combined into a log-likelihood function in Equation 4.3.18. The likelihood has two components; the probability of responses to the attitude scales and the probability of choices. The likelihood of respondent responses to the attitudinal questions is adapted from the Measurement Equation (4.3.17). Hess and Beharry-Borg (2012) states that response I_n is conditional on parameters ζ_n, standard deviations $\sigma_{I,k}$ and latent variable α_n. The likelihood of choices is given by $L_n(y_n|\beta,\tau,\alpha_n)$ for respondent n with their choices being conditional on a vector of preference coefficients β, τ parameters of interaction between the latent variable and the β, and the latent variable α. As both conditional on the latent variable's random element, they must be integrated when combined as in Equation (4.3.18) which is adapted from Hess and Beharry-Borg (2012).

Log-Likelihood function:

$$LL\left(\beta,\gamma,\eta_I,\tau,\sigma_I\right) = \sum_{n=1}^{N} ln \int_{\eta} L\left(y_n|\beta,\tau,\alpha_n\right) L\left(I_n|\eta_I,\sigma_I,\alpha_n\right) g\left(\eta\right) d\eta \tag{4.3.18}$$

4.3.3.2 Application

Starting with the choice model, the ICLV uses the same MXL specification in Table 4.3 and so can be called a Hybrid Mixed Logit Model; HMXL as in Faccioli et al. (2020) and Czajkowski et al. (2017). One ASC is included to create utility differences. Additionally, the three attributes are all randomly distributed and estimated in WTP-space. However, there are two notable differences; the models now include the respondent-specific latent variable α_i, and the socioeconomic variables are no longer interacted with the ASC but instead influence the latent variable.

Indirect Utility for Option B of the CE:

$$V_{iB} = ASC_B + \beta_{Price} * (Price_B + \beta_{Performance} * Performance_B + \beta_{Emission} * Emission_B + \lambda * \alpha_n) \tag{4.3.19}$$

The structural equation linking socioeconomic characteristics to latent environmental attitudes is reported in Equation (4.3.20).

Structural Equation:

$$\begin{aligned}\alpha_i = (\gamma_{Education} * Education) + (\gamma_{Age} * Age) + \\ (\gamma_{Gender} * Gender) + (\gamma_{Distance} * Distance) + \\ (\gamma_{Income} * Income) + (\gamma_{Experts} * Experts) + (\gamma_{Consequentiality} * Consequentiality) + \\ (\gamma_{BP} * BP) + (\gamma_{Charity} * Charity) + \eta_i\end{aligned} \tag{4.3.20}$$

Equation (4.3.21) reports a measurement equation that links the three attitudinal indicators to the latent attitude of precaution. The three attitudinal questions are reported in Table 4.6. A Cronbach's Alpha value of 0.81 (0.80-0.82) strongly indicates that the three indicators test the same attitude of precaution. If there are many indicators, such as the 15 in the New Environmental Paradigm scale, factor analysis could be used to group the indicators (Abate et al., 2020; Faccioli et al., 2020). However, a value of 0.67 from a Kaiser-Meyer-Olkin sampling adequacy test suggested that this was unnecessary in this research (Abate et al., 2020). Given these validity checks, the three indicators are used for the Ordered Probit model, detailed in Equation (4.3.21).

There are several justifications for using ordered models for the measurement equation. Firstly, Faccioli et al. (2020) argues that ordinal models are appropriate for Likert scales with discrete levels where respondents may interpret the differences between levels differently. Although continuous measurement models have been used previously, they may require mean-centring and normalisation to facilitate interpretation (Hess and Palma, 2019; Faccioli et al., 2020; Buckell, Hensher and Hess, 2021). Normalisation is not necessary for this research as discrete measurement models can be analysed using ordered models. Ordered Probit does not require an assumption of equal distances between levels and instead estimates the thresholds between levels. The Ordered Probit model in Equation (4.3.21), adopted from Train (2009); Hess and Palma (2019) estimates the probability P of respondent i in alternative j choosing Likert scale level s. The model compares respondent indirect utility V_{ij} with a Likert scale level τ_s and the one below it τ_{s-1} (Hess and Palma, 2019). As this is Ordered Probit, Φ is the normal cumulative distribution function (Czajkowski et al., 2017). This research uses Ordered Probit for consistency with Abate et al. (2020), although the Appendix shows that the results are robust to instead using Ordered Logits.

Ordered Probit Measurement Equation:

$$P_{Y_{i,j=s}} = \Phi(\tau_s - V_{i,j}) - \Phi(\tau_{s-1} - V_{i,j}) \tag{4.3.21}$$

The model described in Table 4.7 estimates the full-information log-likelihood, which combines these three equations (Hess and Beharry-Borg, 2012; Hess and Palma, 2019; Ben-Akiva et al., 2002). As before, the β represent the effect of that covariate on the likelihood of a respondent choosing a specific alternative. The coefficient λ is the effect of the latent environmental attitude on choices; precautionary attitudes are expected to positively affect the likelihood of choosing the CE option that reduces microplastics release. The coefficients γ on each socioeconomic variable report the effect of socioeconomic characteristics on latent variables; the expected effect differs by variable. The zetas ζ are the effect of latent attitudes on the three indicator questions 13, 14, 15, measuring current and future concern about the effects of microplastic on human and marine health. An increasing concern is expected to positively affect the likelihood of choosing the alternative option in the CE. Finally, the τ represent the interaction between latent attitudes and the β. Four τ are estimated for the five Likert-scale levels. Again, increasing environmental concern is expected to change choice behaviour (Fransson and Garling, 1999; Kollmuss and Agyeman, 2002).

Table 4.7: CE ICLV Model (N = 670).

Coefficient	**Estimate**	**Bootstrap.std.err.**	**Bootstrap.p-val(0)**
μ_{Price}	-0.720***	0.196	0.000
σ_{Price}	-1.820***	0.629	0.000
$\mu_{Performance}$	-3.593***	0.104	0.000
$\sigma_{Performance}$	3.463***	0.088	0.000
$\mu_{Emission}$	-3.470***	0.096	0.000
$\sigma_{Emission}$	-3.850***	0.037	0.000
λ	-1.471***	0.178	0.000
γ_{Age}	-0.002	0.005	0.272
γ_{Gender}	-0.295***	0.088	0.000
$\gamma_{Distance}$	-0.004**	0.003	0.034
γ_{Income}	-0.000	0.000	0.478
$\gamma_{Experts}$	0.464***	0.059	0.000
$\gamma_{Consequentiality}$	0.323	0.077	0.000
γ_{BP}	0.140**	0.098	0.026
$\gamma_{Charity}$	0.126*	0.090	0.052
$\gamma_{Certainty}$	0.001	0.085	0.493
ζ_{Q13}	1.064***	0.107	0.000
ζ_{Q14}	2.036***	0.362	0.000
ζ_{Q15}	0.908***	0.078	0.000
τ_{Q13_1}	-0.532**	0.353	0.016
τ_{Q13_2}	0.377*	0.362	0.059
τ_{Q13_3}	2.386***	0.412	0.000
τ_{Q13_4}	3.734***	0.471	0.000
τ_{Q14_1}	-0.852**	0.631	0.030
τ_{Q14_2}	0.613*	0.585	0.073
τ_{Q14_3}	3.348***	0.658	0.000
τ_{Q14_4}	5.878***	0.880	0.000
τ_{Q15_1}	-1.281***	0.317	0.000
τ_{Q15_2}	-0.365**	0.315	0.045
τ_{Q15_3}	1.012***	0.322	0.000
τ_{Q15_4}	2.247***	0.352	0.000
Estimation Statistics			
Estimation method	bfgs	LL(start)	-3671.691
Convergence	Successful	LL(final, whole model)	-3659.039
Number of individuals	670	LL(final,indic_Q13)	-839.68
Number of observations	2680	LL(final,indic_Q14)	-809.2315
Number of inter-person draws	1000 Halton	LL(final,indic_Q15)	-792.5453
AIC	7382.08	LL(0,choice)	-1857.634
BIC	7570.67	LL(final,choice)	-1459.956
WTP			
Emissions	0.479	Performance	-0.443

4.3.3.3 Results

The discussion of the ICLV results in Table 4.7 has three parts according to the ICLV structure; starting with the choice model and its comparison to the MXL, then discussing the measurement model that links indicators to attitudes before exploring the structural equations linking socioeconomic factors to attitudes.

Starting with the choice model, the ICLV uses three random parameters estimated in WTP-space but without socioeconomic variables. For consistency with the MXL, the price attribute was negative lognormal, while the normal distribution was assumed for the other two attributes. The mean (μ) and standard deviation (σ) parameters on the attributes are highly similar to those in the MXL and are consistent in sign, magnitude and significance. The magnitude of the mean parameters would represent MWTP in the WTP-space MXL, but MWTP in the ICLV requires a different elicitation procedure stated in Buckell, Hensher and Hess (2021) and discussed shortly. The σ parameters in the CE model were highly significant and reported a very large magnitude, indicating substantial individual-level preference heterogeneity. Other notable elements of the choice model are the standard errors and the ASC. The standard errors are smaller than the MXL, which indicates that the ICLV was estimated with greater precision and that the tests are unbiased. The ASC in the ICLV, with smaller standard errors and weakly statistically significant, was small and negative, indicating a small status quo bias. To summarise, the ICLV choice model is consistent with the MXL model; this represents a degree of validity for the ICLV specification.

In the measurement equation, the lambda (λ) represents the effect of latent precautionary attitudes on respondents' choices. The effect is highly statistically significant, which suggests that it strongly influences respondents choices. The positive sign suggests that the effect is to increase support for the alternative. The latent environmental attitudes affect the indicator questions 13, 14, 15 through the ζ parameters. Q14 indicates precautionary concern as it reports future concerns about human health. Therefore, it is not surprising that the magnitude of Q14 is larger than the Q15, which assesses concerns about marine health. This finding is consistent with Fransson and Garling (1999) finding that anthropocentric motivations are typically stronger than ecocentric. The individual levels of each indicator question affect the latent attitude through the τparameters. The lower levels of the Likert scale responses (τ1 and 2) are statistically insignificant, suggesting that the least-concerned respondents had weaker environmental attitudes, which were less likely to influence their choices. However, the magnitude, significance and sign of the τ increase with the level of concern, and again, the latent precautionary attitude positively influences respondents choices.

The γ reveals the effect of socioeconomic variables on latent attitudes. Consistent with the MXL, consequentiality ($\gamma_{Consequentiality}$) and experts ($\gamma_{Experts}$) were again highly statistically significant. The statistical significance of the Certainty ($\gamma_{Certainty}$) and consequentiality variables suggests that there is substantial variance between the remaining two levels ('Quite Sure' and 'Very Sure', 'Don't Know' and 'Consequential' respectively) of these variables [14]. Additionally, the income dummy is statistically significant and positive, implying that high-income households are more precautionary. However, when the same model is re-estimated with income in levels, the coefficient is no longer statistically significant; see Table 8.21 in Section 8.3.5 of the Appendix. Other variables of interest include gender (γ_{Gender}) and BP-viewership (γ_{BP}), which had no statistically significant effect on the latent attitudes. The statistically insignificant parameter for gender suggests no gender bias in precautionary attitudes. The statistically insignificant effect of BP-viewership in contrast to the highly significant charity involvement variable ($\gamma_{Charity}$) corroborates Kollmuss and Agyeman (2002) suggestion that awareness of an issue, in this case through media, does not necessarily translate into behaviour, such as charity involvement. Both the BP and charity questions were included as γ terms in the structural model rather than as indicators in the measurement model as they do not directly measure environmental concern but are instead proxies. Finally, it should be noted that greater distance from the coast has a weakly negative and statistically insignificant effect on latent environmental attitudes suggesting no distance-decay whereby concern falls with distance from the coast; Chapter Six further discusses the extent of distance-decay WTP. To summarise, socioeconomic variables that proxy for environmental concern, such as charity involvement, positively influence respondents latent precautionary attitudes.

Finally, the WTP from the ICLV can be reported. WTP in the ICLV cannot be calculated in the previous methods of dividing coefficients using the MRS approach (MNL), reading the coefficient when estimated in WTP-space (MXL) or calculating class-specific WTP (LCM) but instead relies on drawing from the WTP distribution. The procedure, outlined in Hess and Beharry-Borg (2012), estimates random draws for all the parameters rather than dividing the coefficients which are interacted with the latent

[14]Furthermore, the high statistical significance of perceived policy consequentiality and question certainty motivates their inclusion in this structural equation although the economic intuition to link consequentiality beliefs and Certainty to latent precautionary attitudes is relatively weak. With thanks to Frankie Cho for raising this debate.

variable in the estimation. Using 1000 draws for each respondent, the WTP is the median of the draws from the CE attribute distribution plus the draws from the distribution of the latent variable divided by the draws from the price coefficient. This approach then yields MWTP of similar magnitude to the MXL models. However, a robust result is that respondents value the emissions attribute more highly than the performance attribute. As this result contradicts the MNL, MXL and LCM, it indicates that the effect of including the latent precautionary attitude is to show a stronger preference for precautionary changes in cosmetic products. Therefore, the ICLV suggests that precautionary attitudes exist and positively influence MWTP for changes in cosmetic product attributes.

4.4 CE Model Evaluation

This section determines the most appropriate model from the CL, MNL, MXL, LCM, and ICLV by comparing the MWTP and goodness of fit criteria. To facilitate comparison, Table 4.8 reports statistics from each estimated model. Starting with goodness-of-fit criteria, better models are indicated by larger R^2 and log-likelihood but smaller AIC. As R^2, even adjusted or McFadden, measures are not always available, the models may also be evaluated using AIC and log-likelihood. However, different conclusions are possible with the two measures. For instance, the MXL has slightly worse AIC than the LCM, but its log-likelihood is superior. Goodness-of-fit criteria favour the explicitly treating respondent preference heterogeneity using the MXL or LCM rather than estimating simpler CL or MNL models.

The MXL model is adopted as the most appropriate treatment of respondent preference heterogeneity, given the most plausible MWTP. Specifically, the MXL with three randomly distributed parameters in WTP-space produces a more plausible MWTP than the 3-class LCM. Although the sign and magnitude of MWTP are largely consistent between specifications, the ratio between the two attributes depends on the treatment of unobserved heterogeneity. Specifically, the emissions MWTP is smaller in absolute magnitude than the performance attribute for the CL, MNL, and LCM, while it is larger when using the ICLV. This result suggests that MWTP is strongly influenced by individual heterogeneity in latent precautionary attitudes. To summarise, the MXL produced the most plausible MWTP.

Another evaluation metric is the accuracy of the model's predictions (Bujosa, Riera and Hicks, 2010; Mao et al., 2020; Vij and Walker, 2016). Prediction accuracy is a significant concern for the small but emerging literature at the intersection of machine learning and discrete choice modelling; see Sifringer, Lurkin and Alahi (2018) for a review. Each model reported the average choice probabilities, and these predictions can then be checked with actual choices to determine each model's prediction accuracy. A score greater than 50% indicates that the model is correct the majority of the time. Table 4.8 details how accurate each model predicted respondent choices. The general result is that truncated models and more complex specifications are less accurate than simpler models on the full sample. Again, there is a difference between the MXL and LCM, with the LCM being marginally more accurate, although both are more accurate than the ICLV. Overall, the prediction accuracy for the chosen specification of the MXL is sufficient.

Table 4.8: Model specification, MWTP, and goodness-of-fit criteria.

Specifications	**Emission MWTP**	**Performance MWTP**	**Sample Size**	**AIC**	R^2	**Log-Likelihood**	**Accuracy**
Full Sample							
Conditional Logit (Full)	0.038	-0.043	670	3539.16	0.035	-1765.60	76.27%
MNL (Full)	0.035	-0.044	670	3428.99	NA	-1694.493	63.96%
MNL: Quadratic (Full)	8.304	-0.208	670	3534.31	0.085	-1761.157	77.01%
MNL: Piecewise (Full)	1.242	-0.169	670	3541.349	0.048	-1761.157	77.01%
MXL: Covariates (Full)	0.0353	-0.0413	670	2964.38	0.202	-1461.192	57.76%
MXL: Attributes only (Full)	0.028	-0.0467	670	2974.91	0.203	-1480.455	57.39%
MXL: Income (Full)	0.033	-0.0357	670	2986.49	0.200	-1485.24	56.27%
MXL: Correlated (Full)	0.0314	-0.049	670	-2982.20	0.197	1481.28	57.01%
LCM: 3-class no SD (Full)	Class1: 0.001 Class2: 0.600 Class3: -0.029	Class1: -0.017 Class2: -0.068 Class3: -0.038	670	2976.46	0.205	-1476.23	58.28%
ICLV: (Full)	0.0479	-0.043	670	7382.08	NA	-3659.039	47.09%
Truncated Sample							
Conditional Logit (Truncated)	0.033	-0.057	304	1598.70	0.052	-795.3503	59.87%
MNL: Income Dummy (Truncated)	0.032	-0.056	304	1564.99	0.072	-764.497	56.58%
MXL: Covariates (Truncated)	0.0398	-0.0356	304	1389.77	0.176	-673.883	52.14%
MXL: Attributes only (Truncated)	0.040	-0.034	304	1281.43	0.189	-1281.43	51.23%
MNL: Income Level (Truncated)	0.032	-0.060	304	1462.88	0.0935	-764.0197	57.54%
MXL: Relaxed Income (Truncated)	0.033	-0.038	304	1279.18	0.201	-631.588	52.63%
MXL: Correlated (Truncated)	0.036	-0.041	304	1283.28	0.188	-631.6411	52.98%
LCM: 3-class no SD (Truncated)	Class1: 0.024 Class2: 0.600 Class3: 0.496	Class1: -0.042 Class2: -0.374 Class3: -0.066	304	1388.23	0.176	-682.117	54.11%
ICLV: (Truncated)	0.033	-0.028	304	3063.35	NA	-1499.673	50.18%

The difference between the MWTP for the two attributes may be partially attributed to the commonly observed difference between WTP and WTA (Atkinson et al., 2018a; Bateman et al., 2002; Kahneman, Knetsch and Thaler, 1990; Johnston et al., 2017). In this research, the marginal change in the 'emissions' attribute corresponds to WTP to improve the good. The marginal change in the performance attribute can be understood as the minimum monetary amount necessary to hold utility constant when reducing the cosmetic good's performance, and, therefore, is a WTA (Fujiwara and Campbell, 2011). Another explanation for the larger magnitude of the WTA is that respondents hold cosmetics' performance as the most important attribute and are thus more sensitive to marginal changes in its value. Therefore, the similar magnitude of the emissions attributes suggests that respondents value the product's environmental attributes of similar importance to product performance. Loomis (2014) also suggests that WTA may be greater due to hypothetical bias, although the WTP and WTA in this research are subject to the same bias-mitigating measures; the cheap-talk script and the certainty and consequentiality scales. To summarise, the difference in magnitude of the WTP between the attributes may be partly driven by the difference between WTP and WTA.

A final challenge to evaluating specifications using MWTP is the possibility of endogeneity and multicollinearity in the econometric models. Train (2009) described several controls for potential endogeneity, such as the control function or Berry-Levinsohn and Pakes (BLP) approaches. However, endogeneity through correlated alternatives or omitted variable bias is unlikely in this research for two reasons. Firstly, the three attributes are unlikely to be correlated. Secondly, omitted variable bias is also less likely given that this research follows (Adamowicz et al., 2011) approach of estimating with and without covariates, and MWTP is relatively stable between these. However, treating omitted variable bias by including all possible sources of preference heterogeneity elicited from the survey raises the issue of multicollinearity. Johnston et al. (2017) observed that multicollinearity is more likely when the survey debriefing questions may be correlated, such as employment, education and income. There is evidence of multicollinearity in this research as most of the MNL coefficients were not statistically significant, possibly as they were collinear and masking their effects. Again, models with and without covariates are provided to account for this. Moreover, many socioeconomic variables are explicitly included to avoid potential omitted variable bias. Finally, as the MWTP was broadly consistent across specifications, alternative multicollinearity or endogeneity treatments may make a minimal qualitative difference. One specific area of note is the optimal treatment of the income variable. Options from the literature include income in gross levels, in logs, or in dummy form (Adamowicz et al., 2011; Abate et al., 2020). This research estimated each approach to determine the appropriate treatment of income effects on WTP, settling for the dummy approach in Faccioli et al. (2020) which is statistically significant, but the effects are less relevant. To summarise, the MWTP is broadly robust to specification, although future work can demonstrate this further using contemporary treatments for collinearity and endogeneity.

To summarise, this section compared the goodness-of-fit, MWTP, and prediction accuracy of all the models estimated to analyse the CE. The MXL in WTP-space with three randomly distributed (lognormal and normal) attributes, and all socioeconomic covariates appear to be the most appropriate model given plausible MWTP and sufficient goodness-of-fit. By contrast, the MNL performs well, but with unrealistic and restrictive assumptions, the LCM fits slightly better but produces less plausible MWTP, and finally, the ICLV fits and predicts comparatively poorly. Therefore, the appropriate treatment of respondent heterogeneity in the CE is to model it at the individual level using the MXL.

4.5 CE Validity

Rakotonarivo, Schaafsma and Hockley (2016) reviewed the literature on reliability and validity tests for CEs with the findings summarised in Table 4.9. In this section, both external (criterion and convergent) and internal (theoretical and content) validity tests are considered. However, as a within or between-subjects design was not plausible in this research, given the funding and timing constraints, reliability cannot easily be assessed. Regardless, one major comment on the CE validity concerns the design of the CE itself. Specifically, the elicited values can be interpreted as the marginal price in pounds for a one percent change in the given attribute of that good; values are marginal and per-product. While this was believed to improve scenario credibility, it may complicate the aggregation of the WTP and weaken consumer understanding of the scenario. An alternative approach in the literature was to value bundles of products instead and this remains to future research.

Table 4.9: Summary of CE Validity measures.

Area	**Type**	**Description**	**Evidence**
Reliability	Within	Test-retest of the same respondents at different points	Not attempted in this research given limited time and budget
	Between	Split-sample tests to examine the stability of preferences given design differences	
External Validity	Criterion	Comparison with other non-hypothetical methods	Not possible in this context.
	Convergent	Comparison with other SP methods	Can compare results with the relevant SP literature.
Internal Validity	Theory	Are the preferences consistent with theoretical assumptions	Tests are reported for Attribute-Non-Attendance, Scope-sensitivity Dominated scenarios, Ordering effects.
	Content	Is the survey content appropriate and conducive to accurate and truthful revelation of preferences.	Examined using protest votes, perceived consequentiality and survey understanding.

4.5.1 External Validity

This section discusses two external tests of validity; criterion and convergent validity (Rakotonarivo, Schaafsma and Hockley, 2016). Starting with criterion validity, to the best of this author's knowledge, there is not at the time of writing appropriate data, such as non-hypothetical field experiments or market data, to compare the WTP. Therefore, it is not currently possible to assess the criterion validity of the CE. However, it is possible to consider convergent validity, as other studies have elicited WTP in a similar area. Among CEs, the MWTP in this research is in the same order of magnitude as the MWTP to avoid a microbial illness from water estimated in Adamowicz et al. (2011). However, the MWTP from the CE in (Logar et al., 2014) is closer in value to that elicited from the CV in this research as they reported average annual household WTP to reduce risk from micropollutants of $73. The MWTP in this research, reported in Table 4.8, is more comparable with the Choi and Lee (2018) CVM estimate of $2.59 although there are two significant issues with this. Firstly, the CE in this research reports MWTP per product rather than per person annually. Accurate aggregation to the per-person per-year level is challenging and, as Chapter Seven shows, fraught with assumptions. Secondly, the CE MWTP is for a marginal change and simply multiplying the unit values by 100 unrealistically assumes linearity and ignores the possibility of diminishing marginal utility (DMU). Therefore, while the CE MWTP appears roughly comparable with the literature's values, there are caveats to this. Overall, it is challenging to report external tests of the validity of the CE MWTP.

4.5.2 Internal Validity

This section explores the broad range of tests in the literature for the CE design and results' internal validity. Internal validity tests fall into either theoretical, to test whether preferences are consistent with rational choice theory (Bateman et al., 2002; Johnston et al., 2017), or content to test whether the survey information and scenarios are credible and understandable (Rakotonarivo, Schaafsma and Hockley, 2016; Dugstad et al., 2021).

4.5.2.1 Theoretical Validity

Several measures of theoretical validity are considered here; dominated scenarios, ordering effects, attribute-non-attendance and scope sensitivity.

Before discussing ANA and scope sensitivity, Rakotonarivo, Schaafsma and Hockley (2016) also discussed two small tests of theoretical validity; the dominated scenario and ordering effects. The effect of the dominated scenario in Question eight (Q8) of the survey has been discussed at length in Section 8.1. Q8 tested whether respondents have rational preferences and understand the CE. Those who failed the test do not and are thus removed to maintain the theoretical validity of the responses (Foster and Mourato, 2002; Dugstad et al., 2021; Rakotonarivo, Schaafsma and Hockley, 2016). A majority of the sample passed the dominated scenario test in Q8, again supporting the responses' internal validity.

Although only the order of the CV questions was tested, a dummy variable was also included in the CE models to test whether question ordering affected the subsequent CE choices. However, the evidence of the insignificant dummy and the insignificant Mann-Whitney tests of the CE MWTP by question order suggests a weak and statistically insignificant effect. Therefore, ordering effects do not appear in the CE MWTP; the CE's theoretical validity is encouraging.

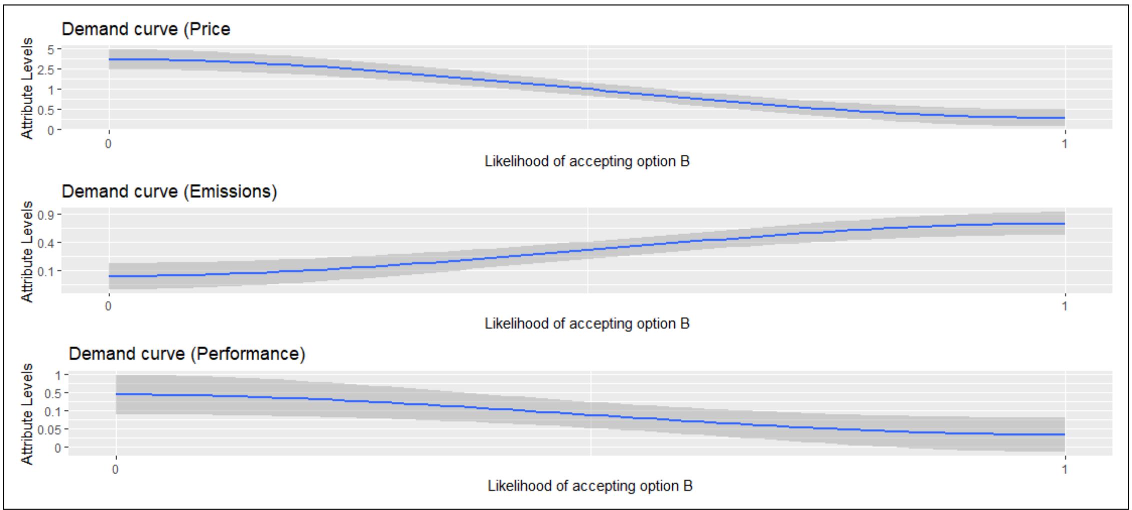
4.5.2.1.1 Attribute-Non-Attendance

Attribute-Non-Attendance (ANA) can be described as respondents ignoring or prioritising specific attributes when making their decisions (Rakotonarivo, Schaafsma and Hockley, 2016; Logar, Brouwer and Campbell, 2020). There are three reasons why there is weak evidence for ANA in this research. Firstly, the pre-test process confirmed that respondents would trade-off different attributes and given there were only three attributes in the model, ANA is less likely. Secondly, the text responses to Q8, the dominated scenario, indicated that respondents considered the full scenario. Finally, each attribute was shown to significantly affect individuals' choices, whereas ANA could lead to one non-significant attribute if respondents routinely do not consider it. Therefore, ANA is unlikely in this CE which supports the internal validity of the CE.

4.5.2.1.2 Scope Sensitivity

There is an emerging focus on scope sensitivity as a test of theoretical validity (Dugstad et al., 2021; Rakotonarivo, Schaafsma and Hockley, 2016; Lew and Wallmo, 2011). Scope sensitivity is analysed in this research using two different approaches. Firstly, graphically using the responsiveness of choice to attribute levels for each attribute. Secondly, using alternative indirect utility specifications to calculate the elasticity of WTP to changes in scope. Figure 4.2 reports the first approach and shows that the alternative chosen (Option A, the status quo, equals zero while Option B, a restriction, equals one) varies with the attribute levels, which is indicative of the CE responses being sensitive to scope (Whitehead and Blomquist, 2006; Lew and Wallmo, 2011). The curves suggest that respondents were more likely to select the alternative option when the product price and performance change was smaller as each attribute is a disutility. By comparison, respondents are more likely to select the alternative option when the reduction in the release of microplastics is higher. Therefore, a graphical analysis of respondent choices and attribute levels suggests that they were sensitive to scope.

Figure 4.2: Relationship between attribute levels and choices.



Dugstad et al. (2021) conference paper suggests that the use of levels in a DCE can be used to estimate scope sensitivity. They do this by estimating three different specifications for the indirect utility function; linear, quadratic and piecewise. The linear indirect utility is the most commonly used in the literature but assumes a constant scope elasticity of one and thus cannot reveal scope-sensitivity (Train, 2009). By contrast, the quadratic specification estimates the attributes and their squares to indicate the extent of diminishing marginal utility and has been used in Adamowicz et al. (2011); Luisetti et al. (2011); McIntosh and Ryan (2002). Alternatively, a piecewise specification with different parameters for different attribute levels can be used to estimate (Howard, Whitehead and Hochard, 2020). Dugstad et al. (2021) reports that scope elasticity can be estimated using the following formula:

$$e_{WTP_{q_s}} \equiv \frac{\%\Delta WTP}{\%\Delta q_s} \tag{4.5.1}$$

Scope elasticity, in this case, refers to the sensitivity of WTP to levels of the attributes (Lew and Wallmo, 2011). The scope elasticity typically ranges between zero and one. A zero scope elasticity would imply that WTP is not sensitive to attribute levels, while a value of one implies proportional changes (Dugstad et al., 2021). Although Rakotonarivo, Schaafsma and Hockley (2016) considered between-sample tests to be stronger, a larger sample would be required given that the question order, bid level, and choice task were all randomised too. The following section firstly comments on diminishing marginal utility using the quadratic specification before calculating scope sensitivity using the piecewise specification.

Quadratic Indirect Utility Function:

$$\begin{aligned} V_{iB} = ASC_B + (\beta_{Price} * Price_B) + \\ (\beta_{Performance} * Performance_B) + \\ (\beta_{Performance_{Square}} * (Performance_B^2)) + \\ (\beta_{Emission} * Emission_B) + \\ (\beta_{Emission_{Square}} * (Emission_B^2)) \end{aligned} \tag{4.5.2}$$

Table 4.10 reports the quadratic model. It should be noted here that the inclusion of the square terms implies collinearity with the linear terms. Although this approach has been previously used in Adamowicz et al. (2011), it does raise the possibility that the variables would be jointly significant but individually insignificant. The linear attributes are larger in magnitude than those from the linear indirect utility specification. They are, however, less statistically significant, with the quadratic model also reporting slightly weaker goodness-of-fit. Importantly, the negative sign of the two quadratic terms indicates DMU in the attributes. The existence of DMU for both non-monetary attributes suggests that linearly scaling the MWTP to estimate the WTP for a 100% change in the attribute would overstate the WTP and is, therefore, imprecise. However, the quadratic model does not support the estimation of scope elasticities, unlike the piecewise model reported in Table 4.11 and cannot calculate scope sensitivity.

Table 4.10: Quadratic Indirect Utility MNL (N = 670).

Variable	**Estimate**	**Robust.std.err.**	**Robust.p-val(0)**
ASC_B	0.433	0.195	0.026
β_{Price}	-0.210***	0.025	0.000
$\beta_{Performance}$	0.043	2.657	0.987
$\beta_{Emission}$	1.744***	0.608	0.004
$\beta_{Performance_{SQ}}$	-1.544	4.736	0.744
$\beta_{Emission_{SQ}}$	-0.942	0.588	0.109
Estimation Statistics			
Estimation method	bfgs	LL(start)	-1857.634
Convergence	Successful	LL(0, whole model)	-1857.634
Number of individuals	670	LL(final)	-1761.157
Number of observations	2680	Rho-square (0)	0.0519
Number of cores used	1	Adj.Rho-square (0)	0.0487
AIC	3534.31	Estimated parameters	6
BIC	3569.68	Iterations	17

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Piecewise Indirect Utility Function:

Note that in the estimation, the β on the middle levels were fixed at zero. However, the WTP and implied scope sensitivity are robust to whichever level is held fixed. The numbers are the levels in the CE design.

$$\begin{aligned} V_{iA} = ASC_A + (\beta_{Price} * Price_A) + \\ (\beta_{Performance_{Low}} * (Performance_A == 0)) + \\ (\beta_{Emission_{Low}} * (Emission_A == 0)) \end{aligned} \quad (4.5.3)$$

$$\begin{aligned} V_{iB} = ASC_B + (\beta_{Price} * Price_B) + \\ (\beta_{Emission_{Low}} * (Emission_B == 0.1)) + \\ (\beta_{Emission_{Medium}} * (Emission_B == 0.4)) + \\ (\beta_{Emission_{High}} * (Emission_B == 0.9)) + \\ (\beta_{Performance_{Low}} * (Performance_B == 0.05)) + \\ (\beta_{Performance_{Middle}} * (Performance_B == 0.10)) + \\ (\beta_{Performance_{High}} * (Performance_B == 0.50)) + \end{aligned} \quad (4.5.4)$$

Table 4.11: Piecewise Indirect Utility MNL (N = 670).

Variable	**Estimate**	**Robust.std.err.**	**Robust.p-val(0)**
ASC_B	0.597***	0.103	0.000
β_{Price}	-0.210***	0.025	0.000
$\beta_{Emission_Low}$	-0.382***	0.098	0.000
$\beta_{Emission_High}$	0.260***	0.1051	0.013
$\beta_{Performance_Low}$	0.010	0.0975	0.921
$\beta_{Performance_High}$	-0.353***	0.1086	0.001
Estimation Statistics			
Estimation method	bfgs	LL(start)	-1857.634
Convergence	Successful	LL(0, whole model)	-1857.634
Number of individuals	670	LL(final)	-1761.157
Number of observations	2680	Rho-square (0)	0.0519
Number of cores used	1	Adj.Rho-square (0)	0.0487
AIC	3534.31	Estimated parameters	6
BIC	3569.68	Iterations	14

Table 4.12: Piecewise indirect utility implied scope sensitivity.

Variable	**MWTP**
Performance_Low	-0.046
Performance_High	-1.685
Emission_Low	1.824
Emission_High	1.242
Estimated Scope	
Performance	1.16
Emission	0.24

The piecewise indirect utility function allows attribute-specific scope elasticity to be calculated as in Table 4.12. The evidence suggests that the emission attribute's scope sensitivity is well within the expected [0,1] range, and the magnitude is consistent with the literature (Dugstad et al., 2021; Rakotonarivo, Schaafsma and Hockley, 2016). However, the scope elasticity of the performance attribute exceeds the value of one. The 1.16 elasticity is not unheard of in the literature and implies greater than proportional substitution between product performance and price (Dugstad et al., 2021). This large value may be due to the statistically insignificant coefficient on the performance attribute's lowest level. This insignificance is robust to specification where the middle or highest levels were fixed instead. Overall, a piecewise indirect utility function supports the calculation of elasticities which indicate scope-sensitivity.

To summarise the tests for scope sensitivity of the CE responses, the responsiveness of choice to attribute levels and the attributes' statistical significance provide weak tests that indicate sensitivity. The quadratic specification is a stronger test that indicates DMU in the levels. Finally, the strongest test is the piecewise utility function which allows for elasticity to be calculated. The sensitivity of the emissions attribute is low and within an expected range. However, the performance attribute reports greater than proportional substitution, which has a clear economic interpretation of consumers' strong preference for product performance and efficacy. Therefore, the CE results are scope sensitive, supporting the CE design's theoretical validity and results.

4.5.2.2 Content Validity

The final major area to test the CE validity concerns the survey instrument's content and construct validity. Construct validity considers whether respondents understand the survey information and tasks. It can be measured in three ways; analysing the protest votes, consequentiality beliefs, and the self-reported understanding of microplastics pre and post information.

Firstly, protest votes were analysed in Section 3.3.2. The majority of the 90 protesters protested Q6, the research scenario, with fewer Q7 and CE protests. The fraction of protest votes in the sample, 13%, is relatively high but is concentrated on the CV scenarios and suggests a reasonable degree of construct validity for the CE scenarios. Furthermore, there were few protests about the CE.

Another test of construct validity concerns perceived policy consequentiality, discussed at length in Section 8.1. Consequentiality is linked to incentive compatibility and hypothetical bias, and so ensuring that respondents believe their participation to be consequential is critical for the theoretical validity of the CE and MWTP (Czajkowski et al., 2017). Although this research only assessed policy consequentiality and not payment consequentiality, the former is more indicative of content validity (Vossler and Watson, 2013; Dugstad et al., 2021). A majority of respondents believed their participation to be consequential rather than inconsequential, which suggests both a low level of hypothetical bias and a sufficient degree of content validity. Although there was a relatively high incidence of 'Don't Know' responses, this is more suggestive of respondents not understanding the policymaking environment rather than a low degree of content validity [15].

The content validity of the information in the survey was also assessed using questions five and fifteen, pre and post the information sections, respectively. The result was that microplastics' understanding increased following the information provided: Median pre: 2.8/5, Median post: 3.0/5. The positive effect of information provision indicates that respondents understood the information provided in the sample. The difference between these questions and their effects on fitted CE and CV WTP are discussed further in Chapter Six. Overall, the low level of protests, primarily about one CV scenario, the high degree of actual and perceived policy consequentiality, the high degree of survey understanding and the positive effect of information provision all suggest that the survey had a high degree of content validity.

Overall, there is encouraging theoretical and content validity, although criterion validity and reliability could not be tested. However, the sign of the MWTP is relatively consistent across specification and sample, the relative magnitudes change when individual-level heterogeneity is included.

4.6 Summary

To summarise, this chapter has estimated and evaluated a range of different approaches to incorporating respondent heterogeneity. Initially, the CL and MNL specifications indicated that respondents had a stronger preference for product performance than marginal reductions in the release of microplastics. However, a random-parameters MXL

[15] Although respondents were not aware of it, the survey does have a reasonable degree of policy consequentiality given the involvement of the EA, HSE, and CTPA.

approach allowing for individual-level preference heterogeneity reported that the opposite; that the absolute magnitude of MWTP was larger for the emissions attribute than the performance attribute. This finding is corroborated when using the ICLV to explore how a latent precautionary attitude influences respondents' choices. Later chapters provide further inference from the MWTP evaluated at the individual level from the MXL. The following chapter now extends the econometric analysis to the CV data.

Econometric Modelling of Contingent Valuation Survey Data.

Chapter Five Abstract:

This chapter undertakes the econometric analysis of the CV data collected in the survey. The primary aim of the econometric analysis is to elicit sample and individual WTP for both CV questions. A secondary aim is to consider the validity of the WTP. Finally, this chapter considers how models from the CE literature, specifically the ICLV, can be applied to CV data.

5.1 Contingent Valuation

This section elicits WTP from the two CV questions in the survey, Q6 and Q7. The method is as follows. Firstly, the Kaplan-Meier-Turnbull survival function is estimated to show the distribution of WTP. Secondly, sample median WTP is elicited with a bid-only probit. Finally, a model with all covariates is estimated to understand influences. Alternative specifications such as bivariate probit and ICLV are also estimated. While using different probit specifications is common in the literature, this chapter uses the ICLV to estimate WTP from CV and not just CE data. The aim of this approach, trialled in Abate et al. (2020), is to evaluate how latent precautionary attitudes influence WTP to resolve uncertainty or irreversibility. Following these models' estimation, the CV results' validity is discussed with specific mention of ordering, anchoring, and consequentiality effects. Finally, a summary of all the CVM WTP elicited by the question, split-sample and measure are reported in Table 5.12. All models presented here are using the full sample with the truncated sample models reported in the Appendix.

5.2 Theoretical foundations

The econometric theory underpinning the SBDC and DBDC models is reported here and then applied by each question. It should be noted that while logit is typically used for CE results, probit is more common for the CV data given the different distributional assumptions required for the errors; see Train (2009) for an elucidation of the motivation for using the normally-distributed probit errors for CV data.

5.2.1 Single-Bound Dichotomous Choice

The SBDC format is analogous to the referenda format recommended by the NOAA panel as it asks respondents a binary [no, yes] question on whether they are willing to pay a given bid amount for a scenario (Arrow et al., 1993). The SBDC is the dominant elicitation format in the literature, given that asking one question reduces anchoring effects and preserves incentive compatibility. The econometric theory to support the SBDC is adapted from Abate et al. (2020) who used the SBDC to elicit WTP for reductions in plastics, but not specifically microplastics, in Arctic ice. Firstly, Equation 5.2.1 states that the utility U_{ij} of respondent i from choice j is a function of the vector X_i which contains income y_i, socioeconomic characteristics, and a normally-distributed error term ε_i. In Equation (5.2.2), the respondents choice j equals zero for 'No' and one for 'Yes'. The probability of each choice C is conditional on the bid level b and depends on the probability of the utility from voting yes being superior to the utility from voting against the proposal. Equation (5.2.3) models the probability of respondents' choices as conditional on their socioeconomic characteristics. The probabilities can be estimated using the univariate probit model where Φ represents the standard normal, σ is the standard deviation of the error term, and β can be estimated (Cameron, 2005). Finally, the log-likelihood to maximise is reported in Equation (5.2.3).

Random utility specification:

$$U_{ij} = U_{ij}(y_i, X_i, \varepsilon_{ij}) \tag{5.2.1}$$

Probabilities:

$$Pr(C_i = 1|b_i) = Pr\left[U_{i1}\left(y_i - b_i, X_i, \varepsilon_{i1}\right) > U_{i0}\left(y_i, X_i, \varepsilon_{i0}\right)\right] \tag{5.2.2}$$

Probit model:

$$\begin{aligned} Pr(C_i = 1|X_i) &= \Phi\left(\frac{\beta X_i}{\sigma}\right) \\ Pr(C_i = 0|X_i) &= 1 - \Phi\left(\frac{\beta X_i}{\sigma}\right) \end{aligned} \tag{5.2.3}$$

Log-likelihood function:

$$lnL\left(\beta_i|X_i, C_i\right) = \sum_{i=1}^{N}\left(\left(C_i\right) ln\Phi\left(\frac{\beta X_i}{\sigma}\right) + \left(1 - C_i\right) ln\left(1 - \Phi\left(\frac{\beta X_i}{\sigma}\right)\right)\right) \tag{5.2.4}$$

5.2.2 Double-Bound Dichotomous Choice

The DBDC format extends the SBDC by asking respondents a follow-up dichotomous choice question depending on their answer to the first question (Bateman et al., 2002; Hanemann, 1984). The follow-up question asks if respondents are willing to pay a higher amount if they voted yes and a lower amount if they voted no to the first question. This leads to a more precise estimate of WTP (Choi and Lee, 2018). While both SBDC and DBDC use the RUM as a theoretical foundation, the DBDC responses can be analysed using the bivariate instead of univariate probit (Hanemann, Loomis and Kanninen, 1991; Watson and Ryan, 2007). Similarly to the SBDC, the probability of a respondent making a choice is a function of their utility.

Given that respondents have two binary Yes/No choices to the first and the follow-up question, there are four possible responses; (Yes, Yes), (Yes, No), (No, Yes), (No, No). The probability of each is stated in Equation (5.2.5), which is adopted from Watson and Ryan (2007). Here the probability for each of the four possible choices is a function of individual utility. The subscript 1 or 2 indicates the first (1) and follow-up (2) questions. Respondents may vote no if their utility is not strictly better off, hence the changing inequalities:

$$\begin{aligned} Pr(Yes, Yes) &= Pr(\beta X_1 + \varepsilon_{1j} > b_1, \beta X_1 + \varepsilon_{1j} \geqslant b_2) \\ Pr(Yes, No) &= Pr(\beta X_1 + \varepsilon_{1j} \geqslant b_1, \beta X_2 + \varepsilon_{2j} < b_2) \\ Pr(No, Yes) &= Pr(\beta X_1 + \varepsilon_{1j} < b_1, \beta X_2 + \varepsilon_{2j} > b_2) \\ Pr(No, No) &= Pr(\beta X_1 + \varepsilon_{1j} < b_1, \beta X_1 + \varepsilon_{1j} < b_2) \end{aligned} \tag{5.2.5}$$

Probit model examples:

$$\begin{aligned} Pr(J_1 = Y, J_2 = Y|\beta_1, \beta_2) &= \Phi\left(\frac{\beta_1 X_1}{\sigma}, \frac{\beta_2 X_2}{\sigma}\right) \\ Pr(J_1 = Y, J_2 = N|\beta_1, \beta_2) &= \Phi\left(\frac{\beta_1 X_1}{\sigma}, -\frac{\beta_2 X_2}{\sigma}\right) \\ Pr(J_1 = N, J_2 = Y|\beta_1, \beta_2) &= \Phi\left(-\frac{\beta_1 X_1}{\sigma}, \frac{\beta_2 X_2}{\sigma}\right) \\ Pr(J_1 = N, J_2 = N|\beta_1, \beta_2) &= \Phi\left(-\frac{\beta_1 X_1}{\sigma}, -\frac{\beta_2 X_2}{\sigma}\right) \end{aligned} \tag{5.2.6}$$

Equation 5.2.7 links the four possible choices to indicator functions. An indicator takes the value of zero unless the WTP is in the boundary between the two bid levels b_1, b_2:

$$\begin{aligned} WTP \geqslant b_2 &\implies I_i^{Y,Y} = 1 \\ b_1 \leqslant WTP < b_2 &\implies I_i^{Y,N} = 1 \\ b_1 > WTP \geqslant b_2 &\implies I_i^{N,Y} = 1 \\ WTP < b_2 &\implies I_i^{N,N} = 1 \end{aligned} \tag{5.2.7}$$

The indicator functions and probabilities can then be included in a joint log-likelihood which can be maximised:

$$\begin{aligned} lnL\left(\beta X_{ij}|b\right) = \sum_{i=1}^{N} \Big\{ & I^{Y,Y} Pr(Y,Y) + \\ & I^{Y,N} Pr(Y,N) + \\ & I^{N,Y} Pr(N,Y) + \\ & I^{N,N} Pr(N,N) \Big\} \end{aligned} \tag{5.2.8}$$

The following section presents the results of the SBDC and DBDC models for Q6 and Q7, respectively.

5.3 Question 6 CVM

Q6 aimed to elicit WTP for research; akin to the value of learning in the economics of uncertainty literature (Riddel, 2011). The pre-tested text is;

"One possible policy option would be to fund research into the long-term environmental and health effects of microplastics in the environment.
The research would definitely resolve the scientific uncertainty about any possible effects, though it would have no effect on the amount of microplastics currently entering the environment from wastewater sewerage.
An increase in your water bills would cover only the cost of this research. Any follow up action, depending on the research findings, would be funded separately. Would your household be willing to pay £X per year in extra water bills specifically for such research?"

The payment vehicle for Q6 was additional water bills per household per year. The payments were not specified as a one-off, and so they may be aggregated over time. There were eight random bid levels ranging from £5 - 100. This section first reports WTP distribution using the Kaplan-Meier-Turnbull (KMT) survival function before reporting the point estimates and determinants of WTP using the univariate probit model.

5.3.1 Question 6 KMT

The KMT survival function was developed by Carson and Steinberg (1990) as a non-parametric extension to the Kaplan-Meier survival function. A survival function in this context reports the probability that respondents will vote yes to a given scenario when the bid level increases. KMT uses maximum-likelihood to recover the survival distribution of WTP and is appropriate for SBDC data which is interval-censored (Lim, Jin and Yoo, 2017). A survival function is appropriate as conventional demand curves suggest that the probability of a respondent accepting any bid level decreases with an increasing bid level. Although the KMT is less common in the contemporary CV literature, it is an instructive validity check in this research as it indicates the respondent's sensitivity to bid levels. The KMT is applied to the Q6 responses from the full sample in Figure 5.1. The results are detailed in Table 5.1 which reports that a bid of zero pounds was accepted with 100% probability while the highest bid level of £100 has an approximately 37.5% probability of being accepted. The high probability remaining here suggests a large right tail of the distribution with WTP higher than £100. Follow-up questions about larger bids could be used to estimate the WTP more precisely (Hanemann, Loomis and Kanninen, 1991). To summarise, the KMT for Q6 indicates that while respondents were sensitive to bid level, many had WTP higher than the maximum bid level.

Figure 5.1: Q6 SBDC KMT Survival Function.

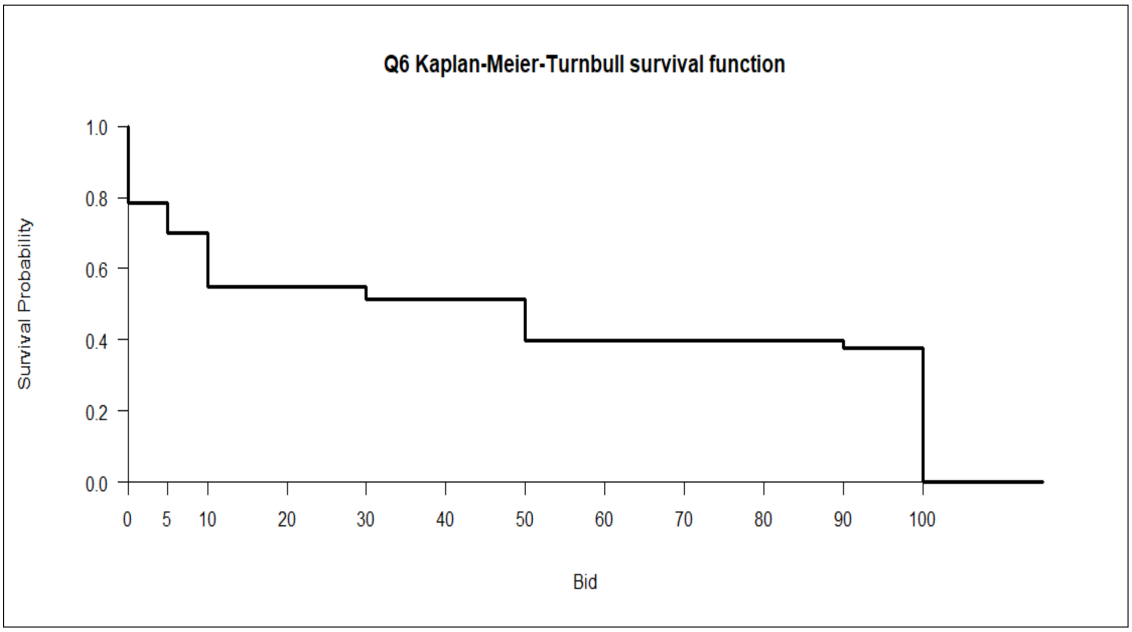


Table 5.1: KMT probability estimates for Q6.

Bid number	Bid value (£)	Survival probability
1	0	1.000
2	5	0.785
3	10	0.689
4	20	0.548
5	30	0.548
6	40	0.515
7	50	0.515
8	60	0.399
9	70	0.399
10	80	0.399
11	90	0.375
12	100	0.375
13	Inf	0.000
WTP Estimates:		
Mean:	£48.35	(Kaplan-Meier)
Mean:	£50.73	(Spearman-Karber)
Median in:	[50 ,60]	

Although the KMT can calculate each bid level's probability of being accepted and indicate scope sensitivity, sample WTP can be estimated more precisely (Jørgensen et al., 2013). Therefore, the following section follows Abate et al. (2020) in estimating a bid-only model to elicit WTP with greater precision and then a full-covariates model to analyse determinants of WTP. Although OLS has been used previously to understand the determinants of WTP (Hooper, 2013; Orset, Barret and Lemaire, 2017), probit is used for both models in this research given the limitations of the linear probability model with binary data. Furthermore, using a simple model and then a more complete model is consistent with the recommendations of Johnston et al. (2017) best-practice guidelines.

5.3.2 Question 6 Bid-Only

The Q6 sample median WTP can be estimated using a bid-only model. The model is specified in Equation (5.3.2) has a constant α_i and idiosyncratic normally-distributed error term ε_i. The results are reported in Table 5.2. WTP can be calculated from the model as the ratio between the constant term α and the estimated coefficient on the bid parameter, represented as γ (Abate et al., 2020; Foster and Mourato, 2003).

Bid-only model to elicit sample WTP:

$$Q6Response_i = \alpha_i + Q6Bid_i + \varepsilon_i \tag{5.3.1}$$

Probit WTP:

$$meanWTP = -\frac{\alpha_i}{\gamma} \tag{5.3.2}$$

Table 5.2: Q6 bid-only Model (N = 670).

Variable	Estimate	Marginal Effect	Std. Error	Pr(>|z|)
(Intercept)	0.821***		0.052	0.000
Bid	-0.015***	-0.003	0.001	0.000

Estimation Statistics	
Log-likelihood:	-3549.52
Pseudo R^2:	0.04
AIC:	7103.03

WTP			
Measure	Mean	Lower	Upper
Mean	£77.10	£72.35	£83.23
truncated Mean	£51.24	£49.95	£52.60
adjusted truncated Mean	£76.25	£72.32	£80.66
Median	£53.37	£49.74	£56.96

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The Q6 bid-only model in Table 5.2 reports a median WTP of £53.37 (£49.74 - £56.96). The median measure is used both for consistency with the literature and to minimise the influence of outliers (Zambrano-Monserrate and Ruano, 2020; Hess and Beharry-Borg, 2012). The median per-household per-year WTP is worth 2.42% (2.29% - 2.61%) of sample median income and is adopted as the unit value for Q6 in the remainder of this research. However, only 51% of the full sample (49% of the truncated sample) answered 'Yes' to the given bid level and were willing to pay for the scenario; therefore, it was not a uniformly popular scenario. Without covariates, little further can be said about the bid-only model save that, consistent with theory; the bid level is highly significant and negative. Although the marginal effect is relatively small, this corroborates parts of Figure 5.1 where the KMT has flat slopes where the marginal change in probability is relatively small for the middle of the bid range. While the bid-only model estimates WTP with precision, the high log-likelihood and AIC with low pseudo-R^2 all suggest that model fit can be improved by including further control variables.

5.3.3 Question 6 All Covariates

Table 5.3 extends the bid-only model by including possible covariates to explain the determinants of WTP. This model, detailed in Equation (5.3.3), includes the constant (α_i), bid level ($Q6Bid_i$), socioeconomic characteristics as controls in the vector X_i. These can all be included in the vector but are noted separately here to indicate the differences in specifications.

Q6 SBDC Model with all covariates:

$$Q6Response_i = \alpha_i + Q6Bid_i + X_i + \varepsilon_i \tag{5.3.3}$$

Table 5.3: Q6 full Model (N = 670).

Variable	**Estimate**	**Marginal Effect**	**Std. Error**	**Pr(>|z|)**
(Intercept)	-0.986***		0.136	0.000
β_{BID}	-0.011***	-0.005	0.001	0.000
$\beta_{Q1Gender}$	-0.018	-0.007	0.038	0.632
β_{Q2Age}	-0.003*	-0.001	0.001	0.072
$\beta_{Q3Distance}$	0.001	0.000	0.001	0.412
$\beta_{Q4Trips}$	0.055***	0.022	0.019	0.005
$\beta_{Q6ResearchCertainty}$	0.099***	0.039	0.028	0.000
β_{Q16BP}	0.222***	0.088	0.029	0.000
$\beta_{Q18Charity}$	0.627***	0.243	0.043	0.000
$\beta_{Q20Consequentiality}$	-0.082***	-0.033	0.028	0.004
$\beta_{Q21Experts}$	0.327***	0.130	0.023	0.000
$\beta_{Q22Education}$	-0.010	-0.004	0.018	0.582
$\beta_{IncomeDummy}$	0.206***	0.082	0.039	0.000
$\beta_{Q25Understanding}$	-0.009	-0.004	0.011	0.406
β_{Order}	-0.012	-0.005	0.037	0.749
Estimation Statistics				
Log-likelihood:			-3070.239	
Pseudo R^2:			0.173	
LR test against Bid-only model:			0.000	
AIC:			6170.477	
WTP				
Measure		Mean	Lower	Upper
Mean		£68.70	£65.16	£72.83
truncated Mean		£51.74	£50.37	£53.11
adjusted truncated Mean		£74.09	£70.46	£77.99
Median		£54.06	£50.85	£57.25

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5.3 reports the marginal effects and WTP from the probit model with covariates. The effect of including covariates is a minimal change in WTP (£54.06 against £53.37) but a notable improvement in goodness-of-fit measures; log-likelihood, AIC, and adjusted R^2. Furthermore, a Likelihood-Ratio test of the two models suggests that including covariates significantly improves the model (p.value < 0.000). Given that the covariates model fits the data better, the following section discusses the inference from the marginal effects of socioeconomic characteristics on WTP.

Two immediate observations concern the effect of the bid levels and respondents income. The coefficient on the bid level (β_{BID}) again has a negative marginal effect on choices, consistent with the KMT survival function in Figure 5.1, the bid-only model in Table 5.2, and with conventional demand theory (ECHA, 2014b). With regards to income, the variable ($\beta_{IncomeDummy}$) was coded as a dummy; zero if income was below the sample median, one otherwise, following Hess and Beharry-Borg (2012) and Faccioli et al. (2020). This approach was favoured as an alternative specification where income was entered in levels, following (Hooper, 2013) and Buckell, Hensher and Hess (2021), produced a minuscule marginal effect and was not statistically significant. The dummy approach means that the marginal effect represents the effect moving from below to above average income rather than the more realistic marginal effect of a respondents household moving up one income bracket cannot be observed. This model's strong positive effect of income suggests that above-average income households were much more likely to support the scenario and be willing to pay for research into microplastics. Overall, the statistical significance, sign, and magnitude of the critical bid and income variables are consistent with theory and the literature.

The effect of question order on choices and WTP is critical for the validity of responses (Johnston et al., 2017). Ordering effects suggest that responses are not independent observations (Day and Prades, 2010). An ordering effect is not observed for Q6 as the question order dummy (β_{Order}) was not statistically significant with a negative sign. The sign indicates that the 306 respondents who answered Q6 secondly were not less likely to vote 'Yes' to the Q6 scenario, contradicting Day et al. (2012) fatigue effects hypothesis. To summarise, the strength of the ordering effect for Q6 is minimal. Further evidence is available in Table 5.12 where the difference in median WTP by question order is $< 1\%$ (£51.76 vs £51.58).

Other variables of interest for the survey's validity were respondent consequentiality which was highly significant and negative; response certainty, which was significant and positive; and survey understanding which did not statistically affect choices. Regarding the socioeconomic variables in this model, only education ($\beta_{Education}$) did not report a statistically significant effect on respondents' likelihood of voting for further research. Only one indicator of distance-decay, the annual number of trips to the coast (β_{Trips}), were statistically significant, consistent with the suggestion in the literature that WTP may be spatially-variant (Faccioli et al., 2020; Glenk and Martin-Ortega, 2018; Jørgensen et al., 2013). Additionally, Blue-Planet viewership, charity involvement, and belief in experts all had large and statistically significant positive marginal effects on respondents' probability of voting for the research scenario. These variables indicate a latent precautionary attitude among respondents which exerts a strong positive influence on willingness to fund further research into the effect of microplastics (Abate et al., 2020; Kollmuss and Agyeman, 2002). Overall, the covariates model reports plausible WTP, improves upon the bid-only model, and indicates the likely determinants of respondents' choices.

5.4 Question 7 CVM

Q7 posed an alternative scenario; what would respondents be willing to pay to invest in enhanced filtration of wastewater that would increase the number of microplastics retained. The hypothetical measure would reduce the release of microplastics to both the terrestrial and marine environments and is similar to the research question in Logar et al. (2014). Compared to Q6, which specified research with no reduction, Q7 would yield an immediate reduction in the release of microplastics to the environment, although no scientific uncertainty would be resolved. Therefore, Q6 represents the option that resolves uncertainty but prolongs irreversible effects, while Q7 represents the option to act immediately but resolve no uncertainty. The precise question was:

"Suppose that the UK was going to introduce a policy that would stop microplastics from wastewater sewerage entering the environment now, before waiting for the results of the research discussed in the previous question.
This policy would pay to upgrade wastewater treatment plants filtering systems so that they would capture all the microplastics in sewerage wastewater heading to the environment.
An increase in your water bills would be used to pay for the cost of this investment.
Would your household be willing to pay £X per year in extra water bills to implement this policy?"

Q7 was, in truth, three questions; the first bound described above (Q7) and then two follow-up questions (Q7C if they voted yes, Q7D if they voted no). As respondents could not update their first response and were not informed that there was a follow-up question, the Q7 responses can be analysed using both the SBDC and DBDC methods. This section first presents the SBDC analysis in the same format as that for Q6. The analysis then includes the responses to the follow-up questions using bivariate, instead of univariate, probit. This dual approach facilitates the comparison of the WTP from each CV question formats.

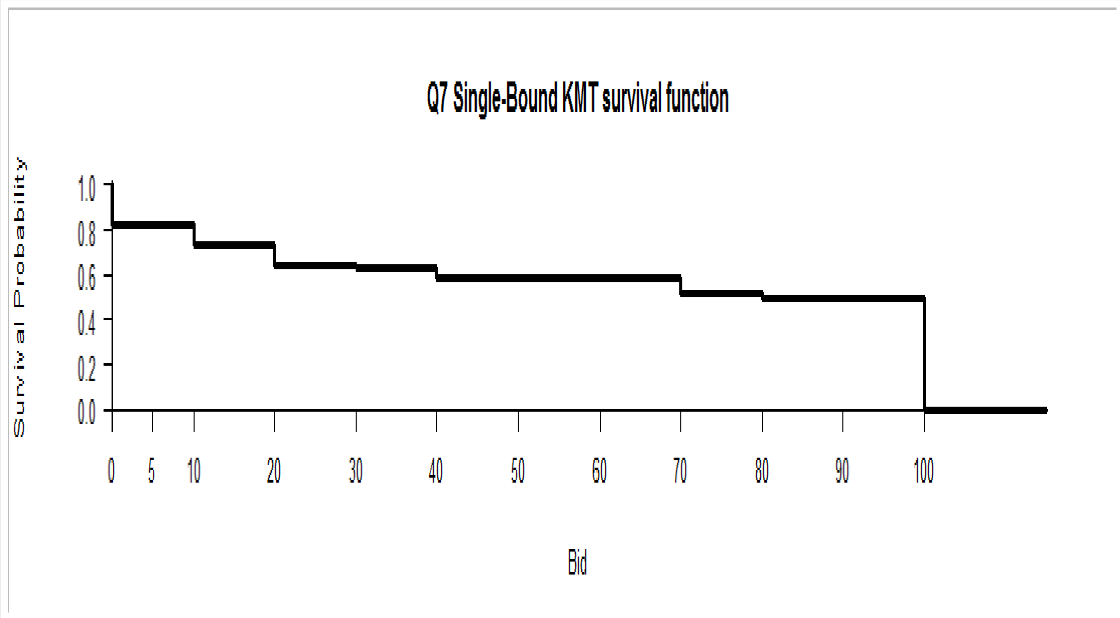
5.4.1 Q7 SBDC Analysis

For consistency with the Q6 analysis, this section uses the KMT and univariate probit to analyse the responses to Q7. Firstly, the KMT function reports the survival distribution of WTP in Figure 5.2. The function is downward-sloping as expected with discrete steps for each bid level. The precise probability for each bid level is reported in Table 5.4. The KMT shows a large right-hand tail of the distribution as the highest bid level, £100, had a 50% probability of being accepted. The large tail supports the use of a follow-up question to estimate sample WTP with greater precision.

Table 5.4: Q7 SBDC KMT Survival Function Estimates.

Bid number	Bid value (£)	Survival probability
1	0	1.000
2	5	0.820
3	10	0.820
4	20	0.736
5	30	0.643
6	40	0.634
7	50	0.590
8	60	0.590
9	70	0.590
10	80	0.514
11	90	0.500
12	100	0.500
13	Inf	0.000
WTP estimates:		
Mean:	£61.17	(Kaplan-Meier)
Mean:	£63.22	(Spearman-Karber)
Median in:	[100, NA]	

Figure 5.2: Q7 SBDC KMT Survival Function.



As WTP estimated by the KMT is typically the lower bound of median WTP, a bid-only probit model can be used to elicit sample median WTP with greater precision (Lim, Jin and Yoo, 2017; Jørgensen et al., 2013; Abate et al., 2020). A bid-only model is specified in Equation (5.4.1). The response variable called 'Q7Response' is a binary 1 or 0 for whether the respondent voted yes or no respectively to the scenario. The subscripts i indicate that each row of the covariates matrix is respondent-specific. The bid variable called 'Q7Bid' is a vector of each respondent's randomly allocated bid level. The model also includes an intercept (α_i) and normally-distributed idiosyncratic error term (ε_i). The results of the bid-only model are reported in Table (5.5).

Bid-only model to elicit sample WTP:

$$Q7Response_i = \alpha_i + Q7Bid_i + \varepsilon_i \tag{5.4.1}$$

Table 5.5: Q7 SBDC Model Bid-only (N = 670).

Variable	Estimate	Marginal Effect	Std. Error	Pr(>|z|)
(Intercept)	1.403***		0.055	0.000
Bid	-0.015***	-0.01	0.001	0.000
Estimation Statistics				
Log-likelihood:			-3316.90	
Pseudo R^2:			0.05	
AIC:			6637.86	
WTP				
Measure		Mean	Lower	Upper
Mean		£102.27	£95.53	£109.51
truncated Mean		£64.12	£62.85	£65.30
adjusted truncated Mean		£117.48	£110.34	£124.39
Median		£88.43	£83.23	£93.92

The model in Table 5.5 reports confidence intervals for several measures of bootstrapped WTP. The median WTP of £88.43 (£83.23 - £93.92) is 64% (65% - 64%) larger than that for the equivalent Q6 model. The difference in WTP is also indicated by the confidence intervals, which do not overlap those for Q6. Moreover, a Wilcoxon (Mann-Whitney) test affirms that the difference in individual-level WTP by question is statistically significant ($p < 0.000$). One possible interpretation of the WTP difference is that respondents are willing to pay a premium for precautionary abatement. However, as with Q6, the bid-only model fits the data relatively poorly. Furthermore, the omission of other covariates limits any inference about the determinants of WTP for precautionary abatement. Therefore, Equation (5.4.2) specifies a univariate probit model with more covariates included. The specification is consistent with Q6 and again contains a constant (α_i), bid vector ($Q7Bid_i$), vector of socioeconomic characteristics (X_i), and a normally-distributed random error term (ε_i). The subscript i is respondent-specific. The results are presented in Table 5.6.

Q7 SBDC Model with all covariates:

$$Q7Response_i = \alpha_i + Q7Bid_i + X_i + \varepsilon_i \tag{5.4.2}$$

Table 5.6: Q7 Model SBDC (N = 670).

Variable	**Estimate**	**Marginal Effect**	**Std. Error**	**Pr(>|z|)**
(Intercept)	-0.706***	0.000	0.227	0.002
β_{BID}	-0.017***	-0.004	0.001	0.000
$\beta_{Q1Gender}$	-0.040	-0.008	0.063	0.532
β_{Q2Age}	-0.013***	-0.003	0.003	0.000
$\beta_{Q3Distance}$	-0.000	0.000	0.002	0.945
$\beta_{Q4Trips}$	0.113***	0.027	0.032	0.000
$\beta_{Q7TreatmentCertainty}$	0.068	0.019	0.049	0.170
β_{Q16BP}	0.253***	0.059	0.050	0.000
$\beta_{Q18Charity}$	0.674***	0.139	0.076	0.000
$\beta_{Q20Consequentiality}$	0.012	0.005	0.046	0.795
$\beta_{Q22Education}$	0.129***	0.027	0.031	0.000
$\beta_{Q21Experts}$	0.461***	0.099	0.038	0.000
$\beta_{IncomeDummy}$	-0.038	-0.010	0.066	0.568
$\beta_{Q25Understanding}$	0.000	-0.001	0.019	0.990
β_{Order}	0.251***	0.055	0.064	0.000
Estimation Statistics				
Log-likelihood:			-3026.23	
Pseudo R^2:			0.132	
LR test p value:			0.000	
AIC:			6082.459	
WTP				
		Estimate	LB	UB
Mean		£102.99	£96.57	£111.41
truncated Mean		£ 65.77	£64.35	£67.15
adjusted truncated Mean		£122.56	£114.94	£131.39
Median		£91.22	£86.02	£97.73

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The covariates model in Table 5.6 includes several socioeconomic characteristics also elicited from the survey. This section first comments on the effect of including covariates on model diagnostics and WTP before discussing inference from each covariate. Firstly, the covariates model reports marginal improvements in model diagnostics including R^2 (0.05 to 0.132), AIC (6637.86 to 6082.459), and prediction accuracy (51.97% to 52.30%). Moreover, a Likelihood ratio test indicates that adding covariates also strongly improves model fit (p.value $<$ 0.000). The result that covariates improve the model's accuracy and fit is consistent with the Q6 models. Consistent with Q6, the median WTP of £91.22 (£86.02 - £97.73) is 3.15% (3.35% - 4.05%) larger when including covariates. This difference corroborates the finding of a premium for precautionary restrictions as the Q7 WTP is 67% (87% - 66%) larger than the WTP from the Q6 covariates model. Therefore, it appears that the benefits of upgrading Wastewater Treatment Plants (WWTP) to restrict the release of microplastics are higher than the benefits of research to resolve the uncertainty.

The sign, magnitude, and statistical significance of some covariates can be used to evaluate the responses' validity. For instance, the income variable ($\beta_{IncomeDummy}$) can indicate the income-elasticity of WTP (Tyllianakis and Skuras, 2016). However, in the Q7 model, it is not statistically significant, robust to sample size and measuring in levels or as a dummy. This compares poorly to the Q6 model, where the income dummy is highly statistically significant. The income dummy is broadly consistent in magnitude and sign with the Q6 model, where the negative sign suggests that higher-income households were less willing to pay for measures (Faccioli et al., 2020). The negative sign suggests that benefits are distributed regressively as lower-income households were more willing to pay. It should be noted that this sign and lack of statistical significance is not common in the CV literature (Tyllianakis and Skuras, 2016; Kim, Lee and Yoo, 2019; Choi and Lee, 2018). Another variable used to determine the validity of the model was self-reported response certainty ($\beta_{Q7Certainty}$), where more certain respondents were less likely to support the measure. Although the effect was not statistically significant, the positive sign supports the finding that greater certainty typically increases WTP (Watson and Ryan, 2007; Blomquist, Blumenschein and Johannesson, 2009; ECHA, 2019). A further limitation of the Q7 model is the question order dummy (β_{Order}) being more statistically significant and with an opposing sign to that in Q6. The interpretation is that respondents are more likely to choose the status quo if they have previously answered a valuation question. This mechanism is consistent with fatigue effects discussed by Day et al. (2012). A final comment on the Q7 covariates model is that the charity involvement variable ($\beta_{Charity}$) reports the largest marginal effect and is highly significant; indicating that respondents who donated or joined environmental charities were much more likely to support the Q7 measure, which effectively preserves the marine environment. To summarise, the Q7 covariates model is an improvement in WTP and model fit compared to the bid-only model. Moreover, there are some noteworthy differences between its Q6 equivalent. The following section establishes whether this holds when using both bounds of the question.

5.4.2 Q7 DBDC Analysis

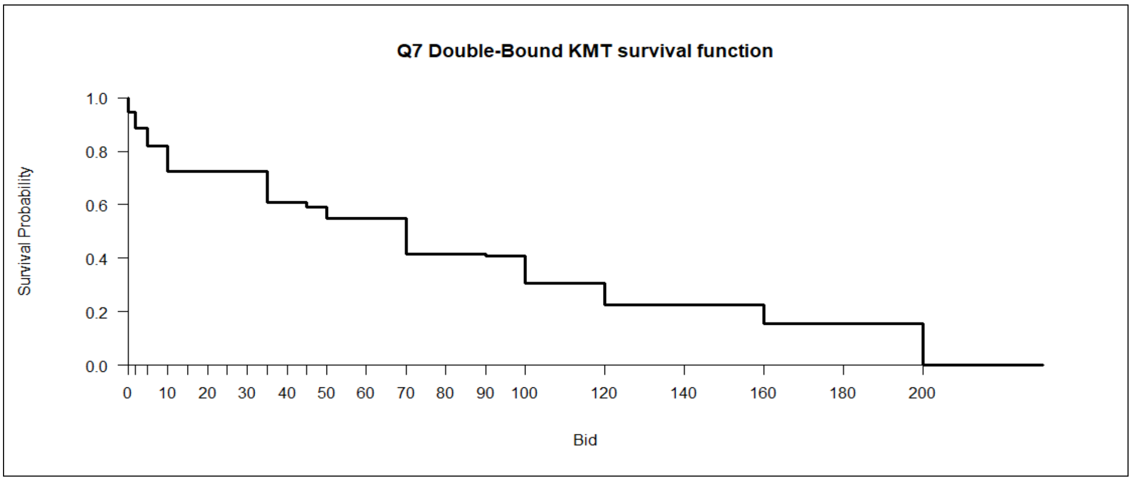
This section repeats the SBDC analysis but uses both the first and follow-up responses to estimate sample median WTP for Q7 with greater precision. Starting with the KMT in Figure 5.3, using the follow-up questions estimates WTP with greater precision. Specifically, the mean WTP increases from £61.17 to £79.21 while the range for the median is more precise ([100, NA] to [70,80]). This change arises as more information is revealed about the distribution's right-hand tail. For instance, the SBDC model was limited to the £100 bid level, while the DBDC model can estimate the probabilities for five higher bid levels, including the highest bid level of £200. The following section re-estimates the bid-only and covariate models with the follow-up responses included.

Table 5.7: Q7 DBDC KMT Survival Function Estimates.

Bid number	Bid value (£)	Survival probability
1	0	1.000
2	2	0.973
3	5	0.920
4	10	0.833
5	15	0.721
6	20	0.721
7	25	0.721
8	30	0.721
9	35	0.721
10	40	0.609
11	45	0.609
12	50	0.582
13	60	0.581
14	70	0.541
15	80	0.399
16	90	0.399
17	100	0.399
18	120	0.388
19	140	0.180
20	160	0.146
21	180	0.146
22	200	0.146
23	Inf	0.000

WTP Estimates:		
Mean:	£79.21	(Kaplan-Meier)
Mean:	£83.61	(Spearman-Karber)
Median in:	[70, 80]	

Figure 5.3: Q7 DBDC KMT Survival Function.



Equation (5.4.3) specifies a bivariate probit model to include the responses to the follow-up questions (Watson and Ryan, 2007; Hanemann, Loomis and Kanninen, 1991). The bivariate probit is a joint model where the two models, one for each question, are linked. The first model is the same as the SBDC analysis, with the second being a probit model for the follow-up responses. Similarly to the previous analysis, the subscript i indicates that the model is respondent-specific and includes constant term α_i and idiosyncratic error ε_i. The results are then reported in Table 5.8.

Bid-only model to elicit sample WTP:

$$\begin{aligned} Q7Response_i &= \alpha_i + Q7Bid_i + \varepsilon_i \\ Q7Response2_i &= \alpha_i + Q7Bid2_i + \varepsilon_i \end{aligned} \tag{5.4.3}$$

The DBDC bid-only model in Table 5.8 is largely consistent with the SBDC bid-only model. The bid coefficient is slightly larger, albeit with a similar marginal effect, and the intercept is slightly larger, albeit of little consequence. Although the bid-only model is instructive in eliciting sample median WTP, the Q6 and Q7 analysis shows that the model fit can be improved when including covariates.

Table 5.8: Q7 DBDC Model Bid-only (N = 670).

Variable	Estimate	Marginal Effect	Std. Error	Pr(>|z|)
(Intercept)	1.482***		0.033	0.000
Bid	-0.020***	-0.01	0.000	0.000
Log-likelihood:			-7459.28	
Pseudo R^2:			0.001	
AIC:			14922.55	
Measure		Mean	Lower	Upper
Mean		£85.50	£83.11	£88.12
truncated Mean		£81.36	£79.38	£83.49
adjusted truncated Mean		£88.28	£85.55	£91.31
Median		£85.21	£81.34	£89.7

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5.9 estimates a bivariate probit with covariates. A simplified version of this model is specified in Equation 5.4.4. This model, adopted from Watson and Ryan (2007) includes control variables in the vector X and an idiosyncratic normally-distributed error term ε_i. The results are reported in Table 5.9.

Q7 DBDC Model with all covariates:

$$(Q7Response_i + Q7Response2_i) = (Q7Bid_i + Q7Bid2_i) + X_i + \varepsilon_i \tag{5.4.4}$$

A noteworthy result of including follow-up questions is to increase WTP; the median WTP of £91.21 (£85.68 - £97.30) is -0.01% (-0.40% - -0.71%) smaller than from the SBDC model although larger than the bid-only model. Overall, however, the positive difference between the Q6 and Q7 WTP appears robust to measurement. The inclusion of the follow-up questions also marginally improves the model fit when considering R^2, log-likelihood and AIC. Furthermore, the DBDC model also influences the magnitude and significance of several covariates. Specifically, the magnitude of the income dummy (β_{Income}) is larger and highly significant. This statistically significant positive sign is consistent with Tyllianakis and Skuras (2016) meta-analysis of the income-elasticity of WTP. Another difference between the univariate and bivariate probit results is the statistical significance of the question order dummy, which goes from statistically significant at the 1% level to weakly significant at any level. The dummy's statistical significance in the univariate

Table 5.9: Q7 Model DBDC with all covariates (N = 670).

Variable	**Estimate**	**Marginal Effect**	**Std. Error**	**Pr(>|z|)**
(Intercept)	-0.742***		0.117	0.000
β_{BID}	-0.013***	-0.004	0.000	0.000
$\beta_{Q1Gender}$	-0.048	-0.008	0.033	0.138
β_{Q2Age}	-0.006***	-0.003	0.001	0.000
$\beta_{Q3Distance}$	0.001	0.000	0.001	0.294
$\beta_{Q4Trips}$	0.087***	0.027	0.017	0.000
$\beta_{Q7TreatmentCertainty}$	0.098***	0.019	0.025	0.000
β_{Q16BP}	0.152***	0.059	0.026	0.000
$\beta_{Q18Charity}$	0.547***	0.139	0.038	0.000
$\beta_{Q20Consequentiality}$	-0.010	0.005	0.024	0.675
$\beta_{Q21Experts}$	0.294***	0.099	0.020	0.000
$\beta_{Q22Education}$	0.126***	0.027	0.016	0.000
$\beta_{IncomeDummy}$	0.165***	-0.010	0.034	0.000
$\beta_{Q25Understanding}$	0.002	-0.001	0.010	0.836
β_{Order}	0.074**	0.055	0.033	0.023
Estimation Statistics				
Log-likelihood:	-6902.673			
Pseudo R^2:	0.1743			
LR test p value:	0.000			
AIC:	13835.347			
WTP				
Measure	Mean	Lower	Upper	
Mean	£102.99	£96.19	£111.15	
truncated Mean	£65.77	£64.42	£67.10	
adjusted truncated Mean	£122.55	£114.77	£130.93	
Median	£91.21	£85.68	£97.30	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

models and the full-sample bivariate model and the Mann-Whitney tests between median WTP suggest that a weak ordering effect exists for Q7. A crucial area of commonality across all specifications is the positive and highly significant coefficients on the charity involvement and belief in experts. These questions indicate an influential and prevalent latent attitude in the sample which affects respondents choices. The DB model had more statistically significant coefficients, possibly due to incorporating the follow-up responses. Overall, the DBDC format's effect was minimal on WTP.

To summarise the CV results, the WTP for Q7 is consistently higher than that for Q6. This result is robust to using univariate or bivariate probit. The adopted WTP for Q7 is £73.71 (£70.94 - £76.55), worth 3.36% (3.23% - 3.49%) of sample median income. Compared to Q6, 64% of the full sample (67% in the truncated sample) answered 'Yes' to the first bound, and only 21% (18% in the truncated sample) of the sample answered 'No' to both bounds of the question. This suggests that respondents attached a premium to the immediate precautionary reduction in microplastics' release to the environment. However, an omission from all the probit models was attitudinal indicators that could illuminate the effects of precautionary attitudes on WTP. Therefore, the following section adopts the ICLV from the CE literature to the CV data.

5.5 ICLV: CV Data

One element lacking from the CV analysis thus far has been the inclusion of environmental attitudes. Although previous CV studies have used OLS or probit to evaluate the influence of attitudes on WTP, this research measures attitudes using Likert scales, which raise two concerns for the econometric analysis. Firstly, as attitudinal scales are imperfect measurements of latent attitudes, there is the possibility of measurement error, which, if ignored, may bias the model errors (Hess and Beharry-Borg, 2012). Buckell, Hensher and Hess (2021) also believed that latent attitudes and utility might be endogenously determined, and thus linearly including attitudes with other covariates may be erroneous. The hybrid approach, which accounts for measurement error by estimating the latent attitudes in a separate model, may avoid any endogeneity issue that could bias estimates from an OLS or probit model. Although the ICLV has been widely used to account for the effect of latent attitudes on CE data, this research follows Abate et al. (2020) example and applies the ICLV methodology to the CV data.

The ICLV has three components, the choice model, the structural equations and then a measurement model with the log-likelihood combining them all for a full-information, rather than sequential, estimation (Vij and Walker, 2016). The choice model is the primary difference between the ICLV used for the CE data and the CV data. Specifically, a mixed logit was used for the CE data for consistency with the literature and previous results. However, in this chapter, the choice model is univariate probit for consistency with the CV literature (Abate et al., 2020). More generally, Train (2009) discusses the choice of either logit or probit models. A general specification for the probit model is reported in Equation (5.5.1), with a specific version in Equation (5.5.5). In Equation (5.5.1), the probability of a respondent n voting 'yes' to the CV scenario i is conditional on a vector of the bid levels c and Q unobserved latent variables $(q_{n1}, q_{n2}, \cdots, q_{nk})$. Φ is the standard normal with σ as the standard deviations of the error term. Finally, β and δ are coefficients to be estimated, representing the effect on choices from the bid level and latent variables, respectively. Although Abate et al. (2020) includes a vector of respondent-specific socioeconomic variables, these are omitted from the choice model and instead used as determinants of the latent attitudes. The econometric specifications are reported in two parts; firstly the general specification for the CV ICLV in Equations (5.5.1) - (5.5.4), and then the actual specification estimated in this research in Equations (5.5.5) - (5.5.7).

Choice model:

$$Pr(y_n = i|Q_n, c_n) = \Phi(\frac{\beta c_n}{\sigma} + \frac{\delta Q_n}{\sigma}) \tag{5.5.1}$$

Structural Equation:

$$\alpha_n = \gamma Z_n + \eta_n \tag{5.5.2}$$

Measurement Equation:

$$I_{nk} = \delta_{I_k} + \zeta_{I_k} \cdot \alpha_n + \upsilon_{kn} \tag{5.5.3}$$

Log-Likelihood function:

$$LL\left(\beta, \delta, \gamma, \tau, \eta_I, \sigma_I\right) = \sum_{n=1}^{N} ln \int_{\eta} L\left(y_n|\beta, \delta, \tau, \alpha_n\right) L\left(I_n|\eta_I, \sigma_I, \alpha_n\right) g\left(\eta\right) d\eta \tag{5.5.4}$$

The precise specification used for the Q6 ICLV in Table 5.10 is reported here. The only changes for the Q7 SBDC ICLV in Table 5.11 are changing the question responses, bid levels, and the certainty variable, which are choice specific. A limitation here is that currently, the ICLV has only been estimated with univariate probit. Until a bivariate probit ICLV is developed, DBDC data cannot be estimated in the ICLV framework [16].

Probit Model:

$$V_B = (\beta_{Bid} * Q6Bid) + (\lambda * LatentVariable) \tag{5.5.5}$$

Structural Equation with socioeconomic determinants:

$$\begin{aligned} \alpha_n = (\gamma_{Age} * Age) + (\gamma_{Gender} * Gender) + \\ (\gamma_{Distance} * Distance) + (\gamma_{Income} * Income) + \\ (\gamma_{Experts} * Experts) + (\gamma_{Consequentiality} * Consequentiality) + \\ (\gamma_{BP} * BP) + (\gamma_{Charity} * Charity) + \\ (\gamma_{Certainty} * Q6ResearchCertainty) + \eta \end{aligned} \tag{5.5.6}$$

Ordered Probit Measurement Equation:

$$P_{Y_{n,t=s}} = \Phi(\tau_s - V_{n,t}) - \Phi(\tau_{s-1} - V_{n,t}) \tag{5.5.7}$$

[16]This limitation is entirely a coding issue. While personal communication with the Hess and Palma (2019) authors did facilitate the estimation of the univariate probit ICLV rather than forcing the CV data to be estimated in the MNL format, we were together unable to develop a bivariate probit extension that would have facilitated the DBDC ICLV model for Q7. This extension remains open for future work that wishes to incorporate environmental attitudes in DBDC data.

Table 5.10: Q6 ICLV Model (N = 670).

Coefficient	**Estimate**	**Bootstrap.std.err.**	**Bootstrap.p-val(0)**
$\beta_{intercept}$	-50.600***	18.384	0.003
β_{Q6BID}	-26.676***	6.877	0.000
λ	24.692***	0.815	0.000
γ_{Age}	-0.001	0.011	0.480
γ_{Gender}	-0.087	0.097	0.186
$\gamma_{Distance}$	-0.001	0.004	0.446
γ_{Income}	0.000	0.000	0.181
$\gamma_{Experts}$	0.468***	0.148	0.001
$\gamma_{Consequentiality}$	0.332***	0.131	0.005
γ_{BP}	0.269***	0.086	0.001
$\gamma_{Charity}$	0.306**	0.160	0.028
$\gamma_{Q6ResearchCertainty}$	0.104	0.189	0.291
ζ_{Q13}	0.628***	0.057	0.000
ζ_{Q14}	0.653***	0.064	0.000
ζ_{Q15}	0.544***	0.054	0.000
τ_{Q13_1}	-0.449	0.434	0.151
τ_{Q13_2}	0.262	0.430	0.271
τ_{Q13_3}	1.859***	0.436	0.000
τ_{Q13_4}	2.892***	0.448	0.000
τ_{Q14_1}	-0.699*	0.440	0.056
τ_{Q14_2}	-0.006	0.428	0.494
τ_{Q14_3}	1.367***	0.428	0.001
τ_{Q14_4}	2.581***	0.432	0.000
τ_{Q15_1}	-1.082***	0.387	0.003
τ_{Q15_2}	-0.377	0.379	0.160
τ_{Q15_3}	0.777**	0.374	0.019
τ_{Q15_4}	1.779***	0.377	0.000
Estimation Statistics			
Estimation method	bfgs	Iterations	107
Convergence	Successful	LL(start)	-4414.918
Number of individuals	670	LL(final, whole model)	-2863.25
Number of observations	2680	LL(final,indic_Q13)	-841.5448
Number of inter-person draws	1000 (Halton)	LL(final,indic_Q14)	-827.0896
AIC	5795.22	LL(final,indic_Q15)	-798.9716
BIC	5954.34	LL(final,choice)	-413.6229
WTP			
Measure	**Mean**	**Lower**	**Upper**
Median	£74.93	£59.35	£90.61

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

This section compares the Q6 ICLV model with the Q6 probit models and the ICLV using the CE data. Starting with the WTP across models, the ICLV WTP for Q6 is £64.71 (£49.99 - £79.45). Compared to the SBDC bid-only model of £53.25 (£45.03 - £57.25) and the covariates model of £50.52 (£46.63 - £54.27), this represents an increase of 21% (11% - 38%) and 28% (7% - 46%) respectively. Therefore, the effect of the ICLV approach is to substantially increase WTP.

This section now evaluates the three component models of the ICLV. Starting with the choice model, the intercept is larger while the bid level is still highly significant but orders of magnitude larger than the univariate probit. The magnitude suggests that respondents were highly sensitive to the bid level, and this, combined with the negative sign, is consistent with a priori theoretical expectations. The standard errors of both the intercept and bid level are also large, indicating heterogeneity in the parameters' magnitude across respondents. Linking the choice model and the latent attitudes is the λ parameter which is large, positive and highly significant. The interpretation is that precautionary attitudes positively influenced the probability of choosing the scenario. Essentially, more environmentally concerned respondents were more willing to pay for research into microplastics.

The γ parameters represent the effect of socioeconomic variables on the latent attitudes rather than the effect on choices as they enter the structural and not the choice model. Therefore, the socioeconomic parameters in the ICLV must be interpreted differently and thus may change sign, magnitude, and statistical significance, compared to the probit models. In this ICLV, only belief in experts ($\gamma_{Experts}$), perceived policy consequentiality ($\gamma_{Consequentiality}$), blue-planet viewership (γ_{BP}), and self-reported response certainty ($\gamma_{Q6ResearchCertainty}$) reported a statistically significant effect on latent attitudes. The significance of consequentiality and certainty show that respondent's perceptions of the survey may also influence their latent attitudes (Czajkowski et al., 2017; Dekker et al., 2016). Curiously, the charity variable ($\gamma_{Charity}$), which was highly significant in all the probit models, is now not statistically significant. As this suggests that charity involvement influences choices but not latent attitudes, it is possible that the effect is masked by the inclusion of other similar variables such as Blue-Planet viewership, which also measures engagement with environmental causes. Furthermore, the involvement variable is statistically significant in the full-sample model in the Appendix, indicating that charity involvement influences attitudes. A final comment on the γ is that the weak and not statistically significant effect of distance suggests that there is no distance-decay effect on precautionary concern; again at odds with the statistically significant influence on choices in all the probit analysis.

The ζ parameters represent the effect of the latent environmental attitudes on the indicator questions, while the τ parameters represent the effect of each level of the indicator questions on latent attitudes. The ζ are all highly significant and positive, with Q14 again representing latent attitudes' strongest influence. This is consistent with the CE, although the values are slightly smaller for the CV data. Finally, the τ parameters are almost all statistically significant, the exception being the lowest levels of the indicators. Moreover, the signs are consistent with the CE ICLV, where higher values on the Likert scale affected the latent precautionary attitude more strongly. The γ, ζ and τ standard errors are all small, indicating that the tests are unbiased and there is little heterogeneity in the sample around these values. To summarise, the Q6 ICLV extends the probit model by showing that socioeconomic variables affect WTP by influencing precautionary attitudes. The effect of including latent environmental concern shows that more environmentally concerned respondents were more willing to pay for the research scenario.

Table 5.11: Q7 ICLV Model (N = 670).

Coefficient	**Estimate**	**Bootstrap.std.err.**	**Bootstrap.p-val(0)**
$\beta_{intercept}$	-41.327***	5.531	0.000
β_{Q7BID}	-30.143***	9.321	0.001
λ	30.169***	2.303	0.000
γ_{Age}	-0.003	0.004	0.180
γ_{Gender}	-0.108	0.142	0.223
$\gamma_{Distance}$	0.000	0.005	0.468
γ_{Income}	0.000	0.000	0.163
$\gamma_{Experts}$	0.427***	0.041	0.000
$\gamma_{Consequentiality}$	0.328***	0.090	0.000
γ_{BP}	0.203***	0.076	0.004
$\gamma_{Charity}$	0.293**	0.138	0.017
$\gamma_{Q7TreatmentCertainty}$	0.088	0.128	0.245
ζ_{Q13}	0.592***	0.059	0.000
ζ_{Q14}	0.675***	0.064	0.000
ζ_{Q15}	0.635***	0.060	0.000
τ_{Q13_1}	-0.676***	0.176	0.000
τ_{Q13_2}	0.005	0.173	0.489
τ_{Q13_3}	1.553***	0.196	0.000
τ_{Q13_4}	2.554***	0.228	0.000
τ_{Q14_1}	-0.875***	0.186	0.000
τ_{Q14_2}	-0.176	0.182	0.167
τ_{Q14_3}	1.193***	0.200	0.000
τ_{Q14_4}	2.406***	0.230	0.000
τ_{Q15_1}	-1.189***	0.196	0.000
τ_{Q15_2}	-0.432***	0.184	0.009
τ_{Q15_3}	0.777***	0.188	0.000
τ_{Q15_4}	1.812***	0.205	0.000
Estimation Statistics			
Estimation method	bfgs	Iterations	105
Convergence	Successful	LL(start)	-4146.733
Number of individuals	670	LL(final, whole model)	-2863.25
Number of observations	2680	LL(final,indic_Q13)	-846.9049
Number of inter-person draws	1000 (Halton)	LL(final,indic_Q14)	-826.855
AIC	5780.5	LL(final,indic_Q15)	-799.3818
BIC	5939.63	LL(final,choice)	-400.3309
WTP			
Measure	**Mean**	**Lower**	**Upper**
Median	£93.00	£77.77	£108.24

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

This section discusses the Q7 ICLV model with reference to the previous ICLV and probit results. One notable result of this research is that ICLV WTP can be recovered from both CV and CE. The method used to elicit WTP from the ICLV is similar to the CE in that random draws from the unconditional distribution of the latent variable are used. Specifically, the WTP is the median of the estimated intercept divided by the estimated bid coefficient, plus the respondent specific mean of the distribution. This adapts method used in Buckell, Hensher and Hess (2021) to the CV scenario, but the significantly larger WTP suggests that further research to verify this procedure would be valuable. The ICLV WTP for Q7 is £121.62 (£107.01 - £132.52). Compared to the SBDC bid-only model of £87.58 (£82.61 - £94.14) and the covariates model of £89.21 (£84.28 - £95.57), the ICLV represents an increase of 38% (29% - 38%) and 35% (26% - 37%) respectively. Therefore, the effect of the ICLV approach is to increase WTP in each question substantially.

Regarding model fit, the AIC and log-likelihood are improvements on all the Q7 models, with the prediction accuracy still considerable. This result suggests that future research can include latent attitudes and follow-up questions to improve model fit substantially. Turning to the key variables, the intercept's value is negative and an order of magnitude larger in the ICLV than the small positive intercept in the Q7 models. Similarly, the bid level is much larger in the ICLV, although it still has the expected negative sign. The λ parameter, which links the latent precautionary attitudes to the probit model, is highly significant and positive. This indicates that more concerned respondents were more likely to vote yes to Q7. The intercept and bid parameters' standard errors are again large, indicating variance in the parameter values. To summarise, the Q7 ICLV fits better than the previous Q7 models.

The γ, ζ, τ parameters can be considered in the context of the Q6 ICLV and the previous Q7 probits. The inference from the γ parameters on the socioeconomic variables is largely that of the Q6 ICLV; age (γ_{Age}), gender (γ_{Gender}), distance ($\gamma_{Distance}$), charity involvement ($\gamma_{Charity}$), and crucially income (γ_{Income}), are not statistically significant influences on latent attitudes; contrary to many of the Q7 models. However, belief in experts ($\gamma_{Experts}$) is positive and significant in all Q7 models and Q6 models, again suggesting that they strongly influence environmental attitudes and choices. The magnitude and significance are also consistent with the Q6 ICLV indicating no difference in the effect between scenarios. Unlike Q6, the consequentiality parameter ($\gamma_{Consequentiality}$) is not statistically significant. Therefore, perceived policy consequentiality may influence latent precautionary attitudes more strongly in Q6. Elsewhere, the ζ parameters are consistent in sign, significance, and magnitude, with the Q6 ICLV with Q14 the strongest influence and Q13 the weakest. The τ parameters' inference is again consistent with the Q6 ICLV, although the Q7 model has more statistically significant parameters. The uniform result is that higher scores on the Likert scales suggest stronger precautionary attitudes. Strong attitudes, then acting with the socioeconomic variables, influence the choice probabilities. The standard errors are minor, suggesting unbiased statistical significance tests that impart confidence in comparing the ICLV with the univariate and bivariate probits. Overall, the Q7 ICLV suggests that respondents precautionary attitudes positively and strongly influenced their willingness to pay for restrictions on the release of microplastics.

5.6 CV Model Evaluation

Table 5.12 reports the WTP and model diagnostics from all estimated models, questions, and samples. There are three notable findings regarding ordering, consequentiality, and questions. Firstly, there was a small but persistent ordering effect in Q6 and Q7 whereby fatigue from previous questions reduced WTP. Secondly, the effect of perceived policy consequentiality is a significant and substantial increase in WTP, consistent with Czajkowski et al. (2017). Finally, there is a positive difference between Q6 and Q7, with respondents willing to pay a significant premium for immediate precautionary restrictions. This difference is robust to sample truncation.

5.7 CV Validity

A significant strand of the non-market valuation literature is dedicated to evaluating the reliability and validity of CV data and results (Bateman et al., 2002; Johnston et al., 2017). Convergent validity can be tested, although criterion validity cannot as this research involved hypothetical scenarios. Regarding the few other similar studies, the CV WTP in this research is far greater than the $2.59 annual household WTP Choi and Lee (2018) and far lower than the $642 annual WTP to reduce Arctic microplastics in Abate et al. (2020). However, the CV WTP is comparable to the $73 estimated from Logar et al. (2014) CE. One critique here is the magnitude of the values. For instance, the mean WTP values are a substantial portion of annual water bills and, if combined with other non-market goods, significantly increase a household's expenditure. There are two possible explanations for the high values. Firstly, they may be attributed to the hypothetical scenario. For example, although it is not possible for Q6 to completely resolve uncertainty, respondents' may have responded if it was, hence the higher values. Future research could remind respondents' of their current consumption to possibly minimise valuations. Secondly, the timing of the survey may have exacerbated concerns about microplastics and thus inflated valuations, although only a test-retest design could clarify this. To summarise, the remaining areas of concern for the CV results' internal validity are ordering, scope-sensitivity, and anchoring effects and are now explored in depth.

Starting with ordering effects, a between-subjects split-sample was used to test any potential ordering effects of randomly assigning respondents to Q6 and then Q7 or vice-

Table 5.12: CVM WTP by model, question, consequentiality, and order.

Specifications	WTP	N	AIC	R^2	Log-likelihood	Accuracy
Q6: Full-Sample						
Q6 Bid-Only	£53.37	670	7103	0.04	-3549.52	50.30%
Q6 Covariates	£53.41	670	6156.99	0.18	-3061.49	71.94%
Q6 ICLV	£74.93	670	5795.22	NA	-2868.25	53.13%
Q6: Truncated-Sample						
Q6 Bid-Only	£53.25	304	2968	0.06	-1482.45	50.66%
Q6 Covariates	£50.52	304	2471.98	0.267	-1220.99	73.68%
Q6 ICLV	£64.71	304	2502.21	NA	-1224.107	56.23%
Q6 Consequential Sample	£61.83	560	5128.65	0.176	-2548.32	71.96%
Q6 Inconsequential Sample	£21.32	110	911.572	0.243	-439.78	70.91%
Q6 Order1 Sample	£51.76	364	2651.87	0.227	-1309.94	50.49%
Q6 Order2 Sample	£51.58	306	3289.31	0.192	-1628.65	50.07%
Q7: Full Sample						
Q7 SB Bid-Only	£88.43	670	6637.86	0.05	-3316.90	64.48%
Q7 DB Bid-Only	£85.21	670	14922.55	0.001	-7549.28	NA
Q7 SB Covariates	£91.39	670	6003.08	0.14	-2984.54	71.34%
Q7 DB Covariates	£73.71	670	14009.67	0.173	-6987.83	NA
Q7 ICLV	£92.00	670	5780.50	NA	-2863.35	51.19%
Q7: Single-Bound Truncated-Sample						
Q7 SB Bid-Only	£87.58	304	2816.11	0.086	-1406.05	68.77%
Q7 SB Covariates	£89.21	304	2545.85	0.174	-1257.925	76.49%
Q7 ICLV	£121.26	304	2504.30	NA	-1225.148	53.51%
Q7 Consequential Sample	£96.02	560	4808.00	0.150	-2392.14	73.04%
Q7 Inconsequential Sample	£45.99	110	1131.42	0.0922	-553.71	66.36%
Q7 Order1 Sample	£94.00	364	2681.47	0.151	-1327.74	70.26%
Q7 Order2 Sample	£87.09	306	3189.48	0.176	-1581.74	73.90%
Q7: Double-Bound Truncated-Sample						
Q7 DB Bid-Only	£73.71	304	6266.32	0.001	-3131.16	NA
Q7 DB Covariates	£89.91	304	5675.54	0.190	-2822.77	NA

versa [17]. Three hundred sixty-four respondents were assigned to the standard order, while three hundred and six were given the reversed order. These small subsamples are slightly unbalanced and at the lower end of minimal valid split-sample sizes (Bateman et al., 2002). The small subsamples may explain why Table 8.1 reports an insignificant Mann-Whitney test of means between the orders, yet Table 5.12 indicates a clear difference in WTP across the split-samples. The evident ordering effects further confirm the finding in the literature that multiple CV scenarios are not independent draws from the individual distribution of WTP (Day et al., 2012; Kjær et al., 2006; Bateman and Langford, 1997). A plausible explanation is question fatigue, whereby respondents are more likely to vote for the status quo and report lower WTP when previous questions had been answered. Overall, there is a notable but small ordering effect on the CV WTP, possibly through question fatigue.

A second concern for the validity of the CV WTP is the possibility of anchoring effects from the DBDC format. The existence of anchoring effects, whereby the follow-up responses are anchored to the first question, are evident from the difference in WTP between the SBDC and DBDC models for Q7; see Tables 5.6 and 5.9 respectively. Indeed, the DBDC valuations are lower across measure and confidence intervals, suggesting that the follow-up reduces respondents' WTP, possibly due to them being anchored on the first bound and unwilling to pay more than they previously agreed. However, with the split-sample and possible interpretation of Q7 as SBDC, WTP can be calculated without ordering or anchoring effects. Therefore, the validity of the CV WTP remains encouraging.

A final area of concern for the validity of the CV WTP is scope sensitivity. Scope-sensitivity is a recurring critique of CV WTP in the literature which argues that CV WTP is insensitive to the scope of the changes being valued (Hausman, 2012; Diamond and Hausman, 1994; Desvousges, Mathews and Train, 2012; Lew and Wallmo, 2011; Foster and Mourato, 2003). Tests for scope-sensitivity may be split into whether CV responses were consistent with economic theory and whether responses were sensitive to survey design (Bateman et al., 2005). The survey design of the CV section in this research did not facilitate external validity tests. Firstly, an external split-sample test was not possible as the sample was only split to test ordering and not scope (Lew and Wallmo, 2011). Secondly, the CV scenarios were not described in increments and, therefore, an adding-up

[17] Given limited funding and time, a split-sample randomly varying the order of the valuation sections, CV then CE or vice-versa, could not be tested. So there is limited evidence on the effect of the CV sections on the CE choices.

test or t-test between scenarios is not plausible either (Desvousges, Mathews and Train, 2012; Diamond and Hausman, 1994; ECHA, 2016). However, some internal tests of scope-sensitivity, what Bateman et al. (2005) termed economic-theoretic, are possible. Firstly, the bid level was statistically significant in each of the nine models estimated, which indicates that respondents were sensitive to the bid level. However, Bateman et al. (2005) suggests that simply showing a coefficient to be statistically different from zero is not sufficient to reject the possibility of scope-insensitivity. Moreover, Desvousges, Mathews and Train (2012) argues that statistical significance does not represent what Arrow et al. (1993) believed to be an 'adequate' response. Therefore, the statistically significant bid level implies but does not prove that respondents were sensitive to the scope of the change (Bateman et al., 2005). Further supporting evidence for the scope sensitivity is that the KMT reports a downward-sloping demand curve consistent with theoretical expectations. Overall, it is challenging to test for scope sensitivity in this survey design, but the available tests indicate sensitivity.

To summarise the CV validity, externally valid WTP can be recovered in this research without the evident ordering and anchoring effects. The effect of task complexity on WTP appears to be substantial given the variability of WTP in Table 5.12. However, the adopted WTP unit values have a high degree of validity for four reasons. Firstly, the valuations are within the range estimated in the literature (Adamowicz et al., 2011; Abate et al., 2020; Logar et al., 2014). Secondly, content validity is supported by the pre-testing process (Johnston et al., 2017). Thirdly, while many scope-sensitivity tests were not viable, the available indications were suggestive of respondents being scope-sensitive (Foster and Mourato, 2003; Desvousges, Mathews and Train, 2012; Lew and Wallmo, 2011). The high level of validity suggests that the results may be generalised in future research. Indeed, the sample was broadly representative of the UK and reported sufficient information to enable benefits transfer. To summarise the WTP analysis from the two CV scenarios, the values are broadly valid and reliable and suitable for inference, aggregation, and benefits transfer.

5.8 Summary

This chapter analysed the CV questions using the KMT survival function, univariate and bivariate probit models, and the ICLV. The KMT survival functions indicated that respondents were sensitive to scope in the bid levels. Three types of probit models were estimated; bid-only to elicit sample WTP, the univariate full-covariates model for SBDC data, and the bivariate model for the DBDC question. The Q7 modelling was split into

SB and DB analysis to evaluate the effect on WTP of including follow-up questions. Unique to the literature, this research also elicited WTP from the ICLV for both CV questions and showed that precautionary attitudes substantially increased WTP. A robust conclusion from all models was that respondents were willing to pay a sizeable premium for the immediate restriction on the release of microplastics to the environment (Q7). A lesson from this chapter, of a preference for immediate precautionary abatement is consistent with the act-then-learn approach in the CBA literature. Further analysis of the covariates and the implications from the econometric models are discussed further in subsequent Chapters with a critical focus on the influence of precaution on respondents' choices.

Interpretation of Willingness-To-Pay Valuations.

Chapter Six Abstract:

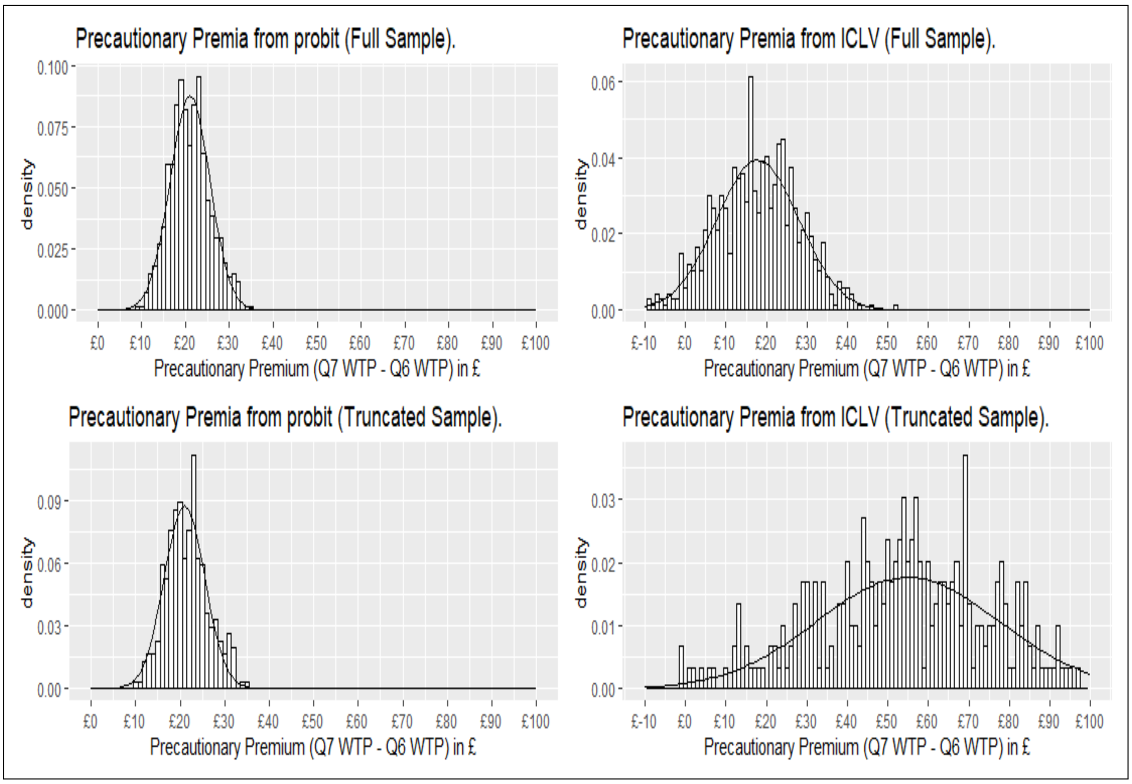
This chapter explores the determinants and implications of the WTP elicited in this research. Firstly, the chapter explores the determinants and implications of the precautionary premium evident in the CV modelling. Secondly, the chapter reflects on the hypotheses about determinants of WTP. Main areas of focus include distance-decay, environmental, and socioeconomic factors. Finally, the chapter considers the effect of the pandemic on valuation.

6.1 Precaution

This section discusses the magnitude and determinants of the positive difference between Q7 and Q6 WTP, henceforth referred to as the precautionary premium. The interpretation of the premium, a term borrowed from (Kuntz-Duriseti, 2004), is the increase in benefits from resolving irreversibility (by investing in WWTP to reduce the release of microplastics) compared to resolving uncertainty (by researching the effects of microplastics). Although Q7 did not explicitly mention irreversibility, the increase in WTP for this question compared to Q6 suggests that respondents preference was for immediate restrictions. The result of a premium can be used to demonstrate respondent support for the precautionary principle. Furthermore, it illustrates that the benefits of immediate abatement are substantial. Figure 6.1 plots the distribution of the precautionary premium in both the full and truncated samples using the bid-only univariate probit and the ICLV.

There are two unique results about the precautionary premium. Firstly, the premium is always positive despite the sensitivity of WTP to question order and econometric specification. The mean precautionary premium was £20.99 (£20.64 - £21.33) indicates a preference for the immediate abatement of irreversible releases over uncertainty resolution. Curiously, there are two peaks of the WTP distribution, above and below £20, in the full sample probit models. The two peaks may suggest two latent classes, some more precautionary than others, although the LCM reported that three classes fit the data better. However, the difference is minimal and disappears in the ICLV plot, which has a density around a single mean value. Secondly, the distribution is broader when latent precautionary attitudes are accounted for using the ICLV. The bid-only model omits any covariates and thus the effect of precaution on WTP. The precautionary premium in the full sample is £20.99 (SD = 4.55) using probit but £17.83 (SD = 10.16) using the ICLV. Despite the lower magnitude, the increased standard deviation indicates how latent precautionary attitudes in the sample act to increase heterogeneity in WTP. The precautionary premium using the ICLV in the full sample was £17.83 (SD = 10.16). The positive effect of the ICLV on the magnitude and heterogeneity of CV WTP is unique to the literature as Abate et al. (2020) did not elicit WTP from their design, although other ICLV's showed similar effects with CE data (Buckell, Hensher and Hess, 2021; Hess and Beharry-Borg, 2012; Beharry-Borg and Scarpa, 2010). Overall, Figure 6.1 indicates that respondents preferred resolving irreversible release to resolving uncertainty.

Figure 6.1: Distribution of the precautionary premium by econometric approach.



6.1.1 Precaution in the CE results

Unlike the CV, it is more challenging to interpret any precaution from the CE MWTP alone. Some evidence for the effect of precaution on MWTP is provided by the ICLV, where latent precautionary attitudes resulted in the emissions MWTP being higher than the performance MWTP. However, the greater absolute magnitude of the emissions MWTP observed in the MXL and ICLV compared to the performance MWTP may indicate that respondents are willing to trade-off product attributes for any measure that can make a precautionary reduction in microplastics. Overall, however, there is less evidence of precaution in the CE results compared to the CV, which was designed to investigate it.

6.2 Covariates

This section discusses the influences of WTP fitted at the individual level. The adopted CE MWTP is fitted at the individual level from the full sample WTP-space MXL using the delta-method; commonly used when WTP is the ratio of two random variables (Hole, 2006; Adamowicz et al., 2011). The adopted CV WTP was fitted at the individual level using the bootstrapping method for the univariate Probit for Q6 and the bivariate Probit for Q7; again standard in the CV literature (Zambrano-Monserrate and Ruano, 2020; Hole, 2006). This section reports on the relationship between fitted WTP and possible covariates from the survey. Although many effects are small or insignificant, comment is made on differences in effects between fitted CV and CE WTP. A quick summary of effects by measure and question is displayed in Table 6.1.

Table 6.1: **Summary of effects.**

Variable	**Effect on CE**	**Effect on Q6**	**Effect on Q7**	**Comment**
Order	None	Negative	Negative	Ordering reduces CV WTP.
Q1Gender	None	None	Negative	Not statistically significant but exerts an income effect.
Q2Age	None	None	Negative	Again only effects Q7.
Q3Distance	None	None	None	Inverse distance-decay whereby greater distance resulted in greater WTP.
Q4Trips	None	Positive	Positive	Weakly positive influence on CV WTP via income effects.
Q5Knowledge	Positive	Positive	Positive	Not included in estimation but more knowledgeable reported higher WTP.
Certainty	Mixed	Positive	Positive	Significantly negative in MNL insignificant in MXL significantly positive in ICLV.
Q8DominatedTest	Positive	NA	NA	Inflates MWTP
Q13 Threat to Self	Positive	Positive	Positive	Can judge using the ICLV zetas.
Q14 Threat to Future	Positive	Positive	Positive	
Q15 Threat to Environment	Positive	Positive	Positive	
Q16 Blue-Planet	None	Positive	Negative	Increased willingness to research
Q17Responsibility_Firms	Positive	Positive	None	Effects are calculated by comparing fitted WTP only and are all small.
Q17Responsibility_Consumers	Positive	Negative	Positive	
Q17Responsibility_Government	Positive	Negative	Positive	
Q17Responsibility_LocalAuthority	None	Negative	Positive	
Q18Charity	Positive	Positive	Positive	Greater involvement increased WTP
Q19Knowledge	Negative	Positive	Positive	Same effect on CV as Q5 but opposite for CE.
Q20Consequentiality	Positive	Positive	Positive	Increased WTP
Q21Experts	Positive	Positive	Positive	Increased WTP
Q22Education	Positive	Negative	Negative	Effects CE and CV differently
Q23Employment	Positive	Positive	Positive	Always increases WTP
Q24A Coronavirus	Negative	Mixed	Negative	Usually negative due to income effect.
Q24Income	Negative	Positive	Positive	Extremely weak effects in either direction
Q25Survey	Negative	Negative	Positive	May effect choices and WTP differently

6.2.1 Coronavirus

Question 24A asked respondents to indicate whether or not their income had been affected by the coronavirus pandemic. This question is an imperfect measurement of the effect of undertaking the data collection in April 2020 during the height of the coronavirus (COVID-19 or SARS-CoV-2) pandemic restrictions. The data collection period could not be changed as there was no certainty as to when the pandemic's effects would abate and, therefore, it was not practical to delay both the Environment Agency grant and the PhD project to allow for pandemic-free data collection. It is also doubtful whether the data would ever have not been influenced by the pandemic even if delayed a significant length of time. However, one change to the data collection due to the pandemic was the introduction of Q24A. This question attempted to assess the impact of the pandemic. Specifically, Q24A asks respondents simply whether their income was affected by the pandemic (answer: Yes, No, Prefer not to say) with the effects reported in Table 6.2. The following section discusses both external and internal tests of the pandemic on WTP.

At time of writing, there is scarce peer reviewed literature on the effect of the pandemic on environmental attitudes, concern about microplastics, or WTP for marine protection. In general, however, some literature discusses the effect of the news on WTP. News events and coverage may be an imperfect proxy for individual attitudes and concern. However, the literature is limited to two main strands. Firstly, examining the effect of the news on WTP but not for environmental projects, and secondly the effect of events on environmental concern but not in terms of WTP; see Ortega, Wang and Olynk Widmar (2015); Ray et al. (2017) respectively. Although not directly relevant to this research, both indicate that attitudes and thus WTP are sensitive to external events. Notably, Ortega, Wang and Olynk Widmar (2015) reports that negative news about food quality from abroad led to reduced WTP for food from abroad and greater WTP for domestically-produced food. Their result implies that negative news about the pandemic will downwardly bias WTP in this research. However, Ray et al. (2017) noted that the effect of extreme weather events on environmental concern diminished sharply over time. The temporal instability of preferences is common to the literature (Schaafsma et al., 2014) and may be driven by differences in income and concern.

Firstly, given increased unemployment and reduced economic activity, the marginal utility of income may have changed, influencing WTP, and income has repeatedly been shown to exert an influence on WTP. Moreover, the pandemic, job losses and economic worries were all cited as reasons for protest votes in the sample. However, the direction and magnitude of the change in the marginal utility of income are unclear. One argument could be that with reduced transport and childcare costs among discretionary expenditure, respondents' budget constraints are relaxed and could afford environmental protection. Specifically, with 47.6% of the sample answering 'Yes' that their income has been affected by the pandemic, there is clear evidence that the pandemic affected income and beliefs about future income, negatively affecting WTP. Note that this implies that environmental quality is a normal good. A second mechanism for the pandemic to affect valuations is that environmental protection is no longer a salient or dominant motivation. As there is a relationship between attitudes, intentions and behaviour, reduced attention or concern for the environment or other non-pandemic threats to health may reduce WTP valuations (Fransson and Garling, 1999; Kollmuss and Agyeman, 2002). Therefore, a three to six-month delay to data collection may have led to systemically higher WTP, although it was not feasible to test the effect of the timing of data collection in this research project.

Internal tests of the pandemic can be understood by evaluating the responses to Q24A as in Table 6.2. Table 6.2 reports fitted CE and CV WTP by whether respondents reported that their income was affected by the pandemic ('Affect' column) and whether their income was above or below the median ('Income' column). The subsamples are similarly sized and do not sum to 670 as some respondents had exactly median income or preferred not to answer. There is a noticeable income effect whereby 'high' income leads to higher WTP in the CV WTP regardless of whether they were affected. In the 'Affect' column, the income effect led to lower-income and lower WTP. Curiously, the MWTP changed signs at the highest effect and income levels, although the mechanism is unclear. Finally, it should be noted here that there is now a body of literature that has tested the sensitivity of preferences and WTP to the pandemic; notably using test-retest designs not feasible in this context. In this research, the lower WTP for both CV and CE questions and the difference between the groups suggests that the pandemic affected income, which influenced WTP.

Table 6.2: COVID-19 Effects.

Affect	Income	N	Performance	Emission	Q6	Q7
No	Low	175	-£0.155	£0.133	£22.99	£44.09
No	High	160	-£0.070	£0.059	£24.19	£46.20
Yes	Low	160	-£0.060	£0.052	£23.97	£43.67
Yes	High	159	£0.041	-£0.035	£23.95	£44.99

6.2.2 Environmental Influences

This section discusses the sign, magnitude, and implication of the relationship between fitted CE and CV WTP and environmental influences. Environmental influences can be broadly grouped into; distance-decay, knowledge of microplastics, concern about the effects of microplastics, responsibility about microplastics, and then environmental attitudes. While there is rich literature on the determinants of environmental attitudes, there is less information on how precautionary attitudes affect WTP (Kollmuss and Agyeman, 2002; Fransson and Garling, 1999; Abate et al., 2020).

6.2.2.1 Distance-decay

Distance-decay effects can be assessed by questions three (Q3: distance from the coast) and four (Q4: trips to the coast). Distance-decay has been commonly observed in the SP literature and exists when WTP is positively correlated with proximity to the valuation site as respondents closer to the site are more strongly impacted (Jørgensen et al., 2013; Glenk and Martin-Ortega, 2018). In this research, the mean distance was 29.48 miles (SD = 18.96) and weakly influenced WTP; see Table 8.6 in the Appendix for a tabulation of distance versus WTP. Figure 6.2 reports that distance had a minimal effect on CE MWTP and positively, albeit weakly, influenced CV WTP. A plausible explanation for the minimal distance-decay is that as microplastics are small and unobservable, they impose no disamenity to coastal visitors and, therefore, proximity to the coast does not influence attitudes and WTP (Sherrington et al., 2013; DEFRA, 2018). This explanation is supported by the distance covariate not being statistically significant in any CE models, indicating that a greater distance from the coast did not influence behaviour in the CE. However, Figure 6.2 suggests that greater distance from the coast positively increased WTP for both CV questions. The positive relationship between distance and CV WTP may be explained by higher-income respondents being able to move away from polluted areas. However, when controlling for income in the econometric models, the distance covariate in the CV models was highly statistically significant with a negative sign, suggesting that respondents who lived further from the coast were less likely to vote for the scenario. Therefore, while distance may correlate with income and higher WTP, observed in Figure 6.3, respondents closer to the coast were more likely to support the CV scenarios. However, it is necessary to explore an alternative proxy for distance, the number of trips, to support the finding of a weak and inconsistent distance-decay effect.

Distance-decay can also be assessed in this research by the number of trips a respondent makes to the coast annually as in Figure 6.2. The mean number of trips was 1.63 per year (SD=0.99), and the shallow negative slope for the number of trips indicates that respondents who travel more often to the coast have slightly lower WTP for microplastics. However, the relationship between the number of trips and WTP is weak in the econometric analysis, whereby the coefficient on trips is often insignificant and reports a weak effect when significant. The insignificance supports the suggestion that as the disamenity effect from coastal microplastics is weak, there is no apparent distance-decay effect in this research, whether measured by distance from or trips to the coast.

As a final addition to the discussion of distance-decay, Figures 6.4 and 6.5 plot choropleth maps of the UK using the mean WTP for each category of distance from the coast. There is an emerging trend of using spatial data in SP surveys to understand spatial heterogeneity in respondent preferences; see Glenk et al. (2020) for a review and Badura et al. (2019) for an application of maps within a CE task. In these two maps, the UK is used as the proposed restriction would apply to the UK, and the respondents were nationally representative of the UK. The two maps use longitude and latitude scales to plot the distance from the coastline. The distance from the coastline is shaded using the discrete categories used in the survey. However, a limitation is that the data was self-reported and imprecise. Choropleth maps use shading to indicate that generally, those living further from the coasts have higher WTP. However, the effect size is small, and, as the previous discussion established, the effect is primarily driven by income effects. To summarise, the hypothesis of a distance-decay effect is rejected in this research across both SP tasks and both distance measures as greater distance led to higher WTP.

Figure 6.2: Distance-Decay of WTP.

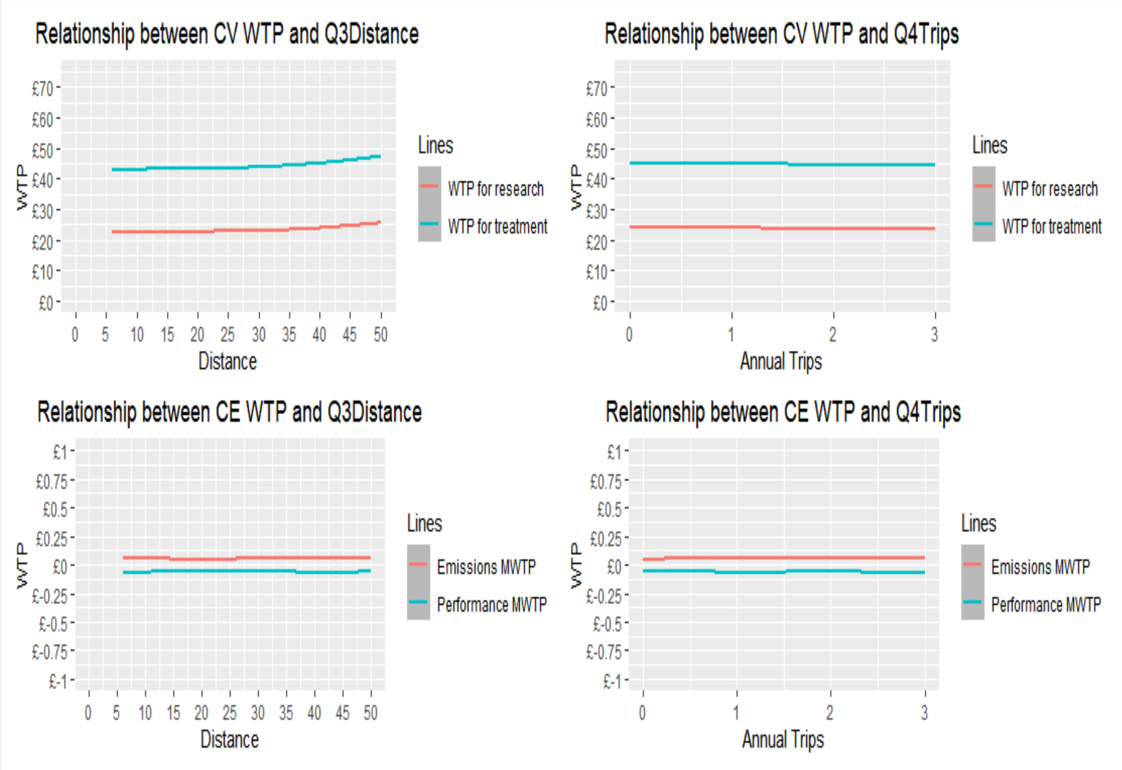


Figure 6.3: Income effects on distance-decay.

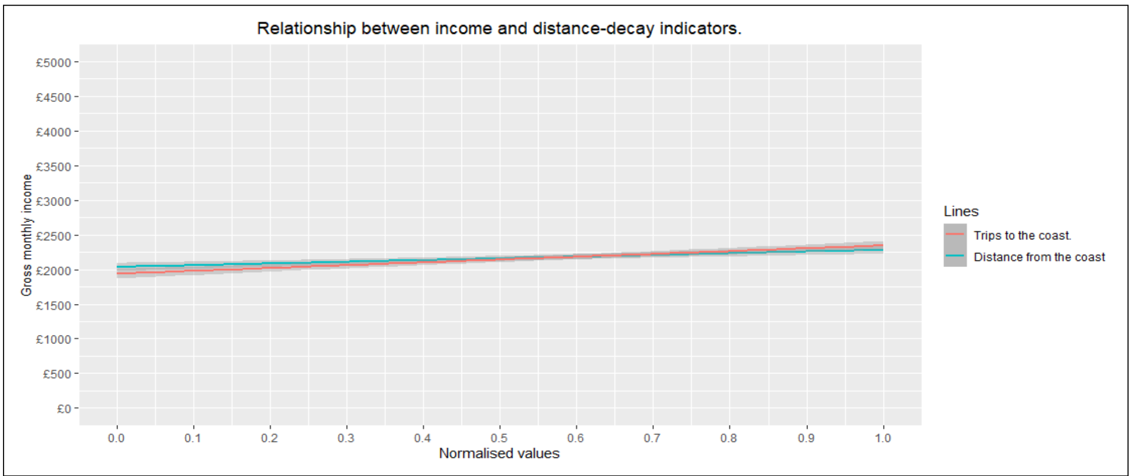


Figure 6.4: Spatial Distribution of Q6 WTP.

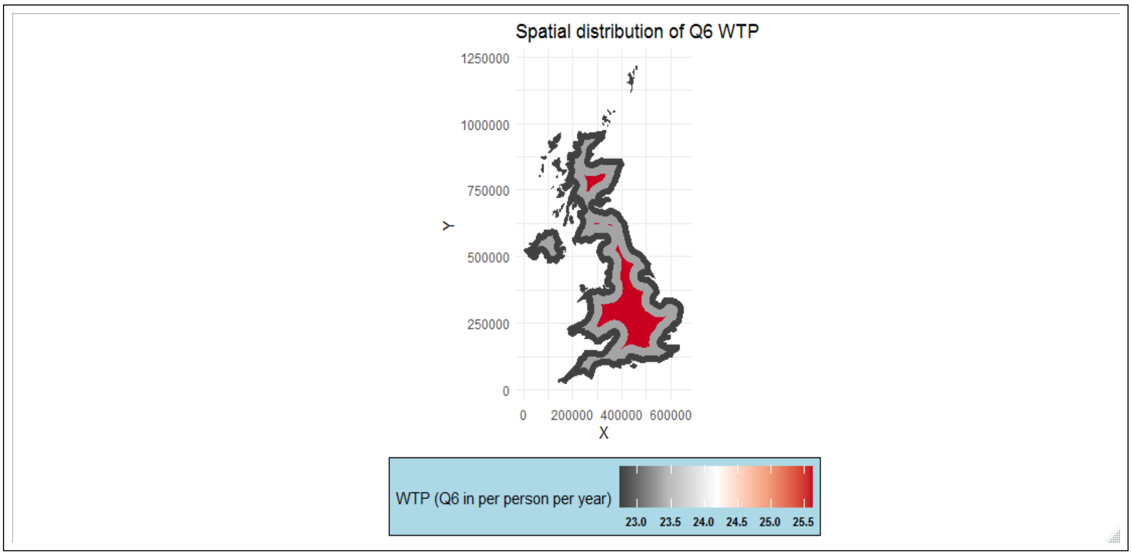
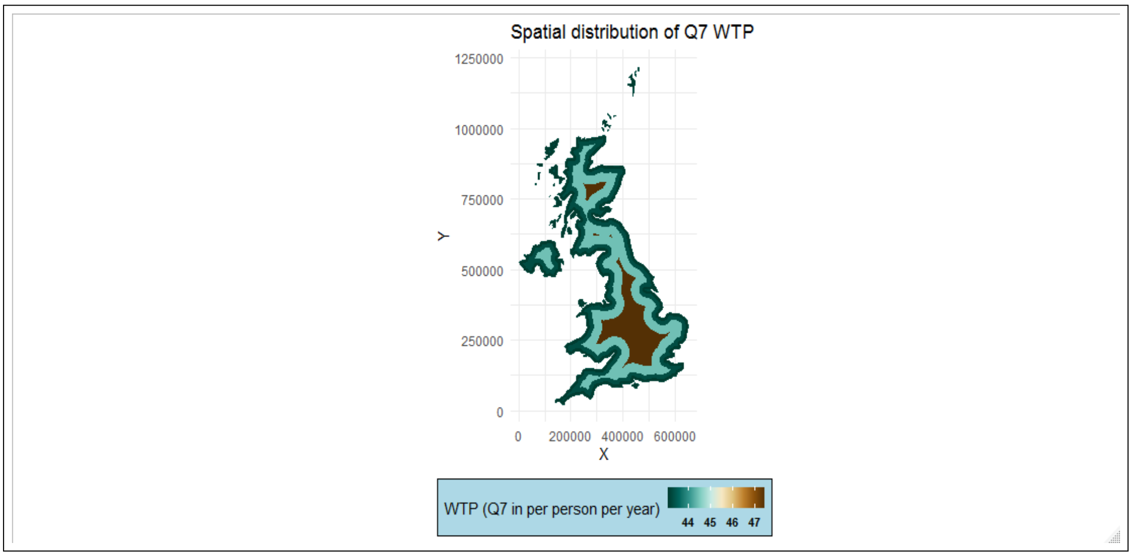


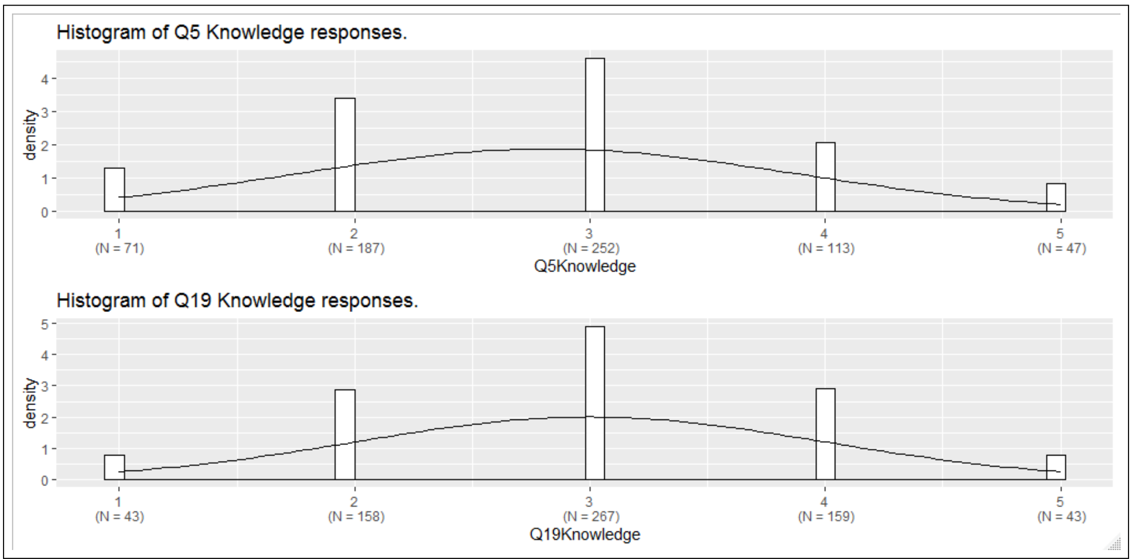
Figure 6.5: Spatial Distribution of Q7 WTP.



6.2.2.2 Knowledge of microplastics

Two questions, questions five (Q5: pre-information) and nineteen (Q19: post-information), assessed respondents' knowledge of microplastics. There are two motivations for this design. Firstly, to assess the effect of information provision on self-reported knowledge. Q5 was at the start of the survey, and Q19 was after the survey provided information about microplastics. The exact information is detailed in Section 3.2.5.2. Oother SP surveys may provide more information, especially in a context so fraught with uncertainty. However, this survey decided to provide sufficient but not extensive information to minimise complexity. The two knowledge questions can be used to evaluate respondents' knowledge of microplastics and the surveys' efficacy. Evaluating the efficacy of the survey information is an essential element for the content validity of the survey (Johnston et al., 2017; Turpie, 2003; Deng et al., 2020). A second motivation is that respondents' level of awareness and knowledge have often been reported in the literature as WTP determinants (Spash, 2006; Kollmuss and Agyeman, 2002; Fransson and Garling, 1999; Laroche, Bergeron and Barbaro-Forleo, 2001; Afroz et al., 2013). This section reports on both motivations for including the two knowledge questions. However, it should be noted that the measure is a self-reported Likert scale, and so respondents may be liable to central tendency or social desirability biases (Johnston et al., 2017).

Figure 6.6: Histograms of Q5 and Q19.



The first motivation for including two knowledge questions pre and post information was to test respondents comprehension of information about the uncertain effects of microplastics. The information had to minimise survey complexity while relating the uncertainty in the literature about potential effects. Figure 6.6 reports that self-reported knowledge increased following the provided information (mean Q5 = 2.82, mean Q19 = 3). The increased knowledge is evident in the albeit small change in means. However, the fact that the medians were equal and the number of respondents reporting the highest knowledge fell post-information suggests that the effect is weak. The fewer people reporting the highest knowledge suggests that respondents updated their beliefs once contextualised with the provided information. In general, including pre and post information questions shows that the information provided effectively increased the respondent's knowledge about microplastics.

A second motivation for Q5 and Q19 was to explore how knowledge influences WTP. The theoretical justification comes from Kollmuss and Agyeman (2002), who suggested that increased knowledge or awareness may alter attitudes and intentions, although the relationship may be weak. Table 6.3 reports the effect of increased knowledge on mean WTP for respondents above or below the median level. Although knowledge is positively correlated with the magnitude of CV WTP, it reduces the size of the precautionary premium. Specifically, respondents reporting higher knowledge also reported higher WTP for research, while treatment WTP fell, robust to both knowledge questions. The increased WTP for research may arise as greater knowledge of microplastics reveals a greater need for research given the high degree of scientific uncertainty. The increased WTP given knowledge has empirical support (Turpie, 2003; Afroz et al., 2013; Laroche, Bergeron and Barbaro-Forleo, 2001). For the CE MWTP, the more information about the quality and composition of their personal care products that respondents are provided, the more respondents are willing to trade-off different product attributes, leading to higher MWTP. Overall, greater specific knowledge increases WTP in each task, but most strongly for Q6.

There are three possible explanations for the increasing relationship between knowledge and WTP for research; education, confidence in experts, and concerns. Firstly, Deng et al. (2020) observed that more highly-educated respondents reported greater knowledge of microplastics. This finding is corroborated in this research by two highly significant Pearson product-moment correlation tests of the effect of education on knowledge. Specifically, the tests found a weakly positive but statistically significant effect of increased education levels on knowledge; correlations of 0.273 (Q5) and 0.227 (Q19) at the 1%

Table 6.3: Statistics and tests for Q5 and Q19 knowledge questions.

Question	**Q5) Please indicate your knowledge of microplastics and their effects on the environment and human health?**	**Q19) Please indicate your knowledge of microplastics and their effects on the environment and human health following this survey?**
Position	Pre-information	Post-information
Median value	3.00	3.00
Mean value Full sample	2.82	3.00
Mean value Truncated sample	2.87	3.08
Q6 WTP	Below Median: £23.14 Above Median: £25.72 P.Value: 0.561	Below Median: £23.53 Above Median: £24.05 P.Value: 0.000
Q7 WTP	Below Median: £44.40 Above Median: £45.84 P.Value: 0.003	Below Median: £45.62 Above Median: £44.84 P.Value: 0.560
Performance	Below Median: -£0.050 Above Median: -£0.130 P.Value: 0.000	Below Median: -£0.028 Above Median: -£0.104 P.Value: 0.000
Emission	Below Median: £0.040 Above Median: £0.110 P.Value: 0.000	Below Median: £0.024 Above Median: £0.089 P.Value: 0.000
Q13	Below Median: 3.27 Above Median: 3.90 P.Value: 0.000	Below Median: 3.34 Above Median: 3.76 P.Value: 0.000
Q14	Below Median: 3.65 Above Median: 4.06 P.Value: 0.000	Below Median: 3.64 Above Median: 4.10 P.Value: 0.000
Q15	Below Median: 3.91 Above Median: 4.34 P.Value: 0.000	Below Median: 3.91 Above Median: 4.41 P.Value: 0.000

significance level. However, it is unclear whether this correlation corresponds to differences in WTP as the education coefficient in the Q6 probit model was not statistically significant, even when also controlling for income and other socioeconomic characteristics. Additionally, only the level and not subject of education were observed in the survey, so no further inference is possible. Therefore, it is unlikely that knowledge influenced WTP through education levels. A second explanation could be that question 21 (Q21: belief in experts) affects respondents confidence in the quality or veracity of the information provided to them. Indeed, the correlation between knowledge and belief in experts is also statistically significant and positive (0.259 and 0.388, respectively, both at the 1% significance level). Therefore, increased belief in experts could support a greater WTP for research as respondents are more confident in experts' ability to conduct new research and provide information. To summarise, the effect of knowledge on WTP appears to be weakly driven by education and belief in experts.

Environmental concerns may also drive the effect of knowledge on WTP. The mechanism here is suggested by Deng et al. (2020) who found that once respondents were informed about the potential effects of microplastics, they were more concerned and willing to abate their release. However, they used face-to-face surveys, possibly leading to social desirability bias, and did not examine the effect on WTP. This research extends their work by finding that greater knowledge leads to greater concern and, therefore, greater WTP for research into microplastics' effects. Support for this theory is the strong and robust positive relationship between knowledge of microplastics and concern about their effects [18] The effect of knowledge is strongest on Q6 WTP, possibly as respondents are more concerned about possible effects and support research more strongly. Therefore, the positive effect of knowledge on WTP for research into microplastics may be underpinned by greater concern about the potential adverse human health effects. However, it should be noted that self-reported concerns are upwardly biased, given that they are elicited post-information provision and post valuation tasks which increase salience. Overall, the effect of including two knowledge questions, Q5 and Q19, was to show that, firstly, survey information provision was comprehensible and increased respondent knowledge and, secondly, increased WTP, possibly driven by education, experts, and awareness.

[18] Correlations between questions are all positive, strong and statistically significant: Q5/Q13 (0.309, p=0.00), Q5/Q14 (0.238, p=0.00), Q5/Q15 (0.273, p=0.00), Q19/Q13 (0.321, p=0.00), Q19/Q14 (0.359, p=0.00, Q19/Q15 (0.364, p=0.00).

6.2.2.3 Concern about microplastics

Similarly to the knowledge questions, questions thirteen (Q13: the current threat to health), fourteen (Q14: the future threat to health), and fifteen (Q5: the current threat to the environment) assessed respondents level of concern about the environmental and health impacts of microplastics. Figure 6.7 reports the distribution of responses. The mean increased each time (Q13 = 3.42, Q14 = 3.74, Q15 = 4.01). The histograms indicate that respondents are more concerned about future impacts with the current threat to the marine environment, perhaps an indicator of future levels of impacts. All the environmental questions (13, 14, 15, 16, 18, 19) were asked post-information and valuation, which may have inflated respondents choices but could not realistically be placed elsewhere in the survey. However, a robust result from the three indicators is that respondents were generally concerned about microplastic's effects.

Figure 6.7: Q13,14,15 Histograms.

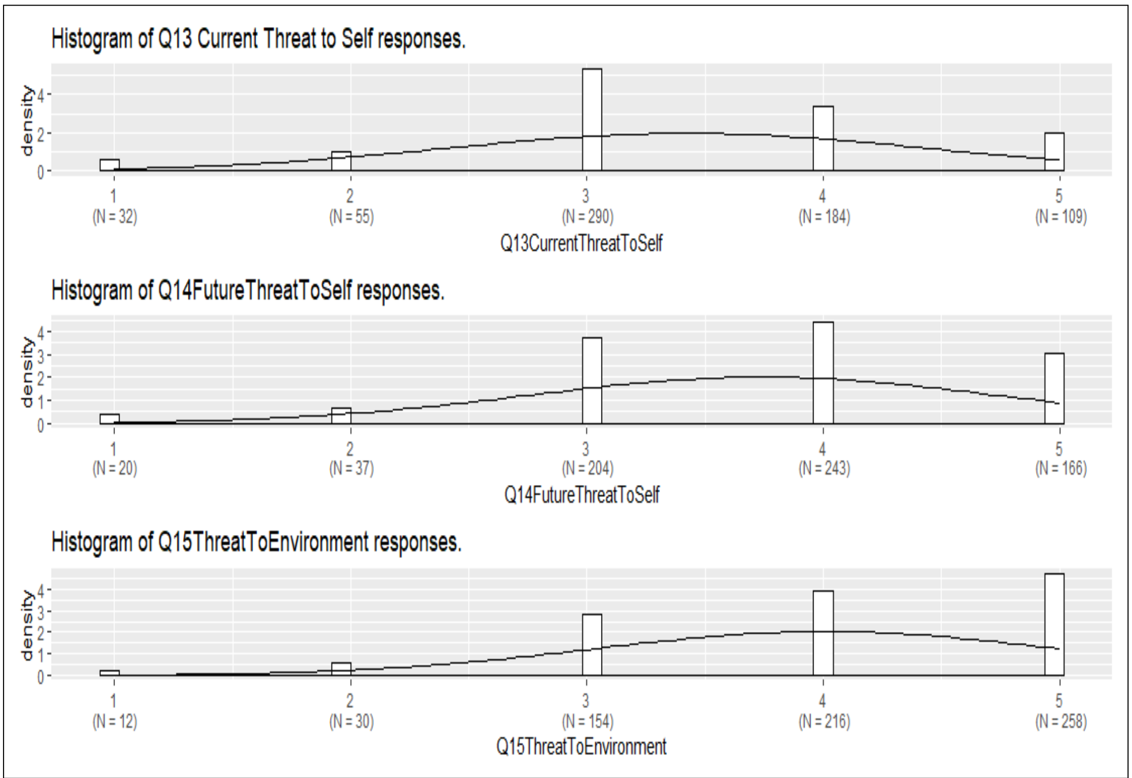


Figure 6.8: Environmental concern against CV WTP.

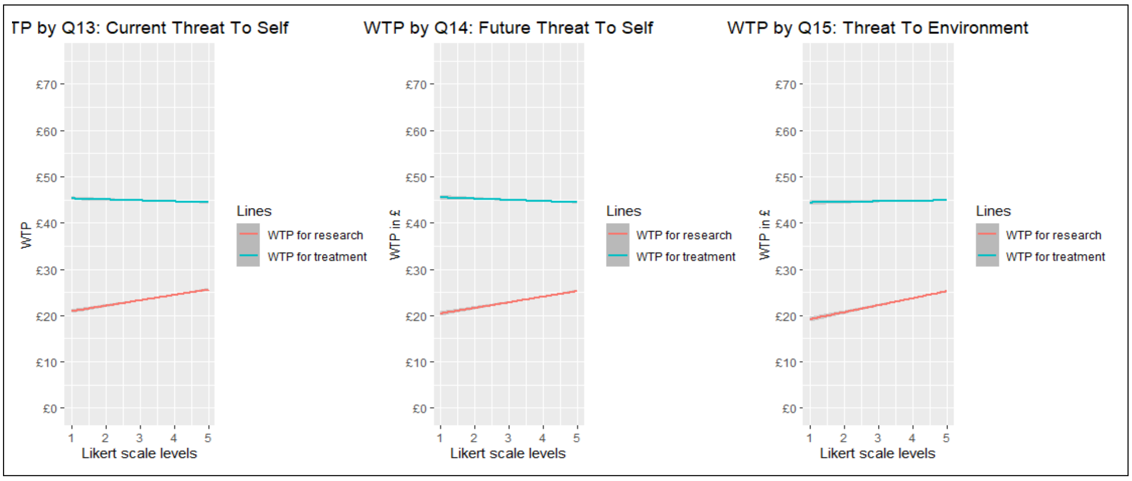
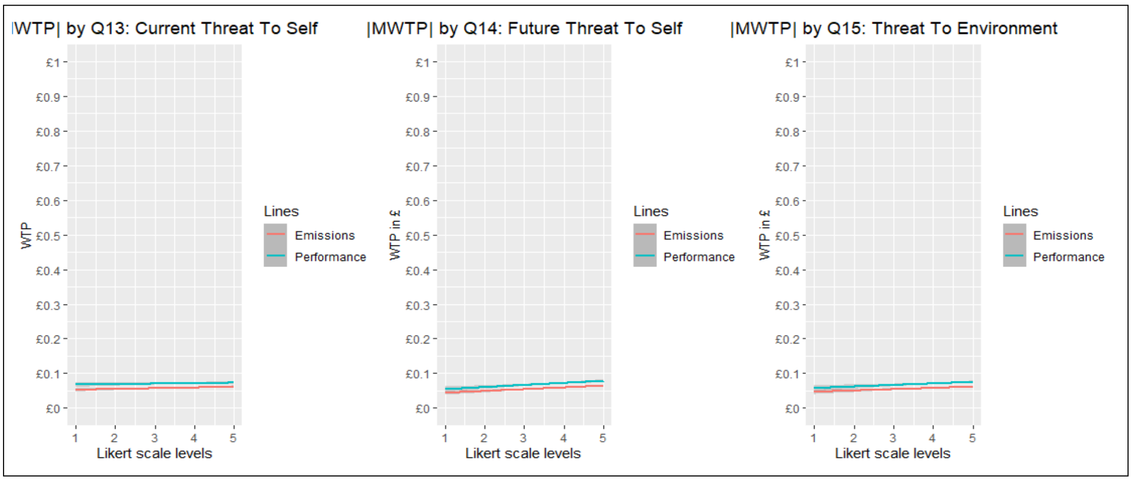


Figure 6.9: Environmental concern against CE MWTP.



The effect of environmental concern on WTP is of critical importance for this research. Firstly, the ICLV method was used for both the CE and CV data to show that precautionary attitudes strongly influenced WTP. Secondly, Figures 6.8 and 6.9 report the relationship between each measure of environmental concern and the CV and CE WTP, respectively. The absolute value of the CE MWTP is used for ease of comparison.

Figure 6.8 shows that, similarly to the effect of knowledge, increasing concern led to a strong increase in WTP for research. Indeed, of all the SP tasks, it appears that Q6 was the most responsive to increasing concern about microplastics, robust to the measurement of concerns. This suggests that more concerned respondents had a greater willingness to resolve the uncertainty. Although the concern is positively correlated with knowledge, the increase may be driven by the scientific uncertainty described in the survey information. Indeed, Faccioli, Kuhfuss and Czajkowski (2019) found that greater uncertainty led to increased WTP, albeit in a split-sample DCE design. Furthermore, the increased willingness supports Deng et al. (2020) who found a strong positive link between concern and willingness to act, but did not elicit WTP. By comparison, the Q7 WTP actually fell or was stable for increasing levels of concern. This suggests that the precautionary premium falls with increased concern about microplastic's effects. One plausible explanation is that the uncertainty about the potential effects reduces the expected benefits of upgrading WWTP, similarly to Kuntz-Duriseti (2004) finding that uncertainty imposed a penalty on welfare. Overall, however, higher concern leading to a smaller premium shows that the premium exists at all levels and measures of concern.

Finally, Figure 6.9 reports each concern indicator's effect on absolute CE MWTP. Consistent with the previous analysis, concern increases MWTP as respondents are more willing to trade off product attributes and avoid releasing microplastics. However, the ratio between the performance and emissions attributes holds throughout, possibly as more-concerned respondents have higher income, although the relationship is weak. To summarise, the effect of any measure of environmental concern is to increase the magnitude of MWTP and Q6 WTP.

6.2.2.4 Q16 Blue-Planet II Viewership

Question sixteen (Q16: Blue-Planet) of the survey asked respondents how much of the Blue-Planet II (BPII) TV programme the respondent had seen. Viewership of the documentary series has been widely acknowledged as raising awareness of marine plastic pollution (The Economist, 2019; Hook and Reed, 2018). Furthermore, Hynes et al. (2020) showed that BP-viewership significantly influenced preferences, albeit not WTP. Figures 6.10 and 6.11 indicates that the effect of this increased awareness is an increase in fitted WTP robust across both SP tasks.

The observed effect of increased viewership is not uniform. While the WTP for research increases sharply, WTP for the treatment option is relatively stable. One plausible explanation for the different effects is that respondents may wish to understand BPII further, so their WTP for research increases. The minimal effect on WTP is consistent with Hynes et al. (2020) finding that WTP was not systematically different between viewing and non-viewing groups. Another effect of Q16 in this research was that viewership was positively correlated (0.317, p=0.000) with charity involvement. The positive relationship between BPII viewership and charity donations is consistent with Hynes et al. (2020) and evidences a latent precautionary environmental attitude of respondents; see the ICLV models. Precautionary respondents may have been involved with relevant media and charities, which increases both their knowledge and level of concern over microplastics, thus leading to greater WTP for research to resolve the scientific uncertainty on the environmental and health impacts of microplastics. Finally, Figure 6.11 indicates that the effect holds for the CE MWTP, although to a lesser extent, perhaps due to the WTP being for marginal changes. Furthermore, an increase in BP viewership affects MWTP for both attributes similarly. The MWTP for performance is reported in absolute terms, so it appears to increase in magnitude. The increased MWTP for marginal reductions in emissions may indicate that the more respondents have viewed the BPII, the more they are willing to trade-off product attributes to reduce the release of microplastics to the marine environment. Caveats for this section are that viewership was self-reported and in three loosely defined categories. Therefore, respondents may have over-reported their viewing if social-desirability bias exists. However, the question format was used to minimise complexity and determine whether higher viewing levels increased environmental attitudes. Overall, the effect of BPII viewership was to influence environmental attitudes, which in turn determine WTP, a finding robust to SP question and attitudinal indicator.

Figure 6.10: Effect of BP viewership on fitted CV WTP.

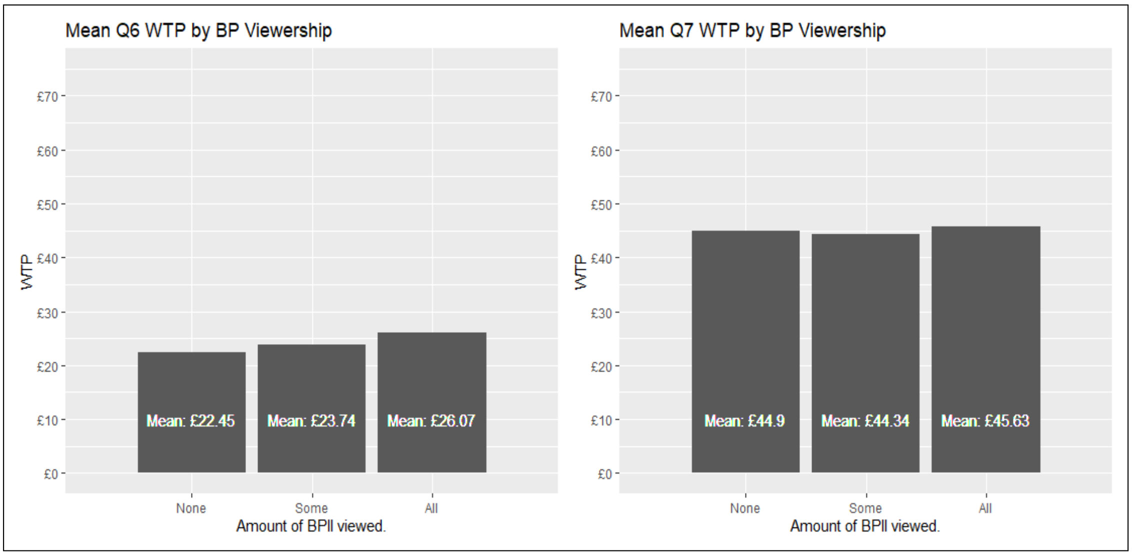
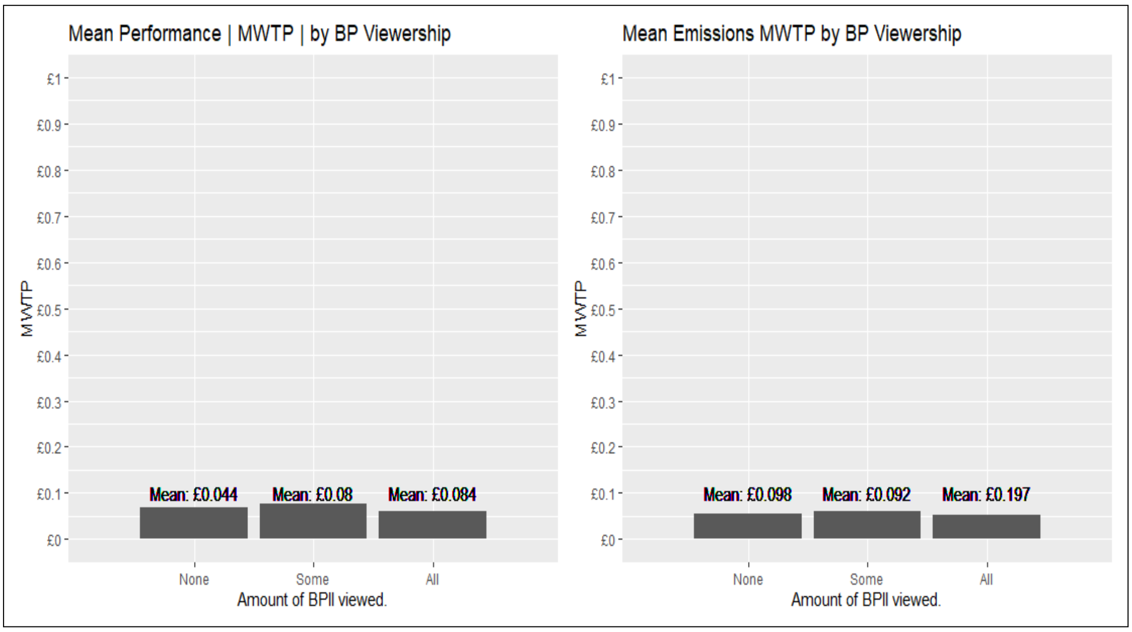


Figure 6.11: Effect of BP viewership on fitted CE MWTP.



To illustrate, the effect of viewing the BP on Q6 WTP was a 16% increase, which would substantially increase the economic viability of a research programme. Moreover, the effect for Q7 was a 0.29% increase in WTP. When aggregated to the UK national population, the annual benefits of the WWTP investment scenario increase by approximately £3.5mn. While it is unclear how the increase in benefits corresponds to the cost of production, it does indicate that increasing awareness can correspond to greater benefits. However, the small magnitude of the effect is consistent with (Hynes et al., 2020). Finally, the effect of watching all of the BPII series was an approximate 101% increase in respondents' MWTP for marginal changes in emissions. This result suggests that greater awareness of the environmental effects of microplastics can substantially increase respondents' willingness to trade-off product attributes. This positive effect of media on WTP supports the positive relationship between knowledge and WTP exhibited in Section 6.2.2.2.

6.2.2.5 Q17 Responsibility for microplastics

Question seventeen (Q17: responsibility) of the survey asked respondents to select among stakeholders (firms, consumers, central or local government, or others) who they thought were responsible for reducing the release of microplastics to the environment. The categories came from the pre-testing process. The majority of the sample believed that firms, or the government that regulates them, were responsible for microplastics. The 'Other' category respondents were allowed text response, and most argued that all stakeholders were responsible. Table 8.7 in the Appendix reports CV and CE WTP by whether respondents chose the respective stakeholder as responsible for microplastics. There are two small noteworthy findings from this question. Firstly, believing consumers to be responsible, having a high degree of Environmental Locus of Control (ELC) reduces the precautionary premium by increasing WTP for research and reducing WTP for treatment. A positive link between a high degree of ELC and WTP is consistent with Trivedi, Patel and Savalia (2015) although it is unclear why ELC would reduce WTP for treatment. A second finding is that believing a stakeholder to be responsible always increases CE MWTP. ELC can again explain why those believing consumers are responsible are more willing to trade-off product attributes (Kollmuss and Agyeman, 2002). Overall, however, the effect of responsibility on WTP is weak and stakeholder-specific. Further research to understand ELC and willingness to trade-off product attributes would be valuable to the marketing literature (Trivedi, Patel and Savalia, 2015; Laroche, Bergeron and Barbaro-Forleo, 2001).

6.2.2.6 Q18 Charity Involvement

Question eighteen (Q18: Charity) asked respondents whether they had been involved with environmental charities. Involvement was defined as donating or membership; more granular information about the level of charity involvement was not available. However, this was self-reported and so may suffer from social desirability biases. Charity involvement indicates the strength of respondents environmental attitudes. Indeed, charity involvement could be an example of a revealed preference of respondents to preserve the marine environment. Figure 6.12 shows that the minority of the sample who had not been involved at all, reported higher Q6 WTP but lower Q7 WTP. The reduction in the precautionary premium is comparable with the effects of knowledge and concern, discussed in Sections 6.2.2.2 and 6.2.2.3 respectively. Again, the reduction is driven by a strong increase in Q6, suggesting that environmentally-focused respondents wished to know more about microplastics' potential effects. Therefore, respondents who reveal a preference for environmental protection via declaring charity involvement also reveal their preference by reporting higher WTP for research into the effects. One possible explanation why this effect does not hold for the Q7 treatment scenario is that charities may be seen as investing in research already, whereas the Q7 scenario of investing in WWTP is less likely to be charitable. For completeness, Figure 6.13 reports that charity involvement also increased the magnitude of CE MWTP. The positive link between charity and WTP is consistent with the CV literature, although there is less evidence on the CE side (Abate et al., 2020; Zambrano-Monserrate and Ruano, 2020). However, the binary involved-or-not approach is limited as it does not recover the extent of involvement; there may be a further difference between members and donors. A further weakness could be social desirability bias to motivate respondents to misrepresent their level of involvement. However, the majority of the sample reported no involvement and, therefore, the evidence for this effect is weak. In summary, environmental charity involvement has a strong and consistently statistically significant effect on respondents choices and WTP.

Figure 6.12: Effect of charity involvement on CV WTP.

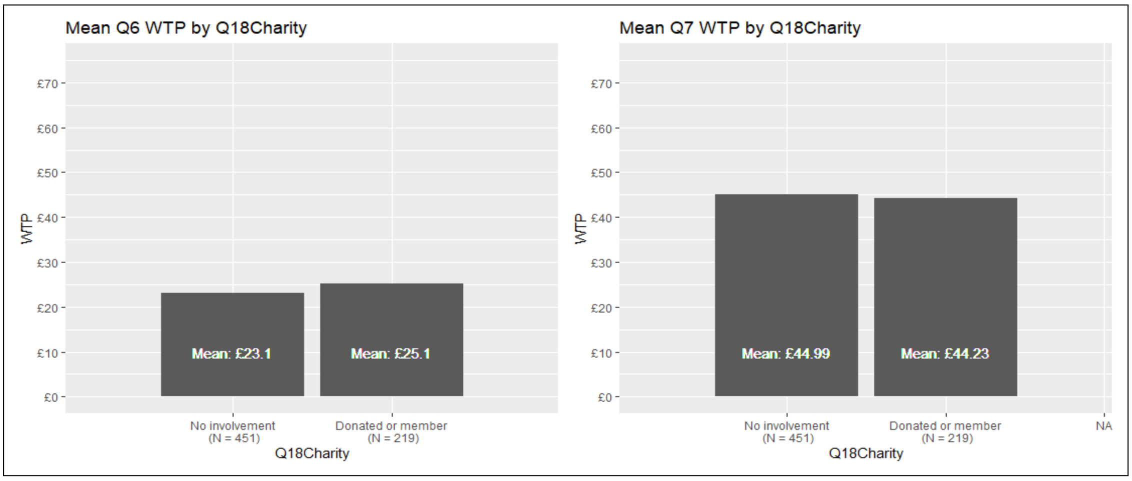
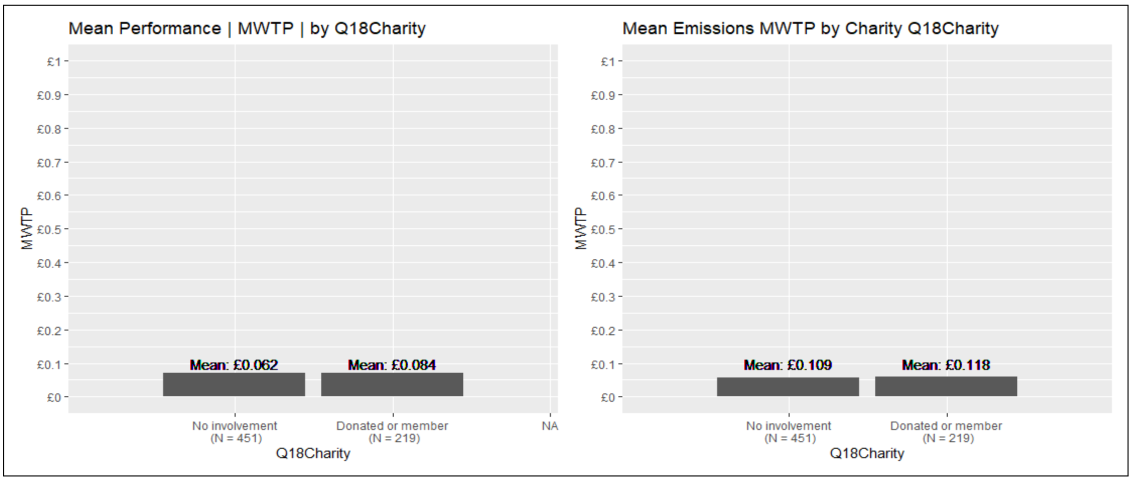


Figure 6.13: Effect of charity involvement on CE MWTP.



6.2.2.7 Q21 Experts Discussion

Question twenty-one (Q21: belief in experts) asked respondents how confident they were in the ability of experts to provide reliable information. The range of responses is reported in Figure 6.14. The subject of which experts and which information was deliberately left ambiguous to avoid any social desirability bias or interviewer effects in the responses. However, this vagueness may also obfuscate respondents' interpretation. This question aimed to understand how respondents trusted the scientific evidence on microplastics' uncertain potential environmental and health impacts. This would, therefore, have consequences for the environmental attitude questions and possibly respondent choices. The mean confidence was 3.6 (SD = 0.938), and Figure 6.15 reports the distribution of the responses and shows that no central tendency bias exists and respondents were mostly confident in experts. The effect of this confidence on CV WTP is reported in Figure 6.15 with CE MWTP in Figure 6.16. Curiously, there is a u-shape effect for both CV questions, possibly due to the very low sample size at the lower values of the Likert scale.

Figure 6.14: Q21 Histogram.

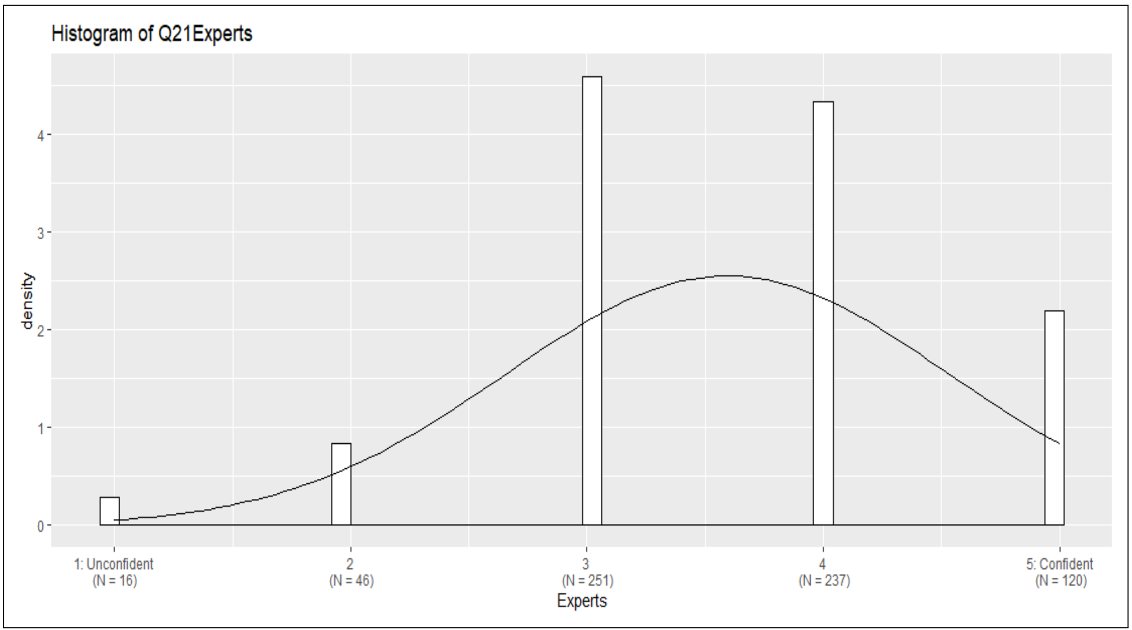


Figure 6.15: Q21 Experts versus CV WTP.

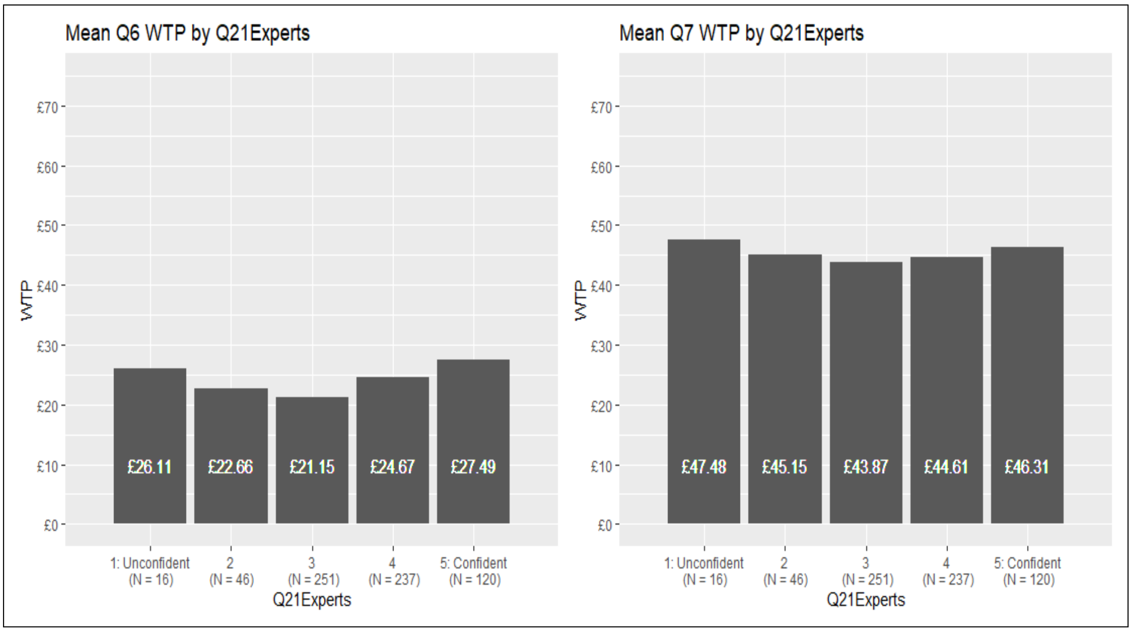


Figure 6.16: Q21 Experts versus CE MWTP.

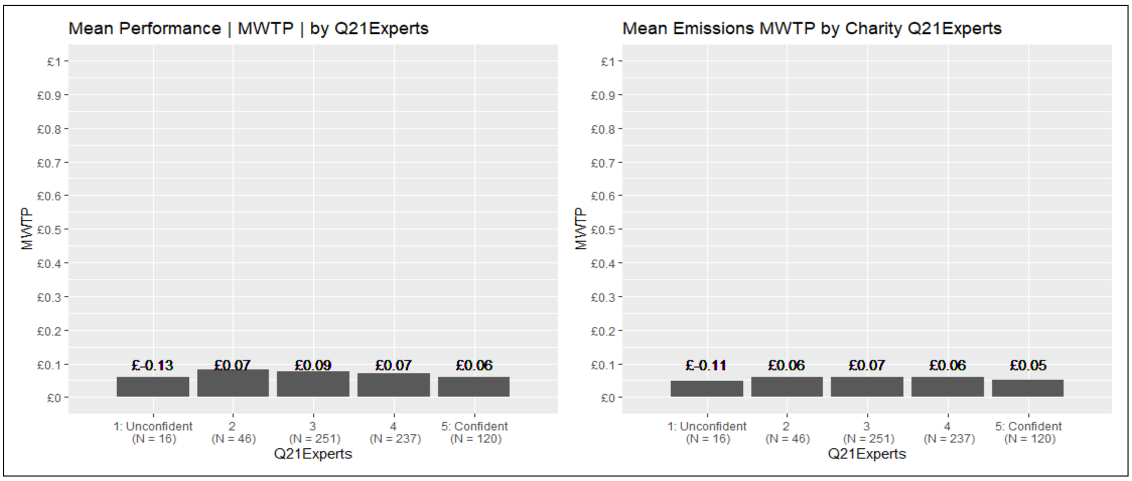


Figure 6.15 reports the relationship between increased confidence in experts and CV WTP. For the fitted CV WTP, the treatment WTP is relatively stable, if weakly increasing, with confidence, whereas the WTP for research increases sharply. The larger effect on Q6 WTP suggests that greater confidence in experts led to a greater willingness to pay for their research and their ability to undertake it. Therefore, the precautionary premium falls with increased belief in the ability of experts. This result is consistent with the knowledge, concern, and charity involvement questions. Regarding the CE MWTP in Figure 6.16, the absolute value of the performance attribute MWTP increased more than the emissions MWTP. The emissions attribute is relatively stable, indicating that respondents were already willing to reduce emissions of microplastics to the marine environment, no matter what experts suggest. Indeed, increased confidence was linked to an increase in the rate that the alternative Option B was chosen in the data. However, the increase in the performance attribute suggests that respondents were less willing to change the quality of their personal care product. Combined with the stable emissions MWTP, this suggests that the more confident in experts respondents were, the lower the difference between the MWTP. To summarise this subsection, the effect of increased confidence was to reduce the difference between WTP valuations. The mechanisms underpinning this are likely to be environmental knowledge and concerns, consistent with other environmental determinants of fitted SP WTP.

6.2.3 Socioeconomic Influences

Given the rich literature on the determinants of WTP and environmental concern, this section discusses the influence on WTP of questions one (Q1: Age), question two (Q2: Gender), question twenty-two (Q22: Education), twenty-three (Q23: Employment), twenty-four (Q24A: Income), and the impact of the coronavirus pandemic.

6.2.3.1 Income effects

Question 24 of the survey asked respondents for their gross monthly income. Given the strong income effects underpinning other survey questions, this section estimates the income elasticity of WTP and discusses how that elasticity compares to the estimates in the literature. Starting with Hökby and Söderqvist (2003) insightful treatment on the derivation and interpretation of the income elasticity of WTP, they note that the two concepts of Income Elasticity of Demand (IED) and Income Elasticity of WTP (ε_{WTP}) must not be confounded. Hökby and Söderqvist (2003) defines ε_{WTP} using changes in income and WTP:

$$\varepsilon_{WTP} = \frac{y}{WTP} * \frac{\partial WTP}{\partial y} = \frac{\partial \ln y}{\partial \ln WTP} \tag{6.2.1}$$

The sign of ε_{WTP} indicates how income changes affect the proportion of income assigned to WTP. For example, where $\varepsilon_{WTP} < 1$, the proportion of income assigned as WTP decreases as income increases and, therefore, environmental benefits are distributed regressively while the ability to pay is not. Indeed, Atkinson et al. (2018a) corroborates Hökby and Söderqvist (2003) in suggesting that, where $\varepsilon_{WTP} < 1$, distributional weights may be used in CBA to address the regressive distribution of benefits.

Following Hökby and Söderqvist (2003) exploration of the interpretation of ε_{WTP}, Tyllianakis and Skuras (2016) undertook a meta-analysis to estimate the precise income elasticity of WTP, reporting a statistically significant positive ε_{WTP} robust to income and wealth measurement. As discussed in Hökby and Söderqvist (2003), whether ε_{WTP} is less than, equal to, or greater than unity is of paramount importance to environmental policymaking as it suggests how pollution abatement benefits are distributed in the population and, accordingly, whether distributional weighting of WTP is valid in CBA. Indeed, Tyllianakis and Skuras (2016) noted that elasticities greater than one indicate that benefits are proportionally higher for high-income households; that is distributed regressively. However, Tyllianakis and Skuras (2016) meta-analysis ε_{WTP} in the range of 0.6 - 1.7, which suggests the possibility of regressive or progressive distributions of pollution control. However, the finding of weights less than or greater than unity was not replicated by Barbier, Czajkowski and Hanley (2017) who observed that low-income groups reported a very low ε_{WTP} of 0.1 - 0.2 while higher-income groups reported ε_{WTP} nearer 0.6 - 0.7. Barbier, Czajkowski and Hanley (2017) advanced one possible explanation as a non-constant ε_{WTP} that varies between income groups. The group-specific elasticity may then be used to calculate distributional weights for CBA (Atkinson et al., 2018a). The following subsection comments on implications for the literature and policy given estimates the income elasticity of fitted WTP.

Income elasticity of WTP can be calculated using mean sample monthly income of £2192, mean WTP for Q6 (£53.25), Q7 (£73.71) and the income coefficient when included in probit models (available in Section 8.3.6.1 of the Appendix) (Hökby and Söderqvist, 2003). For Q6 the result is $\frac{£2192}{£53.25} * 0.00005861 = 0.002$. For Q7 the result is $\frac{£2192}{£73.71} * 0.00037357 = 0.01$. The magnitude and sign are robust to estimating income and bid-only models without covariates. These estimates are in the expected range of 0-1 but are an order of magnitude below those expected from the literature (Hökby and Söderqvist, 2003; Nick and Ysé, 2006; Barbier, Czajkowski and Hanley, 2017; Tyllianakis and Skuras, 2016). The values can be interpreted as a 1% change in income, leading to a 0.002 - 0.01 change in WTP for each question, respectively. The income elasticity is calculated for each CV question for completeness, although the value does not change significantly. While the magnitude of the elasticity was robust to measuring income in monthly or annual terms, it is unclear why the income elasticity is extremely low in this research. As a final comment on the implied income elasticity of WTP, values below unity may indicate that distributional weights in the CBA are necessary to appropriately control for income differences in the population (Hökby and Söderqvist, 2003; Barbier, Czajkowski and Hanley, 2017). Overall, income effects underpin many of the effects of socioeconomic variables on WTP in this research.

6.2.3.2 Age

The empirical evidence on the sign of the age effect is ambiguous as age effects (Question Two: Age) can be underpinned by income or environmental concern; younger respondents may have less income but higher concern (Fransson and Garling, 1999; Orset, Barret and Lemaire, 2017; Abate et al., 2020; Faccioli et al., 2020). Table 6.4 reports fitted WTP from each task by age groups and gender. The precautionary premium, income, and mean environmental concern is also reported to identify the sources of age differences in WTP. Fransson and Garling (1999) suggestion that younger respondents are more concerned is corroborated as the youngest respondents (18-25) reported higher concern than the eldest (71+), although the concern was relatively stable for all other ages. The opposite conclusion holds for income, where income generally increases with age. These two forces act separately on the precautionary premium; Q6 falls with age while Q7 increases. Q6 is again shown to be sensitive to environmental concern as younger, more concerned respondents reported higher WTP. However, the increased income for older respondents led to a substantial increase in Q7 WTP, above the reduction in Q6 WTP from being less environmentally concerned. Therefore, it appears that the older respondents attach a greater premium to immediately resolving the irreversible release of microplastics, possibly as younger groups discount the future benefits of research differently. Although income was controlled for, a curious finding is that higher-income respondents were less willing to trade-off product attributes; evidenced by lower MWTP. This contrasts with Hess and Beharry-Borg (2012), and Buckell, Hensher and Hess (2021) who find no statistically significant effect of age in the CE designs. However, it is consistent with Abate et al. (2020) and Faccioli et al. (2020) who find a significant negative effect of age on environmental concern, although they did not extend the analysis to MWTP differences. Overall, age effects on WTP are underpinned by differences in income and environmental concern.

6.2.3.3 Gender

The direction of gender (Question One: Gender) differences in WTP is again unclear as male respondents typically have a lower concern but higher-income (Kollmuss and Agyeman, 2002; Fransson and Garling, 1999; Faccioli et al., 2020; Abate et al., 2020). In this research, Table 6.4 reports gender differences in fitted WTP, income, and concern. The result is that male respondents were less concerned but had higher income and reported higher WTP for every task. The difference in concern is relatively small, whereas income differences were much larger. However, despite the much higher income, male respondents reported CV WTP only marginally higher than females. However, the difference between the two tasks was smaller for male respondents who reported a marginally smaller precautionary premium. The differences in the CE MWTP were much larger as males appeared more willing to trade-off product attributes. Therefore, it appears that the gender difference may be driven more by income effects than environmental concern. This result holds in the econometric modelling when controlling for income. Indeed, the statistically insignificant gender coefficient is consistent with the literature that reported that males were less concerned (Faccioli et al., 2020; Abate et al., 2020).

Table 6.4: Age and gender effects and covariates.

Measure	Female	Male	18 - 25	26 - 39	40 - 55	56 - 70	71+
Q6	23.49	24.04	25.10	22.69	23.96	23.71	22.29
Q7	44.57	44.90	43.17	45.08	45.46	43.73	46.76
Precaution	21.08	20.87	18.07	22.39	21.50	20.01	24.46
Performance	-0.048	-0.091	-0.052	-0.058	-0.087	-0.058	-0.022
Emission	0.041	0.077	0.045	0.049	0.074	0.049	0.019
Income	1950.14	2400.32	1656.92	2196.43	2326.39	2095.34	2500.00
Concern	3.79	3.65	3.70	3.80	3.70	3.72	3.00

6.2.3.4 Education

This section discusses the existence and mechanism of an education (Question twenty-two: Education) effect on WTP. Regarding the existence of an effect, Figure 6.17 indicates that WTP was sensitive to the level of education, consistent with the literature (Abate et al., 2020; Buckell, Hensher and Hess, 2021; Beharry-Borg and Scarpa, 2010). However, against this graphical evidence is the statistical evidence that the education coefficient was never statistically significant in any of the CE or CV models, even when controlling for income. Therefore, the effect of education on WTP may be weakly positive but is not statistically significant. There are two possible mechanisms for this effect; income effects and knowledge. The relationship between education, knowledge, and WTP was discussed in Section 6.2.2.2 with the suggestion that education and knowledge may correlate, but the relationship to WTP is weaker. Education may influence WTP through income effects given the strong positive and statistically significant correlation between education and income (0.287, p =000) and with employment (0.273, p=0.000), as expected from the literature (Fransson and Garling, 1999). Furthermore, Figure 6.17 provides graphical evidence for the positive link between increased education, leading to higher income, leads to higher CV WTP. Curiously, the effect is more pronounced for Q7 and weaker for Q6; therefore, more highly educated respondents reported a higher premium for immediate precautionary abatement. For the CE MWTP, the effect reduced MWTP and more so on the performance attribute. This corroborates the ICLV result of emissions MWTP being higher than performance MWTP and suggests that more highly educated respondents were more willing to trade-off product attributes.

Figure 6.17: CV WTP by Q22 Education.

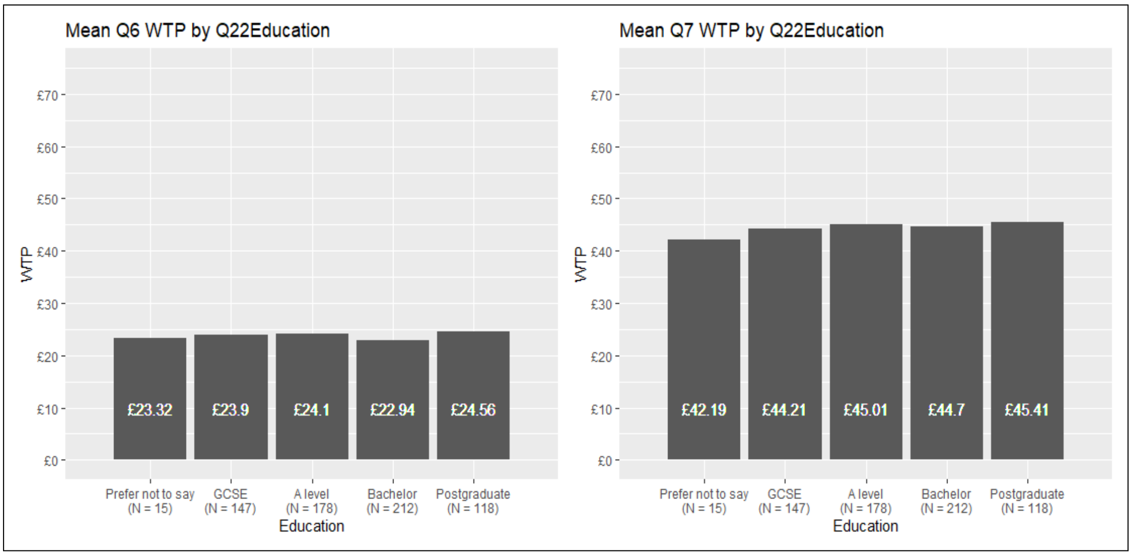
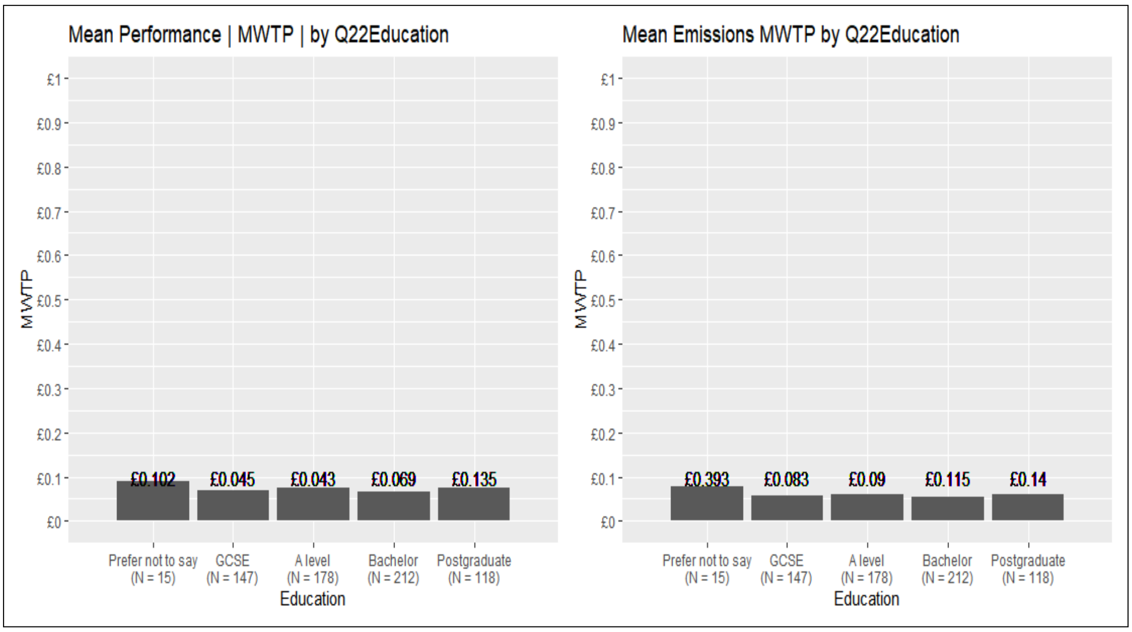


Figure 6.18: CE MWTP by Q22 Education.



6.2.3.5 Employment

Income effects also determine the effect of employment (Question twenty-three: Employment) on WTP. The effect of employment on WTP is expected to be positive and significant given increased income. Although the job sector is unobserved in this survey design, employment was observed using seven major categories roughly ordered according to weekly hours worked; prefer not to say, not in education, employment, or training (NEET), retired, student, part-time, self-employed and full-time. There is a positive relationship between income and employment and this is related to higher WTP. To summarise, education and employment both reported strong positive relationships with income and showed an increasing WTP for treatment. The following section explores income effects in greater detail.

Figure 6.19: Q23 Employment CV WTP.

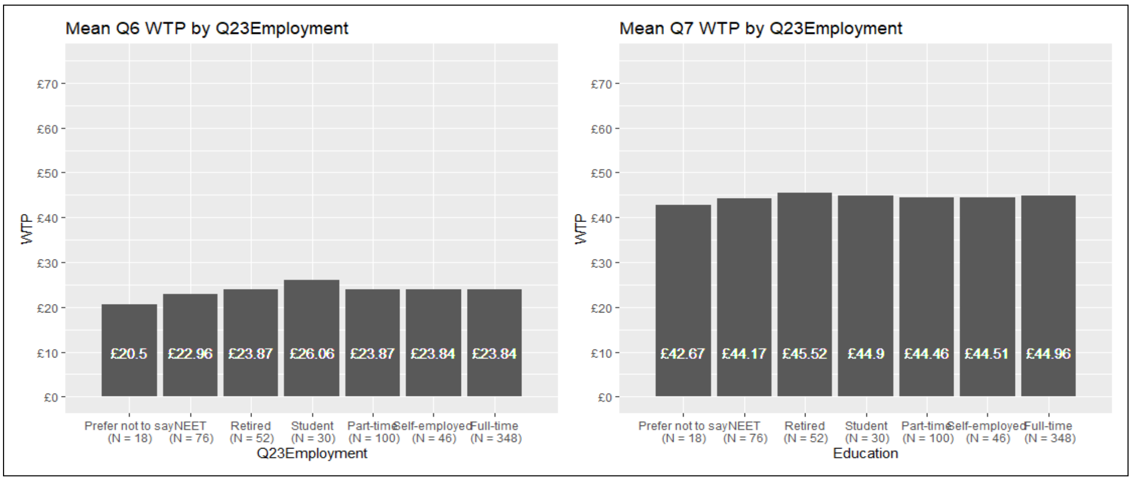
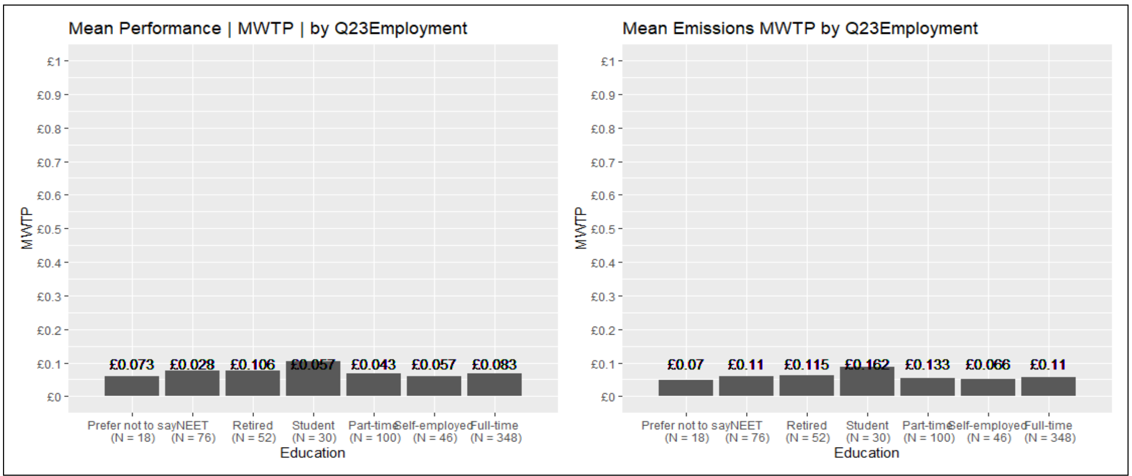


Figure 6.20: Q23 Employment CE MWTP.



6.3 Summary

This chapter has discussed the influence of each survey question on fitted CE and CV WTP. Particular focus is paid to the determinants and influences of the precautionary premium, which is shown to be always positive. The magnitude is highly sensitive to a multiplicity of factors, which usually act by increasing Q6 WTP. Chapter Seven now uses WTP to undertake a CBA of microplastic policies to illustrate the economic viability of precautionary abatement.

Economic Appraisal of Microplastic Policies.

Chapter Seven Abstract:

This chapter undertakes a cost-benefit analysis of three different policy options for microplastics. The policy options, researching the effects of microplastics, investing in WWTP filtration, and reformulating cosmetics, are those valued by respondents in the survey. The benefits are aggregated and predicted using the mean WTP values. The costs are estimated using available data and sensitivity analysis. Following the benefits, distributional weights are considered alongside the potential for benefits transfer of the WTP valuations and this research's policy implications. The chapter closes with a summary of the implications, directions for future work, and conclusion of the thesis.

7.1 Cost-Benefit Analysis

This section undertakes CBA of the three policy scenarios proposed to respondents in the survey; researching microplastics, upgrading WWTPs or reformulating cosmetics. The structure of this chapter is as follows. Firstly, the theoretical framework and practical assumptions necessary for CBA are established. Secondly, a range of costs is estimated using available data for each of the three policies. The WTP from each SP task is then aggregated to represent the total benefits of each policy. Discounting is then used to calculate NPV and report a conclusion about the economic viability of each option. Sensitivity analysis is used to evaluate the robustness of the results from the CBA. Cost-effectiveness analysis and distributional analysis are also provided for completeness of the policy appraisal. Finally, the results and their robustness are reported with regards to the policy implications for microplastic abatement.

7.1.1 Theoretical Framework

Chapter Two established a theoretical framework for CBA, which is restated and applied here. Firstly, CBA assumes that a policy's effect can be valued using individual utility differences (Atkinson et al., 2018a). The difference in utility can be valued in terms of what individuals are willing to pay (accept) for the resulting change from the status quo (Bateman et al., 2002). Therefore, the reduction in potential risks of health or environmental effects from marine microplastics can be measured in WTP terms. Although WTP is measured at the individual level, Bateman et al. (2002) argues that WTP can be aggregated to represent total benefits for society if the sample is representative of the population; a justifiable assumption for the sample used in this research. This research estimates the benefits in WTP terms while the costs are monetised using data from the economic and grey literature. Although WTP is typically elicited on a per annum basis, CBA compares the total estimated costs and benefits over the duration of the project lifetime (Whitehead and Blomquist, 2006). As project impacts extend into the future but are compared in present terms, the impacts must be discounted. Section 7.1.5.1 further motivates the use of discount rates and chooses an appropriate discount factor for this research. Finally, the net value of discounted costs and benefits, the NPV, is used to determine whether the policy should proceed; NPV>0 being the common rule (Traeger, 2014; Boardman et al., 2017). This decision rule implies that CBA omits the distribution of impacts (Nick and Ysé, 2006). This research, therefore, applies distributional weights to incorporate the incidence of impacts. A final consideration is the role of uncertainty and irreversibility, discussed further in Section 7.1.1.1 (Kuntz-Duriseti, 2004). To summarise, CBA monetises then aggregates all potential policy impacts before expressing in NPV terms the value of each outcome (Boardman et al., 2017; Bateman et al., 2002; Atkinson et al., 2018a).

CBA has several limitations when applied to the marine microplastic scenario. Firstly, CBA often ignores the role of uncertainty in decisions (Gollier and Treich, 2003). Uncertainty in this scenario concerns the extent, timing, and value of environmental and health effects from microplastics (ECHA, 2019). To control for this, the research explicitly asked respondents to consider uncertainty when completing the SP tasks. Furthermore, this research also elicited the benefits of undertaking research to resolve the scientific uncertainty. A second issue raised by Traeger (2014) is that CBA may not adequately incorporate the issue of irreversibility. The irreversibility effect enunciated by Arrow and Fisher (1974); Hanemann (1989) was discussed in depth by Courbage, Rey and Treich (2013) who noted that the irreversibility effect of the possibility of new information in the future is to increase the value of delaying a decision. While Ha-Duong (1998) incorporated irreversibility by estimating OV, this research estimated a precautionary premium that explicitly values the options that prolong and resolve irreversibility (Q6 and Q7, respectively). The result of a premium indicates that respondents preferred immediate abatement of the irreversible release of microplastics. A final issue is that CBA is focused on economic efficiency rather than the equity and incidence of potential policy impacts (Nick and Ysé, 2006). This chapter addresses these three challenges when undertaking an indicative CBA of microplastic policies.

7.1.1.1 Uncertainty, Irreversibility, and the Precautionary Principle

Any CBA of microplastic policy is complicated by the uncertainty about the severity of health effects and the irreversibility of releases (ECHA, 2019). Although uncertainty about impacts may be somewhat resolved using sensitivity analysis, another option may be to delay a decision and waiting until either nature or research reveals the severity of future impacts. Indeed, given the scientific uncertainty surrounding the health effects of microplastic ingestion, policymakers may wish to delay a decision on WWTP investment until the impacts are known with greater certainty. However, a delay would lead to more irreversibly released microplastics in the marine environment. Furthermore, the increasing release and concentration of microplastics and their persistence in the environment may indicate to policymakers that the future effects could be more severe (Lebreton, Egger and Slat, 2019). Therefore, there may be a trade-off between resolving uncertainty and resolving irreversibility in this context, which conventional CBA may omit.

ECHA (2019) suggested that the use of the Precautionary Principle can resolve the uncertainty-irreversibility trade-off. The Precautionary Principle suggests that the absence of certainty should not prohibit restrictions (Interdepartmental Liaison Group, 2002; Kuntz-Duriseti, 2004; Aldred, 2012). The precautionary principle is operationalised in this research by using the two CV questions. The two questions refer to resolving uncertainty (Q6) and resolving irreversibility (Q7), respectively, and one of the most important survey results is the robust positive difference between the WTP for the two CV tasks. The conceptualisation of the difference in valuations is similar to the precautionary premium characterisation of the precautionary principle outlined in Kuntz-Duriseti (2004). The premium is inherently precautionary as it resolves the uncertainty before any harm is possibly realised. This greater WTP for precautionary abatement may represent the increase in benefits from abating immediately rather than after research. To conclude, the CV design estimates a precautionary premium that can be used to compare two policy options; delaying to resolve uncertainty through research or immediately resolving irreversible releases via upgrading WWTP. The result of a precautionary premium in the WTP suggests that respondents support the precautionary principle, which argues that uncertainty should not preclude restrictions.

A final note should be made of Krutilla et al. (2021) discussion of deep uncertainty in CBA. Deep, or fundamental, uncertainty exists where even the probability distributions for unknown parameters are unknown or contested. Deep uncertainty applies to this research given the scientific uncertainty about the likelihood, timing, and severity of marine microplastic impacts on human health. Krutilla et al. (2021) used two methods to handle the issue of fundamental uncertainty in deep-sea mining. Firstly, Monte-Carlo simulation was used to estimate uncertain parameter values before a bounding analysis suggests the extent of the range of possible values. Together, these two methods can be used to estimate the probability that a project will be economically viable. In this research, the sensitivity analysis in Section 7.1.6 varies the parameters analogously to a Monte-Carlo analysis, while boundary analysis is used for the upper and lower bounds of the anticipated costs in Section 7.1.2. To summarise, the following CBA attempts to allow for deep uncertainty about the future impacts of marine microplastic pollution by estimating the sensitivity of the NPV to variations in the assumed costs and benefits.

7.1.2 Assumptions

This section states and critiques the assumptions necessary to appraise each different policy option. Starting with the operational level of the CBA, there are then three main assumptions. Firstly, the aggregation period is assumed to be ten years with a discount rate of 3.5% used for both costs and benefits. The policy length is the same as in the ECHA (2019) report, but generalising to a longer duration is possible. Although the choice of discount rate is motivated in Section 7.1.5.1, sensitivity analysis around this is undertaken to indicate that the conclusions are robust. Secondly, the number of UK households is assumed to be 27.8 million; the official 2020 UK government estimate. Although the survey did ask about household distance from the coast, the mixed results on distance-decay effects on WTP suggest any spatially-explicit aggregation of benefits, as in Jørgensen et al. (2013), would not qualitatively alter the conclusions. However, future work that explicitly includes distance from the coast in the design may attempt this alternative aggregation policy as WTP may be spatially sensitive (Badura et al., 2019; Glenk et al., 2020; Sparkman, Lee and Macdonald, 2021; Luisetti et al., 2011; Lanz and Provins, 2013). Finally, the WTP values are the point, lower and upper bounds estimated in Chapter Four and Five. Although the validity of these values has been defended in detail, there are two key caveats. Firstly, as the responses were elicited using SP techniques, hypothetical bias may inflate the responses. However, results were consistent when using the truncated sample where uncertain respondents were removed. Furthermore, it does not appear that RP methods would be viable, given the focus on non-market benefits, in place of SP. A second limitation is the sensitivity of WTP to elicitation formats, econometric strategies, sample sizes, question ordering, and pandemics. Therefore, future research using an alternative design may report different WTP values. This section now critiques the policy-specific assumptions used.

This research assumes that the research option's costs can be calculated using comparable large research projects and the cost of reduced ES while research is undertaken. However, there are two challenges to estimating the financial costs of research microplastics. Firstly, research may not fully resolve the uncertainty. Although respondents were told that the research would 'definitively' resolve the scientific uncertainty, Aldred (2012) notes that some degree of uncertainty may be inevitable. A second related challenge is uncertainty about the research itself. Research is an uncertain activity as there is no certainty on the timing, outcome, and reliability of any findings. Research only needs to indicate whether the effects are severe enough to warrant restrictions rather than resolving all issues. Moreover, research value should not be evaluated in isolation from the context of the trade-off between uncertainty and irreversibility. Specifically, any decision to delay abatement and undertake research implies the continuing release of microplastics. The cost of microplastics on marine ecosystem services, and by extension, the opportunity cost of research, is not well understood. Although Beaumont et al. (2019) estimated the value of marine plastics on ES, such as carbon sequestration, water provision and biodiversity, as \$3300-\$33,000 per tonne, this was not specific to microplastics. To summarise, the financial costs of research projects and the environmental cost of reduced ES are imprecisely calculated. Therefore, this research can only comment on the possible value of delaying abatement to facilitate research.

The WWTP investment scenario requires several assumptions about the upgrading of WWTP. Firstly, this research assumes the benefits are purely from reducing the release of intentionally added microplastics. However, the micropollutants retained by WWTP are not exclusively intentionally added microplastics but also microplastics from abrasions such as tyres and paints and other micro and nano pollutants. Therefore, any investment in WWTP would affect microplastics more broadly than just intentionally-added microplastics. See Logar et al. (2014) for an estimation of the total benefits of upgrading WWTPs rather than just the benefit of reducing microplastics. Secondly, this research assumes, for ease of calculation, that there is one technology that would upgrade WWTP to remove all microplastics from wastewater. Retaining more microplastics from effluent implies that more microplastics are present in sewage sludge. Sludge may be distributed to the terrestrial environment risking the further release of microplastics to the terrestrial, not aquatic environment (Burns and Boxall, 2018; Environmental Audit Committee, 2016). Secondly, in practice, upgrading WWTP would deliver only a marginal increase in the number of microplastics retained in sewage sludge. Indeed, Duis and Coors (2016) estimated that many WWTP are already highly efficient ($> 90\%$ microplastics retained) at capturing microplastics in influent, with the remaining proportion likely to be smaller nanoplastics. Indeed, upgrading would require all WWTP to use tertiary filtering, which would leave a small proportion of microplastics, possibly 5milligrams per litre, remaining in effluent. Currently, less than 50% of WWTP in the UK have primary (large objects screen), secondary (smaller pollutants), and tertiary (sand filters appear to be the best available technology) filtering stages and so the investment would not be uniform or simple but instead vary at the WWTP-level (Environmental Audit Committee, 2016). Moreover, there are different variants of tertiary filtering (sand, membrane, or other emerging technologies) and the choice of one to retain more microplastics may mean the WWTP then retains fewer other chemical pollutants. Given the inert nature of microplastics, investment in filtering may be best targeted at other pollutants. Additionally, upgrading WWTP to specifically retain the smallest microplastics may be costly if the costs are further along the marginal abatement cost curve. Indeed, investment to abate the final marginal microplastics in influent may be highly costly (Environmental Audit Committee, 2016). To summarise, any investment to upgrade WWTP would tackle a relatively small proportion of microplastics at high and uncertain costs. This research, therefore, assumes an extensive range of cost estimates to control for the uncertainty.

This research assumes the costs of a restriction are uncertain and adopts estimates from two sources who possess more complete knowledge. Specifically, Cosmetics Europe (C-E), an industry body, argued that the ECHA-estimated costs of reformulation and material costs were underestimated as they used the previous restriction on D4 and D5 rather than an accurate survey of the use of microplastics. This research assumes that the reformulation costs are calculated more precisely by C-E, who surveyed the industry on the number of formulations affected by any restriction on the use of microplastics in rinse-off, leave-on or all cosmetics. This research also assumes that the costs can be scaled to the UK market using market-share. Using market share to scale the market may miss important cost segment-specific differences and thus overstate the costs. However, sensitivity analysis reveals that the CBA conclusions are robust to re-scaling the costs or using the ECHA costs instead. Overall, the CBA for the restriction is the most challenging to compute, although the necessary caveats have justification.

One critical assumption for monetising the benefits of a restriction is the linearity of WTP for emissions reductions. This research scales the marginal values up linearly, whereas Chapter Four established that this would overstate total WTP given diminishing marginal utility. Therefore, the estimated benefits in this section may be overestimated. A second assumption is that the benefits are estimated by scaling the emissions attribute rather than including the performance attribute. This assumption is necessary as aggregation would require knowledge of the average price of individual personal-care products, the average amount of personal care products purchased per person annually in the UK and an understanding of the relationship between product performance and microplastic use in individual products. This relationship is not only product-specific, as some products such as sun cream are required to maintain their stated levels of protection and firm-specific as different firms will be differently able to invest in research and development to reformulate their products without microplastics. Overall, the relationship between product performance and the use of microplastics is sector, product and brand-specific. This research linearly scales the emission MWTP by 100 to report an upper bound of the per-product benefits. This may also overestimate benefits as it ignores any subsequent change in product performance. Overall, however, these assumptions facilitate an indicative CBA, and later sensitivity analysis suggests the robustness of CBA conclusions.

A final critical assumption regards the annual reduced tonnage of microplastics released from the UK to the marine environment. This figure is not currently known with certainty. The most accurate estimates come from Cosmetics Europe and ECHA, who estimated the tonnage of microplastics that would be reduced by the restriction of microplastics in cosmetics in affected European countries. ECHA reported a central estimate of 3750 (1700-5900) tonnes of microplastics would be reduced annually by the restriction. Cosmetics Europe estimated 4244 tonnes but not a range. This estimate and the ECHA range need to be scaled to the UK. Although scaling by the UK market size omits any industry-specific information about the current use of microplastics in the UK, this research calculates that the reduction in microplastics would be 551 (221 - 767) tonnes. This estimate can be adopted for the WWTP scenario to facilitate comparison, given the absence of other estimates. Indeed, the reduction in released microplastics from upgrading WWTP cannot be readily estimated. Firstly, ECHA (2019) reported that 50-100% of microplastics in cosmetics are disposed of similarly and can, therefore, reach WWTPs. ECHA (2019) also noted that 100% of detergents, paints, and most medicinal uses of microplastics were also disposed of down the drain. These estimates cannot as easily be scaled to the UK context given the different industries and uses. However, as the WWTP investment would only upgrade retention rates rather than begin filtration, it may be that the net reduction is the 551 tonnes of microplastics from other sources. This estimate is derived from the cosmetics restriction but may also apply to the WWTP scenario, given that the WWTP scenario implies a relative increase in retention but applies to microplastics from many sources. For example, retention rates in WWTP can already exceed 90%, so upgrading to remove the final 10%, as stated in the CV scenario, would deliver only a marginal reduction in the release of microplastics to the marine environment (Horton et al., 2020; Murphy et al., 2016). To summarise, this research assumes that the reduced tonnage of microplastics is 551 (221 - 767).

Overall, there are several limitations and necessary, but possibly unrealistic, assumptions necessary to calculate the indicative CBA. However, the robustness checks and sensitivity analysis indicate that addressing these limitations is not likely to adjust the conclusions. As the first CBA of marine microplastic abatement policies to include WTP elicited from SP tasks, this CBA indicates which policies may be economically viable. Future work with complete information about the costs, distribution of impacts, and monetised other benefits could estimate a broader range of impacts for the CBA. For completeness, Table 7.1 established the main categories of costs and benefits estimated in this CBA.

Table 7.1: Summary of the monetised impact categories.

Category	**Comments**	**Section**
Costs of research	Estimated using costs of existing research projects Plus lost ES	Section 7.1.3.1
Costs of WWTP	Estimated using reported costs of investing in WWTP	Section 7.1.3.2
Costs of restriction	Estimated by combining reformulation, raw materials, and other economic costs.	Section 7.1.3.3
Benefits of research	Valued using Q6 WTP. WTP represents the TEV of research.	Section 7.1.4.1
Benefits of WWTP	Valued using Q7 WTP. The benefits are total economic value.	Section 7.1.4.2
Benefits of restriction	Valued using CE MWTP.	Section 7.1.4.3

7.1.3 Estimated Costs

This section estimates the costs of the three policy options with Section 7.1.4 estimating the benefits.

7.1.3.1 Estimating research costs

This section estimates the costs of the research scenario proposed to respondents in Q6 of the survey. The challenge here is that no current research programme matches that described in the hypothetical CV scenario. Therefore, this research uses three examples of current research projects. For instance, a closely related project is the £20 million Plastics Research and Innovation Fund announced by UKRI. This fund invests in multiple research projects but is broader in scope than the survey scenario and, therefore, represents a viable comparison. A much larger research project, the EU Horizon2020 fund, could also be used as a cost estimate. The fund expected more than €100 million to be spent on research on plastics. This fund is again broader than the CV scenario but represents a plausible upper-bound value of a research project. To summarise, while no existing research project mirrors the Q6 CVM scenario, evidence from the field suggests that such a project would have costs in the tens of millions. This research, therefore, uses two existing projects to estimate the potential scale of costs. The result is an estimated cost of £20 million (the total value of the UKRI PRIF) with bounds ranging from £5 million (the value of a single large research project within the PRIF) to £100 million (the Horizon2020 funding).

An important element of the costs of research is the opportunity costs of lost ES. Specifically, research policy would delay a decision, and so the current adverse effects would continue and possibly worsen. Even if the research indicates that the effects are sufficiently severe to motivate a restriction, some ES value will have been lost while undertaking the research. However, there are several challenges to this category of costs. A first technical challenge is the aggregation of values. In particular, it is not clear how long it would take for research to definitively estimate whether damages are severe, and so the total reduction in ES is uncertain. Secondly, even if the timing was known, the value of reduced ES is not. Indeed, the exact effect of microplastics on UK marine ES has not yet been quantified with any certainty. Moreover, there are relatively few valuations of marine ES with Beaumont et al. (2019) perhaps the most comprehensive, albeit drawn from 2011 values and so may be outdated. While Beaumont et al. (2019) estimated values of \$3300 - \$33000 per tonne of marine plastics per year, this research adopts the lower bound of \$3300 per tonne per year.

However, there are several noteworthy caveats to this estimation. Firstly, the values are not specific to any area of service and may omit UK-specific differences in the impacts of microplastics. Secondly, the values were estimated by scaling Kumar (2012) estimates of the value of the marine ES in 2011 values by an arbitrary 1-5%. Beaumont et al. (2019) explicitly state that accurately quantifying the decline in ES from marine plastic is highly uncertain, which is why they adopt the wide range of 1-5%. However, they also believed the range to be the lower bound of the full impacts given the omission of economic costs, unavailability of specific valuations, and now the absence of a decades' worth of changes in the stock of marine plastics. Although the value is not spatially explicit or ecosystem specific, they indicate the opportunity costs of delaying a decision. Furthermore, the value per tonne is held constant at this level over time to smooth any time-variance in damages, although future research could introduce non-linearities into the costs (Luisetti et al., 2011). Section 7.1.2 discusses the validity of scaling this estimate to 551 (221 - 767) tonnes which would lead to an additional annual cost of £1,818,300 (£729,300 - 2,531,100). Therefore the total annual cost of researching microplastics can be initially estimated as £21.82 million (£5.73 million - £102.53 million).

7.1.3.2 Estimating WWTP Costs

Given the uncertainties described in Section 7.1.2, this research uses three different sources to estimate the costs of upgrading WWTP to remove a higher proportion of microplastics from their influent; see Table 7.2 for a summary. Initial estimates are in the billions of pounds, with water companies describing the costs as 'prohibitive' (Environmental Audit Committee, 2016). The best estimate of WWTP upgrade cost currently comes from Eunomia (2019). Their estimate of the approximate cost of upgrading WWTP in Europe to tertiary filtration was €1.49 billion (at time of writing: £1.37billion). This value is calculated with the most extensive detail and precision and is thus adopted. However, their scenario was broader in geographic scope than the UK proposal, so scaling may be overstating the costs. The second best estimate for the cost of upgrading WWTP comes from Logar et al. (2014). They reported that the total cost of a scheme in Switzerland to upgrade 123 WWTP to retain more micropollutants, though not specifically microplastics, was approximately $97 million annually. Converting this estimate to the UK requires currency converting and scaling by the number of WWTP in the UK, estimated to be in the thousands. Although both are possible, this estimate is less reliable than the Eunomia (2019) estimate as Logar et al. (2014) investigated non-specific upgrades for a limited number of WWTP. A third and final estimate comes from personal communication with the Environment Agency, who suggested upgrading costs were plant-specific and that retrofitting those existing plants without tertiary filtration could cost between £1 - 5 billion. The £1-5billion range fits with the Eunomia (2017) estimate and is close to the scaled estimate from Logar et al. (2014). However, the method to reach this estimate was expert deliberation rather than an engineering study, so maybe less precise. To summarise, this research uses three different sources to estimate that the cost of upgrading all WWTP in the UK to tertiary filtration designed to retain more microplastics is £1.37billion (£1billion - 5billion) in total.

Table 7.2: Summary of the estimated costs to upgrading WWTPs.

Source	Estimate	Scaling	Result
Eunomia (2019)	€1.49billion for upgrading all European WWTP to tertiary filtering.	At time of writing, €1 = £0.914	1.37billion
Logar et al. (2014)	Total cost of $97mn to upgrade 123 Swiss WWTPs	Multiplied by number of WWTP and then converting, $1 = £0.78	£920.91mn
Personal communication with the Environment Agency	£1 - £5 billion	None needed	£1bn - £5bn

7.1.3.3 Estimating the costs of a restriction.

The costs of a restriction on cosmetics were separately estimated by both the regulator, ECHA, and the industry body, C-E. The estimated costs from both are reported in Table 7.3 [19]. The estimated costs are then scaled from the European context to the UK using the size of the UK cosmetics market. The UK market is approximately 13% of the EU market (€10.7billion compared to €79.8billion annually). As discussed in Section 7.1.2, scaling the estimates using the size of the market may omit product, firm, and UK-specific cost differences. These differences include the possibility that the UK market has already adapted to the 2018 microbeads restriction in cosmetics (DEFRA, 2017), may have stockpiled raw materials ahead of leaving the EU, or may experience different economic costs as a result of a reformulation. Therefore, the scaling of UK costs may be inaccurate, although the direction of the bias is unclear.

Table 7.3 uses a different approach to balancing the two cost estimates per category. The C-E point estimate is used for the reformulation costs, given greater industry insight using their survey. However, the ECHA bounds are also used as C-E did not report any uncertainty range. For raw materials, the C-E point estimate is below even the lower bound that ECHA estimated. Therefore, the C-E estimate is used as the lower bound with the point, and the upper bound used from ECHA. For other economic costs, such as unemployment and lost profits, the estimates were orders of magnitude different. Indeed, the difference between ECHA and C-E is evident here as ECHA believed the costs would reach €100,000 annually while C-E estimate was €2.2billion. This research split and scaled the difference; 13% of (€2.2billion - €100,000) in GBP [20]. While no confidence intervals were reported, this research calculates 95% confidence intervals for completeness. Finally, while the discrete categories do not sum to the total, the total estimated costs in this CBA use the scaled C-E point estimate and the ECHA upper and lower bounds. The wide reporting range in the estimates alleviates some of the uncertainty about the validity of the estimates. To summarise, the ECHA restriction is assumed to cost £1.01billion (£213mn - £2.5billion) for the UK cosmetics industry.

[19] The ECHA estimates are available from Table 25 of their proposal for a restriction; see ECHA (2019). The C-E estimates use an industry survey. The provenance of the data is the industry response to the restriction proposal, which is not publicly available but was kindly supplied for this research by the CTPA. The data used to scale the estimates is available here `https://cosmeticseurope.eu/cosmetics-industry/#:~:text=Valued%20at%20%E2%82%AC79.8%20billion,the%20largest%20in%20the%20world.`.

[20] All euro estimates were converted to GBP at the rate of €1 = £0.914.

Table 7.3: Summary table of the estimated costs of a restriction on microplastics.

Category	ECHA Estimate	Cosmetics Europe (C-E) Estimate	Agreed Estimate in €annually	**Scaled UK value in £per annum**
Reformulation	€8.4billion (€1.63 billion - €15.3 billion)	€6.276billion	€6.27bn (€1.63bn - €15.3bn)	£746mn (£193.14 mn - £1.81billion)
Raw materials	€46.6mn (€20.4 million - €72.4 million)	€3.4mn	€46.6mn (€3.4mn - €72.4mn)	£5.52 mn (£0.40mn - £8.58mn)
Other economic costs	€0.1 million	€2.2billion	€1.09bn (€1.04bn - €1.15bn)	£136mn (£123mn - £136mn)
Total	€8.5billion (€1.65 billion - €16.5 billion.)	€8.549billion	€8.55bn (€1.65bn - €16.5bn)	£1.01billion (£196mn - £1.96billion)

7.1.4 Estimated Benefits

This section estimates the non-market benefits of the three policy options by aggregating individual-level WTP. As the CVM WTP represents total economic value, other benefit categories are excluded to avoid overstating the benefits through double-counting (Loomis, 2010; Atkinson et al., 2018a). Furthermore, only the MWTP of the emissions attribute is included given uncertainty about the product, firm, sector-specific differences in the trade-off between product performance and emissions. However, if the performance attribute was included, the benefits are likely to be far smaller, if not negative, given the relatively larger WTA for product performance.

7.1.4.1 Estimating research benefits

Starting with the research option from the two CVM scenarios, a purely indicative benefit of UK research into the effects of all microplastics can be crudely calculated using mean (note not median) WTP of £77.10 (£72.35 - £82.23) and the number of UK households (27.8 million) to reach £2.14bn (£2.01bn - £2.28bn) total annual benefit. However, there are challenges to the validity of this estimate. Firstly, the value is almost a sixth of the total UKRI annual budget, a huge proportion for a single research area. Secondly, the WTP is in annual terms while research budgets may be many years, and the WTP may change over the project duration. Indeed, future work can address the non-linearity and specificity of the benefits. Although the WTP values had only minimal differences between econometric model specifications, sensitivity analysis and confidence intervals are used to control for the uncertainty. The benefits of research are calculated in this research to show substantial benefits to delaying any decision.

7.1.4.2 Estimating WWTP Benefits

This section estimates the non-market benefits of upgrading the filtration ability of WWTP. Benefits are calculated by scaling the annual WTP from Q7 of the SP survey. Using the mean Q7 WTP from the DBDC bid-only model using the full sample of £85.50 (£83.11 - £88.12) crude multiplication by the number of UK households (27.8 million) suggests UK WTP of £2.46bn (£2.31bn - £2.61bn). Mean, not median, WTP from the full sample is required for nationally-representative CBA (Atkinson et al., 2018a). Section 7.1.6 evaluates how sensitive the NPV of upgrading WWTP is to the definition and estimation of the benefits.

7.1.4.3 Estimating the benefits of a restriction.

As the CE elicited WTP for a marginal 1% change in product attributes rather than the per-household per-year CV WTP, the aggregation is more challenging. For instance, it is unclear how consumer demand would react to marginal changes in cosmetic prices. To estimate the benefits, the annual value of UK sales of suncream (£279mn) is divided by the average price of a bottle of suncream (£11.78) to reach 23mn units [21]. The number of units can then scale the marginal WTP to reach a total annual UK marginal value of changes to cosmetic products. The mean MWTP for a change in emissions is £0.036 (£0.034 - £0.039). A total per-product WTP can then be estimated as £3.60 (£3.40 - £3.90). Multiplying by the estimated 23mn units leads to a total annual UK WTP of £82.8mn (£78.2mn - £89.7mn). This assumes a linear aggregation of MWTP rather than including any scope elasticity and diminishing marginal utility in the MWTP. Section 7.1.6 reports how the NPV changes when using the elasticities calculated in Chapter Four. Furthermore, the marginal WTA for the product performance attribute is omitted here as the microplastic-performance relationship is uncertain.

This section has detailed the procedure and assumptions to estimate each policy option's annual costs and benefits. The estimates can be used to calculate and undertake a sensitivity analysis of the NPV.

[21] 23,684,210 units precisely but rounding down to 23mn exactly is plausible given that higher-quality suncream can be priced much higher than the average.

Table 7.4: Summary table of the annual costs and benefits per scheme.

Scheme	Researching microplastics	Upgrading WWTP	Reformulating cosmetics
Annual Costs	£21.82 million (£5.73 million - £102.53 million).	£1.37 billion (£1 billion - £5 billion)	£1.01 billion (£213 million - £2.5 billion)
Annual Benefits	£2.14 billion (£2.01 billion - £2.28 billion)	£2.46 billion (£2.31 billion- £2.61 billion)	£82.8 million (£78.2 million - £89.7 million)
Discounted Costs	£187.81 million (£49.32 million - £882.56 million)	£11.79 billion (£8.61 billion - £43.04 billion)	£8.69 billion (£1.83 billion - £21.52 billion)
Discounted Benefits	£18.46 billion (£17.31 billion - £19.67billion)	£21.16 billion (£19.92 billion - £22.47 billion)	£712.72 million (£673.12 million - £772.11 million)
Net Annual Benefits	£2.12 billion (£2.01 billion - £2.18 billion)	£1.08 billion (£1.31 billion - -£2.39 billion)	-£927 million (-£134.8 million - -£2.41 billion)
Net Present Value	£18.26 billion (£17.26 billion - £18.79 billion)	£9.37 billion (£11.31 billion - -£20.57 billion)	-£7.98 billion (-£1.16 billion - -£20.74billion)
Benefit:Cost Ratio	98 (350- 22)	1.79 (2.31 - 0.52)	0.08 (0.36 - 0.04)

7.1.5 Estimated NPV

Thus far, the costs and benefits have been in annual terms and need to be aggregated over the policy lifetime before being discounted (Atkinson et al., 2018a). Thus, discounting facilitates the calculation of policy-specific NPV. However, there is substantial debate around the appropriate choice of the discount rate.

7.1.5.1 Discounting

To compare distant future values with current values, given present bias, the costs and benefits must be discounted over the expected duration of the project (Dunn, 2012; HM Treasury, 2018; Frederick, Loewenstein and O'Donoghue, 2002; Thaler, 1981). Present bias favours immediate values at the expense of future ones and is reflected in higher discount rates. Since this research assumes a ten-year duration of impacts for any policy, consistent with ECHA (2019), discounting is necessary to accurately represent the future benefits of reductions in the release of microplastics. However, there are two challenges to selecting the appropriate choice of discount rate. Firstly, assuming a constant discount rate across the whole sample may omit individual heterogeneity in time preferences. Secondly, different discount rates may be used for different categories of impacts (HM Treasury, 2018). The choice of discount rate for economic impacts is typically lower than that for purely financial impacts as economic impacts accrue more slowly and thus have a longer duration than financial impacts. Table 7.5 chooses three different discount rates, a very low 1%, a mid-range 3.5% commonly used for scaling economic impacts, and a much higher 8% as an upper bound. The central value of 3.5% was recommended by the UK Treasury guidance for appraisals and is used across this research HM Treasury (2018). It is also comparable to the 4% used in Logar et al. (2014). The bounds were recommended by Zhuang et al. (2007) review of discount rates used worldwide. Zhuang et al. (2007) observed that within the EU, discount rates between 1-8% had been used previously for different types of impacts and projects. Therefore, there is justification for the upper (8%) and lower (1%) bounds. Although Howard, Whitehead and Hochard (2020) noted that previous stated preference surveys had calculated individual discount rates in excess of 10%, Egan, Corrigan and Dwyer (2015) noted that rates in the range of 3 - 10% are more commonly observed in the environmental economics literature. The three discount rates are applied to the net annual value from Table 7.4. The NPV is calculated over a ten year period which appears reasonable and is consistent with ECHA (2019) projections, although the benefits may extend beyond that. The sensitivity analysis indicates that the CBA conclusions are robust to the discount rate choice.

Table 7.5: Results in NPV-terms of different discount rates.

Scheme	1% Discount	3.5% Discount	8% Discount
Researching microplastics	£20.29 billion (£19/18 billion - £20.88 billion)	£18.26 billion (£17.26 billion - £18.79 billion)	£15.37 billion (£14.53 billion - £15.82 billion)
Upgrading WWTP	£10.41 billion (£-22.86 billion - £12.57 billion)	£9.37 billion (£-20.57 billion - £11.31 billion)	£7.88 billion (£-17.32 billion - £9.52 billion)
Reformulating cosmetics	- £8.87 billion (-£1.29 billion - -£23.05 billion)	- £7.98 billion (- £1.16 billion - - £20.75 billion)	-£-6.72 billion (-£0.97 billion - -£17.47 billion)

7.1.5.2 NPV Summary

To summarise Table 7.5, the NPV for both CVM scenarios is positive, while the NPV for the CE scenario is negative. The high NPV for research suggests that there is a substantial value to delaying a decision. Despite the high Q7 WTP, the economic viability of upgrading WWTP to retain more microplastics from the effluent is highly sensitive to the estimated costs. Indeed, the substantial capital and operation costs and the doubts about the technology to adopt suggests that the WWTP costs may be uncertain. Finally, the CBA of the ECHA restriction proposal yielded a negative NPV which suggests that it is not economically viable. The negative NPV is consistent with both ECHA and C-E believing that reformulation was a costly option given high abatement costs. The implication of negative NPV, alongside all the caveats necessary to reach that conclusion, is a vote against source-control of microplastics and indicates that economic benefits are larger when controlling effluent. To summarise, there are two notable results of the calculated NPV. Firstly, respondents prefer immediate precautionary action, and secondly, NPV is higher for effluent control over source control.

7.1.6 Sensitivity-Analysis

The CBA's robustness to varying the assumptions can be analysed using sensitivity analysis (Vigsø, 2004). Similarly to Logar et al. (2014), sensitivity analysis is used in this research to examine how the NPV changes with the WTP values, the assumed costs and the choice of the discount factor. Confidence intervals are reported in Table 7.4 and Table 7.5 for the discount rate choice. Two more techniques are presented in this section; determining how different the WTP would have to be to alter the CBA conclusions and evaluating NPV when changing the assumptions about the variables values(Atkinson et al., 2018a).

7.1.6.1 Sensitivity to WTP

This section estimates the change in WTP necessary to change the sign of each policy's NPV. The results indicate that the NPV is robust to design and econometric differences in eliciting WTP. To determine the minimum WTP to change the sign of the NPV in the research scenario (Q6), the estimated annual costs, £21.82 million (£5.73 million - £102.53 million), can be divided by the number of households (27.8 million). This leads to £0.78 (£0.21 - £3.69) per household per year. Compared to the elicited median WTP of £77.10 (£72.35 - £82.23) this is a change of -98.98% (-99.71% - -95.55%). Therefore, the sign of the NPV is robust to even substantial reductions in WTP. At the current level of costs, delaying a decision to facilitate research on microplastics appears to be a highly economically viable option, given how low WTP would have to be to change the conclusions.

The same process can be used to evaluate the robustness of the WWTP investment scenario (Q7). The annual costs of £1.37 billion (£1 billion - £5 billion) divided by the assumed number of households (27.8 million) results in break-even WTP of £49.28 (£35.97 - £179.87). This represents a change of -44.27% (-56.78% - +91.57%) when compared to the elicited median WTP of £88.43 (£83.23 - £93.92). Although the changes in WTP necessary to change the sign of the NPV are smaller than those for Q6, many specifications, especially the ICLV, which includes the influence of a latent precautionary attitude, report higher WTP and, therefore, the benefits may be understated. Indeed since WTP is sensitive to order, sample, and question format, the required 30-40% decrease or 134% increase are possible, albeit unlikely. Regardless, the smaller necessary changes and sensitivity of WTP underscore the uncertainty in the economic viability of effluent control. Therefore, the NPV of the WWTP upgrading policy is somewhat sensitive to large changes in WTP.

Finally, sensitivity analysis for the estimated benefits of the ECHA restriction requires dividing the annual costs, £1.01 billion (£213 million - £2.5 billion) by the number of products, 23 million, to reach a total per-product WTP of £43.91 (£9.26- £108.70). Divided by 100 to reach MWTP yields £0.43 (£0.09 - £1.08). Although the aggregation procedure of WTP ignores the possibility of diminishing marginal utility and aggregating by the number of products sold may overstate the benefits, the +1094% (+164% - +2669%) change from the unit values elicited in this research necessary to outweigh the higher costs of reformulating cosmetics suggests that reformulation is not likely to be economically viable. Therefore, the negative NPV of source-control is robust to large changes in WTP.

7.1.6.2 Sensitivity to assumptions

This section evaluates the sign of NPV when changing the assumptions about the costs of each policy. Tables 7.6, 7.7 and 7.8 report both NPV and B: C ratio with plus or minus five, ten, or twenty per cent changes in the benefits (rows) and costs (columns). Negative NPV values suggest the possibility for the project to be a net loss, while a BC ratio below unity also implies that the project is an inefficient use of resources. The research policy is shown to report a positive NPV. Moreover, the B: C ratios were high, even when accounting for substantial changes to the costs and benefits. The WWTP policy is also robust to even large changes in the values. There is, however, one exception where NPV changes sign. This is possible for a 20% reduction in benefits, definitely plausible when eliciting WTP, and a 20% increase in the costs, which is also plausible given the uncertainty about the upgrade costs. In this scenario, the B: C ratio falls below one with a slightly negative NPV. Therefore, the economic viability of the WWTP is robust to all but large changes in the values. Finally, the cosmetics reformulation policy is always shown to have a negative NPV and B: C ratio closer to zero than one. Even with lower costs and a significant increase in MWTP, the B: C ratio indicates that benefits may amount to fewer than 12% of the estimated costs. The estimated restriction costs were scaled from EU to UK basis Using a single scaling factor, the 13% value of UK sales compared to EU, used in Table 7.3. However, using one factor may omit country, firm, and product-specific differences in the proposed restriction's compliance costs. Therefore, Table 7.8 used a range of different scaling factors to test the robustness of the cosmetics NPV to changes in the costs. The results suggest that the NPV was highly robust to the scaling factor used. Therefore, effluent control is again preferred to source control.

One element missing from the above sensitivity analysis is testing the robustness of NPV to scope sensitivity in the MWTP. Specifically, Chapter Four calculates a scope-elasticity of WTP of 0.24 for the emissions attribute. Therefore, linearly scaling MWTP by 100 ignores diminishing marginal utility, and the per-product benefits may then be overstated. Therefore, after scaling the unit MWTP values by 100, this research applies the attribute-specific calculated scope elasticity of 0.24. For example, the reported MWTP for a change in emissions was reported from the MXL as £0.036 (£0.034 - £0.039). Incorporating scope sensitivity yields per-product WTP as £0.86 (£0.82 - £0.94) instead of £3.60 (£3.40 - £3.90); a difference of 76%. Aggregating the scope-adjusted WTP by the estimated 23mn units leads to a total annual UK WTP of £19.78mn (£18.86mn -

£21.62 mn). As the NPV was negative with possibly overestimated MWTP, the lower WTP results in a far less viable project with NPV of -£8.52bn (£1.67bn - £21.33 bn) and B:C ratio of 0.02 (0.09 - 0.01). Therefore, even when including diminishing marginal utility in the MWTP, the original conclusion of negative NPV for source-control is robust.

Overall, adjusting the impacts indicates the robustness of the NPV of the research (Q6) and source-control (CE) policies and the effluent-control (Q7) policy's sensitivity to cost overruns.

Table 7.6: Sensitivity Analysis of the Research Policy NPV and B:C ratio.

NPV in billions							
Benefits/Costs	**-20%**	**-10%**	**-5%**	**0**	**+5%**	**+10%**	**+20%**
-20%	14.61	14.59	14.58	14.57	14.56	14.55	14.53
-10%	16.45	16.43	16.42	16.41	16.40	16.40	16.38
-5%	17.37	17.35	17.35	17.34	17.33	17.32	17.30
0	18.30	18.28	18.27	18.26	18.25	18.24	18.22
+5%	19.22	19.20	19.19	19.18	19.17	19.16	19.14
+10%	20.14	20.12	20.11	20.10	20.09	20.08	20.07
+20%	21.99	21.97	21.96	21.95	21.94	21.93	21.91
B:C Ratio							
-20%	98.22	87.31	82.71	78.57	74.83	71.43	65.48
-10%	110.50	98.22	93.05	88.40	84.19	80.36	73.66
-5%	116.64	103.68	98.22	93.31	88.86	84.82	77.76
0	122.78	109.14	103.39	98.22	93.54	89.29	81.85
+5%	128.92	114.59	108.56	103.13	98.22	93.75	85.94
+10%	135.06	120.05	113.73	108.04	102.90	98.22	90.03
+20%	147.33	130.96	124.07	117.86	112.25	107.15	98.22

Table 7.7: Sensitivity Analysis of the WWTP Policy NPV and B:C ratio.

NPV in billions							
Benefits/Costs	**-20%**	**-10%**	**-5%**	**0**	**+5%**	**+10%**	**+20%**
-20%	7.49	6.31	5.72	5.13	4.54	3.95	2.78
-10%	9.61	8.43	7.84	7.25	6.66	6.07	4.89
-5%	10.67	9.49	8.90	8.31	7.72	7.13	5.95
0	11.72	10.54	9.95	9.37	8.78	8.19	7.01
+5%	12.78	11.60	11.01	10.42	9.83	9.24	8.06
+10%	13.84	12.66	12.07	11.48	10.89	10.30	9.12
+20%	15.96	14.78	14.19	13.60	13.01	12.42	11.24
B:C Ratio							
-20%	1.79	1.59	1.51	1.44	1.37	1.30	1.20
-10%	2.02	1.79	1.70	1.61	1.54	1.47	1.35
-5%	2.13	1.89	1.79	1.70	1.62	1.55	1.42
0	2.24	1.99	1.89	1.79	1.71	1.63	1.50
+5%	2.35	2.09	1.98	1.88	1.79	1.71	1.57
+10%	2.47	2.19	2.08	1.97	1.88	1.79	1.64
+20%	2.69	2.39	2.27	2.15	2.05	1.96	1.79

Table 7.8: Sensitivity Analysis of the Restriction NPV and B:C ratio.

NPV in billions							
Benefits/Costs	-20%	-10%	-5%	0	+5%	+10%	+20%
-20%	-6.38	-7.25	-7.69	-8.12	-8.56	-8.99	-9.86
-10%	-6.31	-7.18	-7.62	-8.05	-8.49	-8.92	-9.79
-5%	-6.28	-7.15	-7.58	-8.02	-8.45	-8.89	-9.76
0	-6.24	-7.11	-7.55	-7.98	-8.42	-8.85	-9.72
+5%	-6.21	-7.08	-7.51	-7.95	-8.38	-8.81	-9.68
+10%	-6.17	-7.04	-7.48	-7.91	-8.34	-8.78	-9.65
+20%	-6.10	-6.97	-7.40	-7.84	-8.27	-8.71	-9.58
B:C Ratio							
-20%	0.08	0.07	0.07	0.07	0.06	0.06	0.05
-10%	0.09	0.08	0.08	0.07	0.07	0.07	0.06
-5%	0.10	0.09	0.08	0.08	0.07	0.07	0.06
0	0.10	0.09	0.09	0.08	0.08	0.07	0.07
+5%	0.11	0.10	0.09	0.09	0.08	0.08	0.07
+10%	0.11	0.10	0.09	0.09	0.09	0.08	0.08
+20%	0.12	0.11	0.10	0.10	0.09	0.09	0.08

7.1.7 Cost-Effectiveness Analysis

As a final element of the policy appraisal in this chapter, an indicative cost-effectiveness ratio can be calculated for each scenario. The exception is the research scenario (Q6) which proposed no reduction.

Table 7.9 reports that the estimated measure per kilogram is 1833 (884 - 2555) £/kg. This value is arrived at by using the estimated 551 (221 - 767) tonnes reduction estimated by scaling the Cosmetics-Europe and ECHA figures discussed in Section 7.1.2. The resulting pounds per kg cost-effectiveness estimate is higher than that estimated by both Cosmetics Europe and ECHA and suggests that the restriction is relatively cost-ineffective.

Adopting the 551 tonnes assumption for the WWTP scenario then facilitates comparison with the source-control measure. Assuming then, caveats included, that the volume of microplastics removed by the WWTP plan is 551 tonnes, the £/kg is 2486 (4524 - 6519). In this measure, the effluent control via upgrading WWTP appears to be less cost-effective than source control. However, as the estimated tonnage of microplastics retained by WWTP was estimated imprecisely, this conclusion is highly sensitive to the assumptions. To summarise, a cost-effectiveness ratio can be calculated imprecisely and suggests that none of the options is particularly cost-effective.

Table 7.9: Cost-effectiveness of the cosmetics restriction.

Category	Estimate
Source-Control	
Costs	£1.01billion (£195.51mn - £1.96billion)
Tonnes	551 (221 - 767)
Pounds per kg	1833 (884 - 2555)
Effluent-Control	
Cost	£1.37 billion (£1 billion - £5 billion)
Tonnes	551 (221-767)
Pounds per kilo	2486 (4524 - 6519)

7.1.8 Distributional Analysis

Although CBA is primarily concerned with the efficiency of an allocation of resources, the political economy of CBA increasingly requires consideration of the equity of the allocation (Atkinson et al., 2018a). The incidence of policy impacts affects environmental CBA in three ways. Firstly, pollution may be distributed regressively and, therefore, have a disproportionate impact on poorer socioeconomic groups (Tol, 2001). Secondly, some pollution abatement policies can be regressive in their impacts (Kallbekken and Aasen, 2010; Gianessi, Peskin and Wolff, 1979). Thirdly, as WTP is a function of income, wealthier socioeconomic groups are over-represented in the benefits (Barbier, Czajkowski and Hanley, 2017). These three effects imply that CBA must consider the distribution of costs and benefits of pollution abatement. Economists have traditionally evaluated the incidence of impacts using the Kaldor-Hicks compensation criteria, which suggests that a policy is viable if those who gain from a policy are theoretically able to compensate those who lose from a policy and still be better off than the status quo (Atkinson et al., 2018a). However, the Kaldor-Hicks rule does not require any redistributive efforts and is, therefore, a weak treatment of the inequitable distribution of policy impacts. In practice, there are two different approaches to including the distribution of impacts in CBA. Firstly, both UK (HM Treasury, 2018) and European (ECHA, 2008) policymakers suggest estimating and presenting the incidence of costs and benefits on different socioeconomic groups, stakeholders, and spatial areas. Secondly, distributional weights may actively incorporate the distribution of impacts into CBA (HM Treasury, 2018). In this research, Chapter Four reports the WTP disaggregated by different subsamples, and the remainder of this section calculates distributional weights.

Distributional weights, weighting the impacts on different subgroups, allow the calculation of distribution-adjusted NPV and thus are an active treatment of distributional issues in CBA (HM Treasury, 2018; Pearce, 2003; Cowell and Gardiner, 2000). At the theoretical level, Nick and Ysé (2006) illustrates how distributional weights can be calculated and incorporated in a social welfare function. At the practical level, Atkinson et al. (2018a) reported two different approaches to deriving appropriate distributional weights; implicit and explicit weights. Implicit weights are less commonly used as they only indicate how impacts would have to be weighted to change the sign of NPV and only consider two subgroups. By contrast, explicit weights set out to weight different groups in the analysis and then evaluate the NPV. While weights are typically calculated at the subgroup level, this research estimates both implicit and explicit weights at the individual level to account for the individual-level distribution of impacts.

7.1.8.1 Implicit Weights

Implicit weights calculate what the weight would have to be to change the sign of the NPV (Nick and Ysé, 2006). This approach may be appropriate where there is a debate on the appropriate weighting of different subgroups (Atkinson et al., 2018a). This research calculates implicit weights following Atkinson et al. (2018a) procedure. Their procedure is reported in Equation (7.1.1) where the implicit weight for high-income respondents $\alpha_{High-Income}$, that is, respondents with self-reported gross monthly income above the sample median (£2159), is calculated by dividing the Net Benefits of the low-income part of the sample by the net benefits of those from the high-income part of the sample (Atkinson et al., 2018a; Loomis, 2010). Table 7.10 reports the net present value of each policy for both low and high-income groups and divides those to calculate the implicit weight on high-income respondents necessary to change the sign of the NPV.

$$\alpha_{High-Income} = \frac{NB_{Low-Income}}{NB_{High-Income}} \tag{7.1.1}$$

Similarly to Krutilla (2005) tableau format, Table 7.10 reports the NPV for each policy using point estimates and a confidence interval. This presentation of the benefits for each policy and group is consistent with both ECHA (2008) and HM Treasury (2018) suggestions that distributional impacts should be presented, although HM Treasury (2018) argues that these should be explicitly weighted. Calculating implicit weights requires the net benefits for each group. The NPV for low and high-income respondents is calculated in three steps. Firstly, the median fitted WTP for low and high-income respondents is calculated and reported in Table 8.11 in the Appendix. Following the process in Section 7.1.4, the estimated benefits are aggregated to the national level, the estimated costs are subtracted, and the difference is then discounted using the 10-year, 3.5% rate in Section 7.1.5.1 to calculate NPV in £billion terms. This method indicates that net benefits vary significantly between low and high-income respondents. As there was no a priori information on the distribution of costs, this approach equally disaggregates the costs and ignores subgroup variation. Therefore, the implicit weights are not as reliable as those estimated with complete information on the incidence of the policy costs. Finally, the implicit weights are calculated as the ratio of the NPV of each policy for low and high-income groups (Atkinson et al., 2018a).

The implicit weight on high-income respondents for the research policy was calculated as 0.48 (0.38 - 0.52), which suggests that the benefits of above-median income respondents would have to be weighted substantially downwards to change the sign of the NPV. This

Table 7.10: Net Benefits and Implicit Weights by income brackets.

Policy	Q6: Research			Q7: Treatment			Emissions: Source Control		
Category	**Low**	**Point**	**High**	**Low**	**Point**	**High**	**Low**	**Point**	**High**
Sample:	17.26	18.26	18.94	11.31	9.37	-20.56	-1.16	-7.98	-20.75
Low-Income:	18.11	19.59	20.83	9.94	8.44	-20.63	-1.28	-7.91	-20.85
High-Income:	25.61	29.09	33.37	17.05	17.49	-8.78	-1.40	-8.19	-20.96
Implicit Weight	0.71	0.67	0.62	0.58	0.48	2.35	0.91	0.96	0.99

finding suggests that the previous results indicating that research is a highly economically viable policy is robust to the distributional weighting of the net benefits (Nick and Ysé, 2006; Atkinson et al., 2018a). The weights for the treatment policy were 0.32 (0.46 - 1.31), which again suggest that the policy is likely to be economically viable unless low-income respondents are strongly overweighted. However, this scenario does not appear robust to accounting for the distribution of impacts given the 1.31 weight for the high-cost scenario. If the costs of upgrading WWTP were substantially higher than previously estimated, the NPV becomes negative and is lowest for the low-income respondents. This result indicates that the benefits of the treatment scenario may be distributed regressively. Finally, the implicit weights for the source control measure evaluated using the CE range from 0.96 (0.91 - 0.99), suggesting nearly equal weighting of both income groups. Although the NPV is always negative, the benefits appear to be marginally higher for lower-income groups. To summarise, implicit weights can be calculated using the net benefits of low and high-income respondents. The results for the research and source control policies show that previous findings were robust to distributional analysis. However, the treatment scenario is again dependent on the estimated costs.

7.1.8.2 Explicit Weights

There are two justifications for alternatively using explicit weights. Firstly, Layard, Mayraz and Nickell (2008) argues that explicit distributional weights can scale individual-level benefits to appropriately represent wealth differences in the sample and population. Secondly, Hökby and Söderqvist (2003) argued that explicit weights are appropriate where the income elasticity of WTP is less than one, as established in Chapter Four. Income elasticity is relevant here as WTP is a positive function of income and, therefore, higher-income respondents report higher WTP but may actually be less concerned for the policy. Therefore, explicit weights can be used in the CBA to consider income differences when scaling WTP (Atkinson et al., 2018a). Equation 7.1.2 calculates explicit weights.

$$a_i = \left(\frac{\bar{Y}}{Y_i}\right)^e \tag{7.1.2}$$

In Equation 7.1.2, adapted from Atkinson et al. (2018a), $\bar{Y}$ represents mean sample gross monthly income of £2192, Y_i is individual income and e is the elasticity of the marginal utility of income. While implicit weights use net benefits as they aim to adjust the NPV of a policy, explicit weights are estimated using individual income as they aim to adjust individual impacts (Loomis, 2010; Nick and Ysé, 2006; HM Treasury, 2018). In this research, the sample mean and individual-level income are known, so the equation's key parameter is e the elasticity of the marginal utility. This parameter can also be interpreted as a degree of income inequality aversion at the societal level (Pearce, 1998). In unweighted CBA, the parameter is set to zero to weight each individual equally. However, in weighted CBA, there is a debate on the appropriate magnitude of the parameter. For instance, reviews in Cowell and Gardiner (2000); Nick and Ysé (2006); Layard, Mayraz and Nickell (2008) report plausible ranges of 0.5-4 (broad) or 1.2-1.4 (narrow), 0.5-1.5, and 1.19-1.34 respectively. Finally, HM Treasury (2018) notes that the commonly adopted value for the marginal utility of income in UK policymaking is 1.3. This research uses sensitivity analysis to examine how NPV is affected by the assumed elasticity of the marginal utility of income. This analysis is reported in Table 7.11. The result is that sample WTP increases with the assumed value of the elasticity of the marginal utility of income.

Table 7.11 examines the sensitivity of median WTP and policy NPV to changes in the assumed value for e, the elasticity of the marginal utility of income. This section explores both the choice of e and the calculation of NPV. The range of e values used was 0 - 1.5, which is consistent with the ranges estimated by calculation or survey in the literature Layard, Mayraz and Nickell (2008); Nick and Ysé (2006); Cowell and Gardiner (2000). The results in the first column are equal to those in Table 7.4 as a e weight equal to zero weights each respondent equally as in standard CBA practice. Although the weights are estimated at the individual level, the results are likely robust to estimating at the group level. Indeed, both Cowell and Gardiner (2000) and Layard, Mayraz and Nickell (2008) established that the weights do not vary substantially across different socioeconomic groups. Additionally, the NPV was calculated by scaling both the benefits, WTP estimated at the individual level, and the costs. The NPV used the same parameters as Section 7.1.5.1, 3.5% discount rate and 10-year project duration and was calculated using the difference between aggregated costs and benefits. The costs were the total values in Section 7.1.3 divided by the number of households (for the research and WWTP scenarios) or the number of products (for the restriction) to estimate an individual cost estimate. The costs were divided equally between respondents but then scaled by the individual weights. Future work with complete information on the distribution of costs could estimate the individual costs with greater precision. To summarise, Table 7.11 reports the robustness of WTP and NPV to distributional analysis.

Table 7.11: Scaling sample median WTP and policy NPV by assumed *e* values.

Category	**e0**	**e0.5**	**e0.75**	**e1**	**e1.25**	**e1.5**
Median weight	1.0	1.4	1.65	1.95	2.31	2.72
Q6 WTP (Mean household annual)	£77.10	£109.49	£130.47	£155.47	£185.27	£220.78
Q6 NPV (in £billions)	£18.26bn	26.01	31.03	37.02	44.15	52.64
Q7 WTP (Mean household annual)	£88.43	125.57	149.64	178.32	212.49	253.22
Q7 NPV (in £billions)	£9.37bn	18.26	24.02	30.88	39.06	48.80
Emissions MWTP (£per product)	£0.04	- £0.05	£0.06	£0.07	£0.09	£0.10
Emissions NPV (in £billions)	-£8.69bn	-£12.13bn	-£14.34bn	-£16.94bn	-£20.02bn	-£23.66bn

The results of Table 7.11 indicate that the effect of using explicit weights is to increase the magnitude of the NPV. The research policy in Q6 is again economically viable with a large NPV. Therefore, Q6 is robust to sensitivity analysis and distributional analysis. While the Q7 WWTP scenario is closer to changing the sign of the NPV and may even be negative using sensitivity analysis, the effect of explicit weights is to increase the magnitude of the WTP and the NPV by a substantial amount. This result of Q7 being robust to distributional analysis further supports it being implemented as an economically viable policy to restrict microplastics. One explanation for WWTP being robust to weighting could be that lower-income respondents have lower water bills due to spending constraints and also benefit more as they are less able to substitute away from sources of microplastics in water; see Kosuth, Mason and Wattenberg (2018) for examples of common products being contaminated with microplastics. However, the link between water bills and income is relatively weak, given that they are calculated on usage. Regardless of the mechanism, explicitly weighing the distribution of impacts reinforces the economic viability of the research and WWTP scenarios.

Finally, the final two rows of Table 7.11 report the restriction MWTP and NPV. Unlike the two CV scenarios, the effect of explicitly weighting the impacts of the proposed cosmetics restriction is to make the policy less economically viable. This result is contrary to ECHA (2019) which believed there to be no significant distributional issues. The mechanism behind the increasingly negative NPV is two-fold. Firstly, while the sample mean MWTP increases given weighting, the increase is less than the sensitivity analysis in Section 7.1.6 established would be necessary for the NPV to change sign. Secondly, the restriction costs were also distributionally weighted, and the resulting negative NPV indicates the regressive nature of increasing the price of personal care products. Cosmetic product price rises may be regressive for two reasons. Firstly, cosmetics may be a normal good in which those with higher income consume more (ECHA, 2019). Secondly, the demand for cosmetics may be relatively price-inelastic as it is often determined by many non-price factors (DEFRA, 2017). Both of these reasons suggest that any reformulation costs could be passed through from firms to consumers with relatively little change in market share or demand. Therefore, it may be that passing on the costs of reformulating cosmetics via product price increases is regressive. This regressive impact is then reflected in the increasingly negative NPV when explicitly weighting the restriction impacts. To summarise, using explicit distributional weights increases the magnitude of NPV in each case and underscores that effluent control, via WWTP upgrading, is more economically viable than source control via cosmetic restrictions.

This section compares the implicit and explicit approaches. The range of implicit weights, 0.32 - 1.31, is narrower than the explicit weights of 1.0 - 2.72. However, caution should be applied when comparing the two. The implicit weights suggest the weighting applied to high-income groups for the sign of NPV to change (Atkinson et al., 2018a), while the explicit weights suggest the appropriate weighting for each respondent given their relative income. The implicit weights suggest that the research policy is robust to even a substantial weighting of high-income groups. This result is corroborated by the explicit weights showing that the NPV only increases when relative income is considered. Although the treatment policy is sensitive to higher than expected costs, explicitly weighting respondents shows that the NPV is increasingly positive and economically viable if the incidence of impacts is accounted for. Finally, both implicit and explicit weights indicate that the source control measure is not economically viable. The implicit weights were close to unity, suggesting that the NPV for both low and high-income groups was negative. This result is corroborated by the explicit weights, whereby accounting for income differences only reduced the NPV. Generally, the distributional analysis corroborates the sensitivity analysis and the initial conclusions. Overall, distributional weighting can be used in an indicative CBA to suggest the impact on NPV of weighting impacts differently per stakeholders.

7.1.9 CBA Discussion

The sensitivity analysis indicates that each scenario is robust to even massive changes in WTP; this completes the CBA of the three policy options in this research. The CBA is intended only to indicate how much socioeconomic analysis could proceed using the unit values of WTP elicited from this research. Thus the results are only illustrative given uncertainty about the elicitation, aggregation and estimation of the costs and benefits. This research is among the first to estimate the benefits of microplastic restrictions for use in policy appraisal, and future work may estimate the values with greater precision. The results show that effluent control may be more economically viable than source control. While both have high implementation costs, respondents WTP indicates a preference for investment in WWTP. The greater NPV for the research scenario, including the opportunity cost of reduced ES, suggests that delaying a decision to resolve the scientific uncertainty may be valuable. However, the calculations are not intended to produce a full appraisal of a research programme. Indeed, as the unit WTP values are extremely high considering the unrealistic scenarios and sampling during the pandemic, the aim of this process is more for future researchers to show how each aspect, including distributional weights, can be calculated with more realistic values. Indeed, the CBA is produced to illustrate that there are benefits to delaying a decision. Finally, the distributional analysis indicated that weighting different socioeconomic groups might substantially alter the net benefits, although of a magnitude unlikely to affect the central conclusions. Section 7.2 discusses the policy implications of this CBA.

7.2 Thesis Discussion

This final section of the thesis addresses the limitations and implications of the SP survey, elicited and scaled WTP, and the CBA of proposed microplastic restrictions.

7.2.1 Limitations

This section critically comments on the limitations of the methods and results of this research. While each chapter comments on its own limitations, this section remarks on a few limitations that affect all chapters. Future research may build upon these critiques to increase the reliability and validity of the results contained in this research.

The first major issue is collecting data during the height of the pandemic restrictions, which could not be avoided given the time constraints from the PhD project and Environment Agency funding. The anticipated effect was on response rates and income. The high response rates indicate that using an online survey effectively mitigated any effect on response rates. However, the responses to Question 24A, which asked respondents whether their income had been affected, suggests that the effect of collecting data during the pandemic was an income effect that reduced WTP. A test-retest design could be used in future work to evaluate whether the pandemic's influence diminishes over time and whether WTP is temporally stable (Schaafsma et al., 2014). The limitations of Q24A as a method of evaluating the pandemic's influence have been discussed; namely, it only reveals an effect but not the magnitude of the effect.

An alternative approach to addressing the uncertainty and irreversibility in this context may have been to estimate Quasi-Option Value. QOV is the value of delaying a decision to learn about future policy impacts. In this context, QOV would represent the value of delaying a restriction on microplastics to facilitate research that would resolve the scientific uncertainty about microplastics' health and environmental impacts. The pilot attempted to estimate QOV by asking respondents to select whether they preferred an uncertain or irreversible option. However, the pre-testing and expert consultation suggested splitting this one question into the two CVM questions used in the main final survey design; one eliciting WTP for research (Q6) and one eliciting WTP for reductions via investment into enhanced filtering capabilities of WWTPs (Q7). Although the two CV questions were initially intended to recover QOV, it is unclear whether the elicited value can be correctly interpreted as QOV. Specifically, it has been suggested that QOV cannot be isolated as the scenarios differ along two dimensions; whether research is undertaken and whether there is a reduction in microplastics [22]. Therefore, the appropriate interpretation of the difference between the WTP for the two scenarios is as a precautionary premium. However, future work could use two CV scenarios, one for research with a reduction in microplastics and one for reducing microplastics. If this research had elicited QOV in this framework, then the QOV of delaying a decision to undertake research could be isolated and included in CBA following Traeger (2014) suggestion.

A further design issue is the relatively small sample size. A linked issue is the truncated sample size of 304, which indicates that more than half the sample is eventually excluded, possibly indicative of an overly complex design despite the pre-testing process. However, the high median level of survey understanding (9/10) and robustness of MWTP to sample truncation indicates that the complexity may still be manageable for respondents. The limited subsample sizes meant that the order of the CVM-CE sections could not be randomised. For an indication of the effect, the ordering dummy was statistically significant in the CE results, which indicates that the CV question before the CE influenced choices. Despite these limitations, the CE attribute MWTP is broadly similar across specifications suggestive of stable estimates. Future work to expand the sample would be valuable to test the WTP's robustness in this study.

Some minor possible limitations are complementarity, substitution, and transferability. For instance, the CBA did not consider whether cosmetic products' reformulation could lead to possible regrettable substitution. Understanding the substitution of microplastics in cosmetics would require knowledge of the sector, firm, and product-specific relationship between microplastic use and product performance. Furthermore, both DEFRA (2017) and ECHA (2019) noted that inert substitutes for microplastics already exist and, therefore, regrettable substitution as a result of this research is unlikely. Furthermore, the survey elicits no information about consumer use, understanding, price expectations or different types of cosmetic products. Observing this information would have provided greater insight into individual-level heterogeneity in WTP for marginal changes in cosmetics products. For instance, respondents may have been allocated to latent classes according to their cosmetics use. Alternatively, if the CE was not described in relatively general terms, the survey design could have evaluated how WTP varies with types of cosmetic products. Moreover, consumer surplus under different reformulations could also have been calculated if more complete information on reformulations was available.

[22] With thanks to Dr Lucy O'Shea, Dr Stavros Georgiou, Dr Christoph Rheinberger, Professor Brett Day, and various seminar and conference participants for their insight on the interpretation of the difference between the two CV scenarios and comments regarding estimating QOV.

Although the generality increases understanding and policy relevance, this extension is open for future work on the influence of product use on WTP. A final notable limitation of the SP tasks is the transferability of the values. While previous chapters have explicitly commented on the possibility of benefits transfer for the CV WTP, the CE scenario is specific to microplastics in cosmetics and is harder to transfer to other sectors using microplastics. However, the WTP in both SP tasks of this research indicates respondents' preferences for the precautionary restriction of microplastics. In general, the survey design limitations were pragmatic responses to the project constraints, although future work could address them and improve the validity and reliability of the WTP.

7.2.2 Implications and future work

This section mentions the practical implications of this research before discussing how future work can further the research. The primary implication is that respondents are willing to pay a premium for precautionary abatement policies. Additionally, the CBA indicates that effluent control is more viable than source control. A practical implication of these two findings was to provide a summary report to the Environment Agency, which the CTPA later submitted to ECHA.

Future work using a refined survey instrument could do much to enhance the validity of this research. Given the high values for Q6 and Q7, and inability to elicit QOV from the CV questions, future research is advised to attempt another survey with several modifications. Firstly, as mentioned in Section 7.2.1, a future survey could elicit QOV. Where this research elicited a precautionary premium, empirically a close analogue to QOV, future work could use two CV scenarios that differ in only one dimension and estimate QOV. While Traeger (2014) discussed how to include QOV in CBA theoretically, future research could do this empirically. QOV can be incorporated in CBA to understand how respondents trade-off irreversibility and uncertainty. Therefore, this research has contributed a framework to empirically elicit QOV and future work is advised to use the same survey instrument here with slightly modified CV questions [23].

Future work may also investigate how respondent's trade-off polluting product attributes. For the microplastic sector, future work can explore the relationship between microplastic use and performance of personal-care products and the value of restricting microplastics

[23]I am grateful to my examiners, Dr Bruce Morley and Prof. Susana Mourato for their time discussing plans for future work. Future researchers should note that online survey costs and effort are becoming more accessible. Thus a re-test of this survey's design, while not feasible to include in this thesis given the difference in time and design between survey versions, would be possible.

in other sectors which emit more microplastics than cosmetics. Alternatively, future work may investigate other micro and nano pollutants affecting water quality, including metals and flame retardants. Finally, future work can expand the sample and subsample size with a test-retest design to evaluate the pandemic's effects on WTP and support the validity of the estimated WTP.

7.2.3 Summary

This study elicited WTP from a representative sample of 670 UK adults for three different measures to control the loss of intentionally added microplastics to the terrestrial and marine environments. The CE asked respondents about their preferences for the price, performance, and loss of microplastics from their personal care products. The CE was developed in collaboration with the EA and CTPA and thus had a degree of credibility with respect to its information content. The involvement of the EA and CTPA is acknowledged, appreciated, and a summary report of these results was submitted to both. Sample representative WTP is £0.036 for a one percentage point decrease in the number of microplastics lost per product, and negative £0.048 for a one percentage point loss of product performance. Respondents reported relatively high emissions MWTP compared to that for performance, indicating a willingness to trade off product attributes; but insufficiently high MWTP to offset the high abatement costs for any cosmetics restriction. Finally, the two CVM questions used the SBDC format with Q6 results of £53.25 (£50.11 - £56.55) and Q7 results of £73.71 (£70.94 - £76.55). The difference of £20.25 (£20.00 - £20.83) indicates an individual preference, expressed as a premium for precautionary restrictions. This finding is important as it demonstrates respondent-level support for the precautionary principle. This thesis uses the ICLV to demonstrate that latent precautionary attitudes underpin this premium. A final, purely indicative, and approximate step of the thesis was to aggregate the mean full-sample WTP for use in CBA. The CBA suggests that research was economically viable, effluent-control via WWTP investment viability was sensitive to cost overruns, and source-control via cosmetics restrictions was unlikely to have a positive NPV due to high reformulation costs. Despite several caveats to the CBA, precautionary effluent control appears preferable to source control. Overall, this thesis has estimated the value of precautionary microplastic abatement policies.

Bibliography

Aadland, D. and Caplan, A.J., 2003. Willingness to pay for curbside recycling with detection and mitigation of hypothetical bias. *American Journal of Agricultural Economics*, 85(2), pp.492–502. Available from: https://academic.oup.com/ajae/article/85/2/492/122592#938065.

Abate, T.G., Börger, T., Aanesen, M., Falk-Andersson, J., Wyles, K.J. and 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, p.106521. Available from: https://www.sciencedirect.com/science/article/pii/S0921800919307360#bib0345.

Abbott, A., Nandeibam, S. and O'Shea, L., 2013. Recycling: Social norms and warm-glow revisited. *Ecological Economics*, 90, pp.10–18. Available from: https://www.sciencedirect.com/science/article/pii/S0921800913000761.

Adamowicz, W., Dupont, D., Krupnick, A. and Zhang, J., 2011. Valuation of cancer and microbial disease risk reductions in municipal drinking water: An analysis of risk context using multiple valuation methods. *Journal of Environmental Economics and Management*, 61(2), pp.213–226. Available from: https://www.sciencedirect.com/science/article/pii/S0095069610001063.

Afroz, R., Masud, M.M., Akhtar, R. and Duasa, J.B., 2013. Survey and analysis of public knowledge, awareness and willingness to pay in kuala lumpur, malaysia– a case study on household weee management. *Journal of Cleaner Production*, 52, pp.185–193. Available from: https://www.sciencedirect.com/science/article/pii/S095965261300053X.

Alberini, A., Boyle, K. and Welsh, M., 2003. Analysis of contingent valuation data with multiple bids and response options allowing respondents to express uncertainty.

Journal of environmental economics and management, 45(1), pp.40–62. Available from: https://www.sciencedirect.com/science/article/pii/S0095069602000104.

Alberini, A. and Scasny, M., 2014. *Stated-preference study to examine the economic value of benefits of avoiding selected adverse human health outcomes due to exposure to chemicals in the european union: Part iii: Carcinogens.* European Chemicals Agency. Available from: https://echa.europa.eu/documents/10162/13630/study_economic_benefits_avoiding_adverse_health_outcomes_3_en.pdf/ccf1db6e-fa50-45e3-a0b4-178a05cc8b96.

Aldred, J., 2012. Climate change uncertainty, irreversibility and the precautionary principle. *Cambridge Journal of Economics*, 36(5), pp.1051–1072. Available from: https://doi.org/10.1093/cje/bes029.

Allsopp, M., Walters, A., Santillo, D. and Johnston, P., 2007. Plastic debris in the world's oceans. *Greenpeace*. Available from: http://www.greenpeace.org/austria/Global/austria/dokumente/Studien/meere_Plastic_Debris_Study_2006.pdf.

Andreoni, J., 1990. Impure altruism and donations to public goods: A theory of warm-glow giving. *The economic journal*, 100(401), pp.464–477. Available from: https://www.jstor.org/stable/pdf/2234133.

Anstine, J., 2000. Consumers' willingness to pay for recycled content in plastic kitchen garbage bags: a hedonic price approach. *Applied Economics Letters*, 7(1), pp.35–39.

Arrow, K., Solow, R., Portney, P., Leamer, E., Radner, R. and Schuman, H., 1993. Report of the N.O.A.A panel on contingent valuation. *Federal Register*, 58(10), pp.4601–4614. Available from: https://www.researchgate.net/profile/Edward_Leamer/publication/277297107_Kenneth_Arrow/links/572a241108ae2efbfdbc1959/Kenneth-Arrow.pdf.

Arrow, K.J. and Fisher, A.C., 1974. Environmental preservation, uncertainty, and irreversibility. *The Quarterly Journal of Economics*, pp.76–84. Available from: https://academic.oup.com/qje/article-abstract/88/2/312/1861520.

Atkinson, G., Braathen, N.A., Mourato, S. and Groom, B., 2018a. *Cost benefits analysis and the environment: Further developments and policy use.* Organisation for Economic Co-operation and Development. Available from: https://doi.org/10.1787/9789264085169-en.

Atkinson, G., Groom, B., Hanley, N. and Mourato, S., 2018b. Environmental valuation and benefit-cost analysis in uk policy. *Journal of Benefit-Cost Analysis*, 9(1), pp.97–

119. Available from: http://eprints.lse.ac.uk/87615/1/Mourato_Environmental%20Valuation.pdf.

Atkinson, G., Morse-Jones, S., Mourato, S. and Provins, A., 2012. 'when to take "no" for an answer'? using entreaties to reduce protests in contingent valuation studies. *Environmental and Resource Economics*, 51(4), pp.497–523. Available from: https://link.springer.com/article/10.1007/s10640-011-9509-3.

Atkinson, G., Mourato, S., Szymanski, S. and Ozdemiroglu, E., 2008. Are we willing to pay enough toback the bid'?: Valuing the intangible impacts of london's bid to host the 2012 summer olympic games. *Urban studies*, 45(2), pp.419–444. Available from: https://doi.org/10.1177%2F0042098007085971.

Auta, H., Emenike, C. and Fauziah, S., 2017. Distribution and importance of microplastics in the marine environment: a review of the sources, fate, effects, and potential solutions. *Environment international*, 102, pp.165–176. Available from: https://www.sciencedirect.com/science/article/pii/S016041201631011X.

Azzarello, M. and Van-Vleet, E., 1987. Marine birds and plastic pollution. *Marine Ecology Progress Series*, 37, pp.295–303. Available from: http://www.int-res.com/articles/meps/37/m037p295.pdf.

Badura, T., Ferrini, S., Burton, M., Binner, A. and Bateman, I.J., 2019. Using individualised choice maps to capture the spatial dimensions of value within choice experiments. *Environmental and Resource Economics*, pp.1–26. Available from: https://link.springer.com/article/10.1007/s10640-019-00358-3#enumeration.

Baker, R., Ruting, B. et al., 2014. *Environmental policy analysis: a guide to non-market valuation*. Productivity Commission. Available from: https://www.pc.gov.au/research/supporting/non-market-valuation/non-market-valuation.pdf.

Barbier, E.B., Czajkowski, M. and Hanley, N., 2017. Is the income elasticity of the willingness to pay for pollution control constant? *Environmental and resource economics*, 68(3), pp.663–682. Available from: https://link.springer.com/article/10.1007/s10640-016-0040-4#enumeration.

Bateman, I.J., Carson, R.T., Day, B., Hanemann, M., Hanley, N., Hett, T., Jones-Lee, M., Loomes, G., Mourato, S., Pearce, D.W. et al., 2002. *Economic valuation with stated preference techniques: A manual*. Edward Elgar Publishing Ltd. Available from: https://www.cabdirect.org/cabdirect/abstract/20043091507.

Bateman, I.J., Cooper, P., Georgiou, S., Navrud, S., Poe, G.L., Ready, R.C., Riera, P., Ryan, M. and Vossler, C.A., 2005. Economic valuation of policies for managing acidity in remote mountain lakes: Examining validity through scope sensitivity testing. *Aquatic Sciences*, 67(3), pp.274–291. Available from: https://link.springer.com/content/pdf/10.1007/s00027-004-0744-3.pdf.

Bateman, I.J. and Langford, I.H., 1997. Budget-constraint, temporal, and question-ordering effects in contingent valuation studies. *Environment and Planning A*, 29(7), pp.1215–1228. Available from: https://journals.sagepub.com/doi/abs/10.1068/a291215.

Bateman, I.J., Langford, I.H., Turner, R.K., Willis, K.G. and Garrod, G.D., 1995. Elicitation and truncation effects in contingent valuation studies. *Ecological Economics*, 12(2), pp.161–179. Available from: https://www.researchgate.net/publication/242420394_The_impacts_of_changing_willingness_to_pay_question_format_in_contingent_valuation_studies_an_analysis_of_open-ended_iterative_bidding_and_dichotomous_choice_formats_CSERGE_Working_paper_GEC_1993-05/stats.

Baumol, W.J., Oates, W.E., Bawa, V.S., Bawa, W. and Bradford, D.F., 1988. *The theory of environmental policy*. Cambridge university press. Available from: https://www.google.co.uk/books/edition/The_Theory_of_Environmental_Policy/32-rON8l9BgC?hl=en&gbpv=0.

Beaumont, N.J., Aanesen, M., Austen, M.C., B¨orger, T., Clark, J.R., Cole, M., Hooper, T., Lindeque, P.K., Pascoe, C. and Wyles, K.J., 2019. Global ecological, social and economic impacts of marine plastic. *Marine pollution bulletin*, 142, pp.189–195. Available from: https://www.sciencedirect.com/science/article/pii/S0025326X19302061.

Beharry-Borg, N. and Scarpa, R., 2010. Valuing quality changes in caribbean coastal waters for heterogeneous beach visitors. *Ecological Economics*, 69(5), pp.1124–1139. Available from: https://doi.org/10.1016/j.ecolecon.2009.12.007.

Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T. and Polydoropoulou, A., 2002. Integration of choice and latent variable models. *Perpetual motion: Travel behaviour research opportunities and application challenges*, pp.431–470. Available from: http://www.joanwalker.com/uploads/3/6/9/5/3695513/benakivawalkeretal_iclv_chapter_2002.pdf.

Ben-Akiva, M.E., Lerman, S.R. and Lerman, S.R., 1985. *Discrete choice analysis: theory and application to travel demand*, vol. 9. MIT press. Available from: https://www.google.co.uk/books/edition/Discrete_Choice_Analysis/oLC6ZYPs9UoC?hl=en&gbpv=1&dq=ben+akiva+lerman+discrete+choice+analysis+&pg=PR11&printsec=frontcover#v=onepage&q&f=true.

Bennett, J. and Adamowicz, V., 2001. Some fundamentals of environmental choice modelling. *The choice modelling approach to environmental valuation*, pp.37–69. Available from: https://books.google.co.uk/books?hl=en&lr=&id=8-KLGW9yT6QC&oi=fnd&pg=PA37&dq=bennett+adamowicz&ots=1qmoD1Jbg2&sig=3pSeGY6wtaMGgsnrJjaDCAhXdQ4#v=onepage&q=bennett%20adamowicz&f=false.

Bergmann, M., Gutow, L. and Klages, M., 2015. *Marine anthropogenic litter*. Springer. Available from: https://www.oapen.org/download?type=document&docid=1001966.

Best, H. and Kneip, T., 2011. The impact of attitudes and behavioral costs on environmental behavior: A natural experiment on household waste recycling. *Social Science Research*, 40(3), pp.917–930. Available from: https://www.sciencedirect.com/science/article/pii/S0049089X10002802.

Bhat, C.R., 2001. Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transportation Research Part B: Methodological*, 35(7), pp.677–693. Available from: https://www.sciencedirect.com/science/article/pii/S019126150000014X.

Blomquist, G.C., Blumenschein, K. and Johannesson, M., 2009. Eliciting willingness to pay without bias using follow-up certainty statements: comparisons between probably/definitely and a 10-point certainty scale. *Environmental and Resource Economics*, 43(4), pp.473–502. Available from: http://gattonweb.uky.edu/faculty/blomquist/ERE%202009%20Aug%20Blomquist%20Blumenschein%20Johannesson.pdf.

Boardman, A.E., Greenberg, D.H., Vining, A.R. and Weimer, D.L., 2017. *Cost-benefit analysis: concepts and practice*. 4th ed. Prentice Hall. Available from: https://www.nrc.gov/docs/ML1233/ML12338A400.pdf.

Brouwer, R., Hadzhiyska, D., Ioakeimidis, C. and Ouderdorp, H., 2017. The social costs of marine litter along european coasts. *Ocean & coastal management*, 138, pp.38–49. Available from: https://www.sciencedirect.com/science/article/pii/S0964569117300297#bib43.

Brouwer, R. and Martín-Ortega, J., 2012. Modeling self-censoring of polluter pays protest votes in stated preference research to support resource damage estimations in environmental liability. *Resource and Energy Economics*, 34(1), pp.151–166. Available from: https://doi.org/10.1016/j.reseneeco.2011.05.001.

Buckell, J., Hensher, D.A. and Hess, S., 2021. Kicking the habit is hard: A hybrid choice model investigation into the role of addiction in smoking behavior. *Health Economics*, 30(1), pp.3–19. Available from: https://onlinelibrary.wiley.com/doi/pdfdirect/10.1002/hec.4173.

Bujosa, A., Riera, A. and Hicks, R.L., 2010. Combining discrete and continuous representations of preference heterogeneity: a latent class approach. *Environmental and Resource Economics*, 47(4), pp.477–493. Available from: https://link.springer.com/content/pdf/10.1007/s10640-010-9389-y.pdf.

Burns, E.E. and Boxall, A.B., 2018. Microplastics in the aquatic environment: Evidence for or against adverse impacts and major knowledge gaps. *Environmental toxicology and chemistry*, 37(11), pp.2776–2796. Available from: https://setac.onlinelibrary.wiley.com/doi/full/10.1002/etc.4268.

Cameron, T.A., 2005. Individual option prices for climate change mitigation. *Journal of Public Economics*, 89(2-3), pp.283–301. Available from: https://www.sciencedirect.com/science/article/pii/S0047272704000131.

Carson, R.T., Flores, N.E. and Meade, N.F., 2001. Contingent valuation: controversies and evidence. *Environmental and resource economics*, 19(2), pp.173–210. Available from: https://link.springer.com/article/10.1023/A:1011128332243.

Carson, R.T. and Steinberg, D., 1990. Experimental design for discrete choice voter preference surveys. *1989 Proceeding of the Survey Methodology Section of the American Statistical Association*, pp.821–822. Available from: https://www.researchgate.net/profile/Dan_Steinberg2/publication/246138041_Experimental_Design_for_Discrete_Choice_Voter_Preference_Surveys/links/567dcf8408ae051f9ae493ff/Experimental-Design-for-Discrete-Choice-Voter-Preference-Surveys.pdf.

Charities Aid Foundation, 2019. *Caf uk giving 2019. an overview of charitable giving in the uk.* London: Charities Aid Foundation. Available from: https://www.cafonline.org/docs/default-source/about-us-publications/caf-uk-giving-2019-report-an-overview-of-charitable-giving-in-the-uk.pdf?sfvrsn=c4a29a40_4.

Chen, Q., Allgeier, A., Yin, D. and Hollert, H., 2019. Leaching of endocrine disrupting chemicals from marine microplastics and mesoplastics under common life stress conditions. *Environment international*, 130, p.104938. Available from: https://pubmed.ncbi.nlm.nih.gov/31234003/.

Chen, W.Y. and Cho, F.H.T., 2019. Environmental information disclosure and societal preferences for urban river restoration: Latent class modelling of a discrete-choice experiment. *Journal of cleaner production*, 231, pp.1294–1306. Available from: https://www.sciencedirect.com/science/article/pii/S0959652619318438#sec2.

Cheraghi-Sohi, S., Bower, P., Mead, N., McDonald, R., Whalley, D. and Roland, M., 2007. Making sense of patient priorities: applying discrete choice methods in primary care using 'think aloud'technique. *Family practice*, 24(3), pp.276–282. Available from: https://academic.oup.com/fampra/article/24/3/276/483376.

Choi, E.C. and Lee, J.S., 2018. The willingness to pay for removing the microplastics in the ocean–the case of seoul metropolitan area, south korea. *Marine Policy*, 93, pp.93–100. Available from: https://www.sciencedirect.com/science/article/pii/S0308597X17304803.

Clark, M.D., Determann, D., Petrou, S., Moro, D. and Bekker-Grob, E.W. de, 2014. Discrete choice experiments in health economics: a review of the literature. *Pharmacoeconomics*, 32(9), pp.883–902. Available from: https://link.springer.com/article/10.1007/s40273-014-0170-x.

Competition Commission, 2010. *Review of stated preference and willingness to pay methods*. Competition Commission. Available from: https://webarchive.nationalarchives.gov.uk/+/http:/www.competition-commission.org.uk/our_role/analysis/summary_and_report_combined.pdf.

Convery, F., McDonell, S. and Ferreira, S., 2007. The most popular tax in europe? lessons from the irish plastic bags levy. *Environmnental and resource economics*, 38(1), pp.1–11. Available from: https://link.springer.com/content/pdf/10.1007%2Fs10640-006-9059-2.pdf.

Cooper, P., Poe, G.L. and Bateman, I.J., 2004. The structure of motivation for contingent values: a case study of lake water quality improvement. *Ecological Economics*, 50(1-2), pp.69–82. Available from: https://www.sciencedirect.com/science/article/pii/S0921800904001557.

Courbage, C., Rey, B. and Treich, N., 2013. Prevention and precaution. *Handbook of insurance*, Springer, pp.185–204. Available from: http://publications.ut-capitole.fr/15772/1/wp_tse_445.pdf.

Cowell, F.A. and Gardiner, K., 2000. *Welfare weights.* Office of Fair Trading London. Available from: https://www.researchgate.net/profile/Frank_Cowell/publication/30522485_Welfare_Weights/links/02bfe5101990a17c11000000.pdf.

Cummings, R.G. and Taylor, L.O., 1999. Unbiased value estimates for environmental goods: a cheap talk design for the contingent valuation method. *American economic review*, 89(3), pp.649–665. Available from: https://www.jstor.org/stable/pdf/117038.

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

Day, B., Bateman, I.J., Carson, R.T., Dupont, D., Louviere, J.J., Morimoto, S., Scarpa, R. and Wang, P., 2012. Ordering effects and choice set awareness in repeat-response stated preference studies. *Journal of environmental economics and management*, 63(1), pp.73–91. Available from: https://www.sciencedirect.com/science/article/pii/S0095069611001239.

Day, B. and Prades, J.L.P., 2010. Ordering anomalies in choice experiments. *Journal of Environmental Economics and Management*, 59(3), pp.271–285. Available from: https://www.sciencedirect.com/science/article/pii/S0095069610000239.

DEFRA, 2007. *An introductory guide to valuing ecosystem services.* Department for Environment, Food and Rural Affairs: HM Government. Available from: http://ec.europa.eu/environment/nature/biodiversity/economics/pdf/valuing_ecosystems.pdf.

DEFRA, 2017. *Implementation of the environmental protection (microbeads) (england) regulations 2017.* London: DEFRA. Available from: https://www.legislation.gov.uk/ukia/2017/160/pdfs/ukia_20170160_en.pdf.

DEFRA, 2018. *Introducing a deposit return scheme on beverage containers.* DEFRA. Available from: https://consult.defra.gov.uk/environment/introducing-a-deposit-return-scheme/supporting_documents/depositreturnconsultia.pdf.

DEFRA, 2020. *Enabling a natural capital approach: Guidance.* Department for Environment Food and Rural Affairs: HM Government. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/869801/natural-capital-enca-guidance_2_March.pdf.

Dekker, T., Hess, S., Brouwer, R. and Hofkes, M., 2016. Decision uncertainty in multi-attribute stated preference studies. *Resource and Energy Economics*, 43, pp.57–73. Available from: https://doi.org/10.1016/j.reseneeco.2015.11.002.

Deng, L., Cai, L., Sun, F., Li, G. and Che, Y., 2020. Public attitudes towards microplastics: Perceptions, behaviors and policy implications. *Resources, Conservation and Recycling*, 163, p.105096. Available from: https://doi.org/10.1016/j.resconrec.2020.105096.

Derraik, J., 2002. The pollution of the marine environment by plastic debris: a review. *Marine pollution bulletin*, 44(9), pp.842–852. Available from: https://www.sciencedirect.com/science/article/pii/S0025326X02002205.

Desvousges, W., Mathews, K. and Train, K., 2012. Adequate responsiveness to scope in contingent valuation. *Ecological Economics*, 84, pp.121–128. Available from: https://www.sciencedirect.com/science/article/pii/S0921800912003813.

DFA, 2006. *Handbook of cost-benefit analysis*. Department of Finance and Administration, Commonwealth of Australia. Available from: https://www.finance.gov.au/sites/default/files/Handbook_of_CB_analysis.pdf.

Diamond, P.A. and Hausman, J.A., 1994. Contingent valuation: is some number better than no number? *Journal of economic perspectives*, 8(4), pp.45–64. Available from: https://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.8.4.45.

Dillingham, R., 2016. *A latent-class discrete-choice model to demonstrate how course attributes and student characteristics influence demand for economics electives: the challenge to increase enrollment*. Ph.D. thesis. ProQuest Dissertations and Theses. Available from: https://digitalcommons.mtu.edu/cgi/viewcontent.cgi?article=1310&context=etdr.

Dugstad, A., Grimsrud, K., Kipperberg, G., Lindhjem, H. and Navrud, S., 2021. *Scope elasticity of willingness to pay in discrete choice experiments*. Springer. Available from: https://doi.org/10.1007/s10640-021-00577-7.

Duis, K. and Coors, A., 2016. Microplastics in the aquatic and terrestrial environment: sources (with a specific focus on personal care products), fate and effects. *Environmental Sciences Europe*, 28(1), p.2. Available from: https://enveurope.springeropen.com/articles/10.1186/s12302-015-0069-y.

Dunlap, R. and D. Van Liere, K., 2008. The "new environmental paradigm". *The Journal* *of Environmental Education*, 40, pp.19–28. Available from: http://doi.org/10.3200/JOEE.40.1.19-28.

Dunn, H., 2012. *Accounting for environmental impacts: Supplementary green book guidance.* HM Treasury: HM Government. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/191507/Optimism_bias.pdf.

ECHA, 2008. *Guidance on socio-economic analysis restrictions.* European Chemicals Agency. Available from: https://echa.europa.eu/documents/10162/23036412/sea_restrictions_en.pdf/2d7c8e06-b5dd-40fc-b646-3467b5082a9d.

ECHA, 2014a. *Appendix: Willingness to pay for avoiding respiratory sensitisation outcomes.* European Chemicals Agency. Available from: https://echa.europa.eu/documents/10162/13630/appendix_study_economic_benefits_avoiding_adverse_health_outcomes_1_en.pdf/67d7b29e-6d16-4167-8163-46b3d39cab30.

ECHA, 2014b. *Stated-preference study to examine the economic value of benefits of avoiding selected adverse human health outcomes due to exposure to chemicals in the european union: Part i: sensitization & dose toxicity.* European Chemicals Agency. Available from: https://echa.europa.eu/documents/10162/13630/study_economic_benefits_avoiding_adverse_health_outcomes_1_en.pdf/5c884e27-8ce7-4ffd-97dc-5e7875ee67e0.

ECHA, 2016. *Valuing selected health impacts of chemicals.* European Chemicals Agency. Available from: https://echa.europa.eu/documents/10162/13630/echa_review_wtp_en.pdf.

ECHA, 2019. *Annex xv restriction report proposal for a restriction.* European Chemicals Agency. Available from: https://echa.europa.eu/documents/10162/12414bc7-6bb2-17e7-c9ec-652a20fa43fc.

Egan, K.J., Corrigan, J.R. and Dwyer, D.F., 2015. Three reasons to use annual payments in contingent valuation surveys: Convergent validity, discount rates, and mental accounting. *Journal of Environmental Economics and Management*, 72, pp.123–136. Available from: https://doi.org/10.1016/j.jeem.2015.05.002.

Environment Agency, 2015. *Annex xv restriction report proposal for a restriction: Octamethylcyclotetrasiloxane.* Environment Agency. Available from: https://echa.europa.eu/documents/10162/9a53a4d9-a641-4b7b-ad58-8fec6cf26229.

Environmental Audit Committee, 2016. *Environmental impact of microplastics.* Environmental Audit Committee. Available from: http://data.parliament.uk/writtenevidence/committeeevidence.svc/evidencedocument/environmental-audit-committee/growing-a-circular-economy/oral/9460.pdf.

Environmental Audit Committee, 2018. *Growing a circular economy.* Environmental Audit Committee. Available from: http://data.parliament.uk/writtenevidence/committeeevidence.svc/evidencedocument/environmental-audit-committee/growing-a-circular-economy/oral/9460.pdf.

Eunomia, 2017. *Impacts of a deposit refund system for one-way beverage packaging on local authority waste services.* DEFRA. Available from: https://www.mcsuk.org/media/eunomia-report-on-drs.pdf.

Eunomia, 2019. *Investigating options for reducing releases in the aquatic environment of microplastics emitted by (but not intentionally added in) products.* London: Eunomia. Available from: https://www.eunomia.co.uk/reports-tools/investigating-options-for-reducing-releases-in-the-aquatic-environment-of-microplastics-emitted-by-products/.

Faccioli, M., Czajkowski, M., Glenk, K. and Martin-Ortega, J., 2020. Environmental attitudes and place identity as determinants of preferences for ecosystem services. *Ecological Economics*, 174, p.106600. Available from: https://www.sciencedirect.com/science/article/pii/S0921800919308626.

Faccioli, M., Kuhfuss, L. and Czajkowski, M., 2019. Stated preferences for conservation policies under uncertainty: insights on the effect of individuals' risk attitudes in the environmental domain. *Environmental and resource economics*, 73(2), pp.627–659. Available from: https://link.springer.com/article/10.1007%2Fs10640-018-0276-2.

Forrest, A., 2018. Only one third of uk's plastic food packaging is recycled, study finds. *The Independent.* Available from: https://www.independent.co.uk/environment/uk-plastic-food-packaging-recyclable-third-government-study-a8476431.html.

Foster, V. and Mourato, S., 2002. Testing for consistency in contingent ranking experiments. *Journal of environmental Economics and Management*, 44(2), pp.309–328. Available from: https://www.sciencedirect.com/science/article/pii/S0095069601912033.

Foster, V. and Mourato, S., 2003. Elicitation format and sensitivity to scope. *Environmental and resource economics*, 24(2), pp.141–160. Available from: https://link.springer.com/article/10.1023/A:1022856329552.

Fransson, N. and Garling, T., 1999. Environmental concern: Conceptual definitions, measurement methods, and research findings. *Journal of environmental psychology*, 19(4), pp.369–382. Available from: https://www.researchgate.net/profile/Niklas_Fransson/publication/222252867_Environmental_Concern_Conceptual_Definitions_Measurement_Methods_and_Research_Findings/links/5a0c5866a6fdcc39e9bf6438/Environmental-Concern-Conceptual-Definitions-Measurement-Methods-and-Research-Findings.pdf.

Frederick, S., Loewenstein, G. and O'Donoghue, T., 2002. Time discounting and time preference: A critical review. *Journal of economic literature*, 40(2), pp.351–401. Available from: https://www.jstor.org/stable/pdf/2698382.

Fujiwara, D. and Campbell, R., 2011. *Valuation techniques for social cost-benefit analysis.* HM Treasury: HM Government. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/209107/greenbook_valuationtechniques.pdf.

Fullerton, D. and Wolverton, A., 1997. *The case for a two-part instrument: presumptive tax and environmental subsidy.* National Bureau of Economic Research. Available from: https://www.nber.org/papers/w5993.pdf.

Ghosh, S., Maitra, B. and Das, S.S., 2013. Effect of distributional assumption of random parameters of mixed logit model on willingness-to-pay values. *Procedia-Social and Behavioral Sciences*, 104, pp.601–610. Available from: https://www.sciencedirect.com/science/article/pii/S187704281304545X.

Gianessi, L.P., Peskin, H.M. and Wolff, E., 1979. The distributional effects of uniform air pollution policy in the united states. *The Quarterly Journal of Economics*, pp.281–301. Available from: https://www.jstor.org/stable/pdf/1883195.pdf.

Glenk, K., Johnston, R.J., Meyerhoff, J. and Sagebiel, J., 2020. Spatial dimensions of stated preference valuation in environmental and resource economics: methods, trends and challenges. *Environmental and Resource Economics*, 75(2), pp.215–242. Available from: https://link.springer.com/content/pdf/10.1007/s10640-018-00311-w.pdf.

Glenk, K. and Martin-Ortega, J., 2018. The economics of peatland restoration. *Journal* *of Environmental Economics and Policy*, 7(4), pp.345–362. Available from: https://www.tandfonline.com/doi/pdf/10.1080/21606544.2018.1434562.

Gollier, C. and Treich, N., 2003. Decision-making under scientific uncertainty: the economics of the precautionary principle. *Journal of Risk and Uncertainty*, 27(1), pp.77–103. Available from: https://link.springer.com/content/pdf/10.1023/A:1025576823096.pdf.

Granero-Gomez, P., 2005. *The efficiency of indirect instruments for waste externalities. integrated approaches to environmental policy.* EAERE. Available from: https://pdfs.semanticscholar.org/e0f9/ec1a7fe458139176bf30b00170c6085967ed.pdf.

Green Alliance, 2018. *Growing a circular economy.* Green Alliance. Available from: http://data.parliament.uk/writtenevidence/committeeevidence.svc/evidencedocument/environmental-audit-committee/chinese-restriction-on-imported-waste/written/77179.html.

Ha-Duong, M., 1998. Quasi-option value and climate policy choices. *Energy Economics*, 20(5-6), pp.599–620. Available from: https://www.sciencedirect.com/science/article/pii/S0140988398000115.

Hammer, J., Kraak, M. and Parsons, J., 2012. Plastics in the marine environment: the dark side of a modern gift. *Reviews of environmental contamination and toxicology*, pp.1–44. Available from: https://www.researchgate.net/profile/John_Parsons3/publication/225049699_Plastics_in_the_Marine_Environment_The_Dark_Side_of_a_Modern_Gift/links/0912f5072f10dd513a000000/Plastics-in-the-Marine-Environment-The-Dark-Side-of-a-Modern-Gift.pdf.

Hanemann, M., Loomis, J. and Kanninen, B., 1991. Statistical efficiency of double-bounded dichotomous choice contingent valuation. *American journal of agricultural economics*, 73(4), pp.1255–1263. Available from: https://doi.org/10.2307/1242453.

Hanemann, W.M., 1984. Discrete/continuous models of consumer demand. *Econometrica: Journal of the Econometric Society*, pp.541–561. Available from: https://www.jstor.org/stable/pdf/1913464.

Hanemann, W.M., 1989. Information and the concept of option value. *Journal of Environmental Economics and management*, 16(1), pp.23–37. Available from: https://www.sciencedirect.com/science/article/pii/0095069689900429.

Harse, G., 2011. Plastic, the great pacific garbage patch, and international misfires at a cure. *UCLA Journal of Environmental Law and Policy*, 29, p.331. Available from: https://cloudfront.escholarship.org/dist/prd/content/qt4pp84809/qt4pp84809.pdf.

Hauber, A.B., Fairchild, A.O. and Johnson, F.R., 2013. Quantifying benefit–risk preferences for medical interventions: an overview of a growing empirical literature. *Applied health economics and health policy*, 11(4), pp.319–329. Available from: https://search.proquest.com/docview/1466285987/fulltextPDF/C7E3E61430BE49F1PQ/1?accountid=17230.

Hausman, J., 2012. Contingent valuation: from dubious to hopeless. *Journal of Economic Perspectives*, 26(4), pp.43–56. Available from: https://pubs.aeaweb.org/doi/pdf/10.1257/jep.26.4.43.

Hausman, J.A. and McFadden, D., 1981. Specification tests for the multinomial logit model. *Cambridge, Mass.: Dept. of Economics, Massachusetts Institute of Technology*. Available from: https://www.jstor.org/stable/pdf/1910997.

Henderson, J., 2001. A pre- and post-marpol annex v summary of hawaiian monk seal entanglements and marine debris accumulation in the northwestern hawaiian islands. *Marine Pollution Bulletin*, 42, pp.584–589. Available from: https://www.sciencedirect.com/science/article/pii/S0025326X00002046.

Henry, C., 1974. Investment decisions under uncertainty: the"" irreversibility effect"". *The American Economic Review*, 64(6), pp.1006–1012. Available from: https://www.jstor.org/stable/pdf/1815248.

Hensher, D.A., Rose, J.M. and Greene, W.H., 2005. *Applied choice analysis: a primer*. Cambridge University Press. Available from: https://www.google.co.uk/books/edition/Applied_Choice_Analysis/8yZrtCCABAgC?hl=en&gbpv=1&dq=Hensher,+D.,+Rose,+J.+and+Greene,+W.+2005.+Applied+Choice+Analysis:+A+Primer.+Cambridge:+Cambridge+University+Press.&pg=PR13&printsec=frontcover#v=onepage&q&f=true.

Hess, S. and Beharry-Borg, N., 2012. Accounting for latent attitudes in willingness-to-pay studies: the case of coastal water quality improvements in tobago. *Environmental and Resource Economics*, 52(1), pp.109–131. Available from: https://link.springer.com/content/pdf/10.1007/s10640-011-9522-6.pdf.

Hess, S. and Daly, A., 2014. *Handbook of choice modelling*. Edward Elgar Publishing. Available from: https://www.google.co.uk/books/edition/Handbook_of_Choice_Modelling/XghCBAAAQBAJ?hl=en&gbpv=0.

Hess, S. and Palma, D., 2019. Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of choice modelling*, 32, p.100170. Available from: `https://doi.org/10.1016/j.jocm.2019.100170`.

HM Treasury, 2018. *The green book. central government guidance on appraisal and evaluation.* HM Treasury: HM Government. Available from: `https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/938046/The_Green_Book_2020.pdf`.

Hoel, M. and Karp, L., 2002. Taxes versus quotas for a stock pollutant. *Resource and Energy Economics*, 24(4), pp.367–384.

Hoffman, S.D. and Duncan, G.J., 1988. Multinomial and conditional logit discrete-choice models in demography. *Demography*, 25(3), pp.415–427. Available from: `https://link.springer.com/article/10.2307/2061541`.

Hökby, S. and Söderqvist, T., 2003. Elasticities of demand and willingness to pay for environmental services in sweden. *Environmental and resource economics*, 26(3), pp.361–383. Available from: `https://link.springer.com/content/pdf/10.1023/B:EARE.0000003581.97411.75.pdf`.

Hole, A.R., 2006. A comparison of approaches to estimating confidence intervals for willingness to pay measures. *National Primary Care Research and Development Centre*. Available from: `https://www.york.ac.uk/media/che/documents/papers/researchpapers/rp8_comparison_of_approaches_to_estimating_confidence_intervals_for_WTP.pdf`.

Hook, L. and Reed, J., 2018. Why the world's recycling system stopped working. *The Financial Times*. Available from: `https://www.ft.com/content/360e2524-d71a-11e8-a854-33d6f82e62f8`.

Hooper, T.L., 2013. *Evaluating the costs and benefits of tidal range energy generation*. Ph.D. thesis. University of Bath. Available from: `https://purehost.bath.ac.uk/ws/portalfiles/portal/187948106/Hooper_Tara_PhD_Thesis_17_12_13.pdf`.

Horton, A.A., Cross, R.K., Read, D.S., J¨urgens, M.D., Ball, H.L., Svendsen, C., Vollertsen, J. and Johnson, A.C., 2020. Semi-automated analysis of microplastics in complex wastewater samples. *Environmental Pollution*, 268, p.115841. Available from: `https://www.sciencedirect.com/science/article/pii/S0269749120365301`.

Howard, G., Whitehead, J.C. and Hochard, J., 2020. Estimating discount rates using referendum-style choice experiments: An analysis of multiple methodologies. *Journal* *of Environmental Economics and Management*, 105, p.102399. Available from: https://www.sciencedirect.com/science/article/pii/S0095069620301224?dgcid=rss_sd_all&utm_campaign=RESR_MRKT_Researcher_inbound&utm_medium=referral&utm_source=researcher_app#sec7.

Hoyos, D., 2010. The state of the art of environmental valuation with discrete choice experiments. *Ecological economics*, 69(8), pp.1595–1603. Available from: https://www.sciencedirect.com/science/article/pii/S0921800910001540#bib73.

Hynes, S., Ankamah-Yeboah, I., O'Neill, S., Needham, K., Xuan, B.B. and Armstrong, C., 2020. The impact of nature documentaries on public environmental preferences and willingness to pay: entropy balancing and the blue planet ii effect. *Journal of Environmental Planning and Management*, pp.1–29. Available from: https://doi.org/10.1080/09640568.2020.1828840.

Interdepartmental Liaison Group, 2002. *The precautionary principle: Policy and application.* INTERDEPARTMENTAL LIAISON GROUP ON RISK ASSESSMENT. Available from: http://www.hse.gov.uk/aboutus/meetings/committees/ilgra/pppa.pdf.

Jambeck, J., Geyer, R., Wilcox, C., Siegler, T., Perryman, M., Andrady, A., Narayan, R. and Law, K., 2005. Plastic waste inputs from land into the ocean. *Science*, 347(6223), pp.768–771. Available from: http://science.sciencemag.org/content/sci/347/6223/768.full.pdf.

Johnston, R., Boyle, K., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T., Hanemann, W., Hanley, N., Ryan, M., Scarpa, R. and Tourangeau, R., 2017. Contemporary guidance for stated preference studies. *Journal of the Association of Environmental and Resource Economists*, 4(2), pp.319–405. Available from: http://aura.abdn.ac.uk/bitstream/handle/2164/10529/691697.pdf?sequence=1.

Jørgensen, S.L., Olsen, S.B., Ladenburg, J., Martinsen, L., Svenningsen, S.R. and Hasler, B., 2013. Spatially induced disparities in users' and non-users' wtp for water quality improvements—testing the effect of multiple substitutes and distance decay. *Ecological Economics*, 92, pp.58–66. Available from: https://www.sciencedirect.com/science/article/pii/S0921800912002790?via%3Dihub#s0030.

Kahneman, D., Knetsch, J.L. and Thaler, R.H., 1990. Experimental tests of the endowment effect and the coase theorem. *Journal of political Economy*, 98(6), pp.1325–1348. Available from: https://www.journals.uchicago.edu/doi/pdfplus/10.1086/261737.

Kallbekken, S. and Aasen, M., 2010. The demand for earmarking: Results from a focus group study. *Ecological economics*, 69(11), pp.2183–2190. Available from: https://www.sciencedirect.com/science/article/pii/S0921800910002284.

Kallbekken, S., Kroll, S. and Cherry, T.L., 2011. Do you not like pigou, or do you not understand him? tax aversion and revenue recycling in the lab. *Journal of Environmental Economics and Management*, 62(1), pp.53–64. Available from: https://www.sciencedirect.com/science/article/pii/S0095069611000192.

Kallbekken, S. and Sælen, H., 2011. Public acceptance for environmental taxes: Self-interest, environmental and distributional concerns. *Energy Policy*, 39(5), pp.2966–2973. Available from: https://www.sciencedirect.com/science/article/pii/S0301421511001868.

Karlsson, T.M., Arneborg, L., Broström, G., Almroth, B.C., Gipperth, L. and Hassellöv, M., 2018. The unaccountability case of plastic pellet pollution. *Marine pollution bulletin*, 129(1), pp.52–60. Available from: https://www.sciencedirect.com/science/article/pii/S0025326X18300523.

Kershaw, P., Katsuhiko, S., Lee, S. and Woodring, D., 2011. *Plastic debris in the ocean*. United Nations Environment Programme. Available from: https://fagarkivet-hioa.archive.knowledgearc.net/bitstream/handle/20.500.12199/219/Samseth_Plastic%20debris%20in%20the%20ocean.pdf?sequence=2.

Kildow, J. and McIlgorm, A., 2010. The importance of estimating the contribution of the oceans to national economies. *Marine Policy*, 34(3), pp.367 – 374. Available from: http://www.sciencedirect.com/science/article/pii/S0308597X09001225.

Kim, H.J., Lee, H.J. and Yoo, S.H., 2019. Public willingness to pay for endocrine disrupting chemicals-free labelling policy in korea. *Applied Economics*, 51(2), pp.131–140. Available from: https://www.tandfonline.com/doi/full/10.1080/00036846.2018.1494803.

Kinnaman, T.C., Shinkuma, T. and Yamamoto, M., 2014. The socially optimal recycling rate: evidence from japan. *Journal of Environmental Economics and Management*, 68(1), pp.54–70. Available from: https://www.sciencedirect.com/science/article/pii/S0095069614000230.

Kjær, T., Bech, M., Gyrd-Hansen, D. and Hart-Hansen, K., 2006. Ordering effect and price sensitivity in discrete choice experiments: need we worry? *Health economics*, 15(11), pp.1217–1228. Available from: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hec.1117.

Koelmans, A.A., Bakir, A., Burton, G.A. and Janssen, C.R., 2016. Microplastic as a vector for chemicals in the aquatic environment: critical review and model-supported reinterpretation of empirical studies. *Environmental science & technology*, 50(7), pp.3315–3326. Available from: https://pubs.acs.org/doi/pdf/10.1021/acs.est.5b06069.

Kollmuss, A. and Agyeman, J., 2002. Mind the gap: why do people act environmentally and what are the barriers to pro-environmental behavior? *Environmental education research*, 8(3), pp.239–260. Available from: https://www.tandfonline.com/doi/pdf/10.1080/13504620220145401.

Kolstad, C.D., 1996. Learning and stock effects in environmental regulation: the case of greenhouse gas emissions. *Journal of environmental economics and management*, 31(1), pp.1–18. Available from: https://pdfs.semanticscholar.org/1a4e/7a406eeb38381218f2218c05f640ec5d6597.pdf.

Kosuth, M., Mason, S.A. and Wattenberg, E.V., 2018. Anthropogenic contamination of tap water, beer, and sea salt. *PloS one*, 13(4), p.e0194970. Available from: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0194970.

Kotchen, M.J. and Reiling, S.D., 2000. Environmental attitudes, motivations, and contingent valuation of nonuse values: a case study involving endangered species. *Ecological Economics*, 32(1), pp.93–107. Available from: https://www.sciencedirect.com/science/article/pii/S0921800999000695.

Krutilla, K., 2005. Using the kaldor-hicks tableau format for cost-benefit analysis and policy evaluation. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, 24(4), pp.864–875. Available from: https://onlinelibrary.wiley.com/doi/pdf/10.1002/pam.20147?casa_token=AO-aqeXmDOwAAAAA:gveWz9PlDJc1GEI51-EJmIuRuxzlIEHJAN2lLGdi0xvDQxa4tVc1vSB62N5s2XBeUsrNBrOeukU7suQ5.

Krutilla, K., Good, D., Toman, M. and Arin, T., 2021. Addressing fundamental uncertainty in benefit–cost analysis: The case of deep seabed mining. *Journal of Benefit-Cost Analysis*, 12(1), pp.122–151. Available from: https://doi.org/10.1017/bca.2020.28.

Kumar, P., 2012. *The economics of ecosystems and biodiversity: ecological and economic foundations*. Routledge. Available from: https://www.taylorfrancis.com/books/9781136538803.

Kuntz-Duriseti, K., 2004. Evaluating the economic value of the precautionary principle: using cost benefit analysis to place a value on precaution. *Environmental Science & Policy*, 7(4), pp.291–301. Available from: https://www.sciencedirect.com/science/article/pii/S1462901104000619.

Laist, D.W., 1997. Impacts of marine debris: entanglement of marine life in marine debris including a comprehensive list of species with entanglement and ingestion records. *Marine debris*, Springer, pp.99–139. Available from: https://www.researchgate.net/profile/David_Laist/publication/235768493_Impacts_of_Marine_Debris_Entanglement_of_Marine_Life_in_Marine_Debris_Including_a_Comprehensive_List_of_Species_with_Entanglement_and_IngestiOn_Records/links/02bfe5136037d75c73000000.pdf.

Lancaster, K.J., 1966. A new approach to consumer theory. *Journal of political economy*, 74(2), pp.132–157. Available from: https://www.jstor.org/stable/1828835.

Lancsar, E. and Louviere, J., 2008. Conducting discrete choice experiments to inform healthcare decision making. *Pharmacoeconomics*, 26(8), pp.661–677. Available from: https://link.springer.com/article/10.2165/00019053-200826080-00004.

Lanz, B. and Provins, A., 2013. Valuing local environmental amenity with discrete choice experiments: Spatial scope sensitivity and heterogeneous marginal utility of income. *Environmental and Resource Economics*, 56(1), pp.105–130. Available from: https://link.springer.com/content/pdf/10.1007%2Fs10640-013-9648-9.pdf.

Laroche, M., Bergeron, J. and Barbaro-Forleo, G., 2001. Targeting consumers who are willing to pay more for environmentally friendly products. *Journal of consumer marketing*, 18(6), pp.503–520. Available from: https://pdfs.semanticscholar.org/80cd/5da90022eb6e412d67a9479e5c591ec1fe5a.pdf.

Łaszkiewicz, E., Czembrowski, P. and Kronenberg, J., 2019. Can proximity to urban green spaces be considered a luxury? classifying a non-tradable good with the use of hedonic pricing method. *Ecological Economics*, 161, pp.237–247. Available from: https://doi.org/10.1016/j.ecolecon.2019.03.025.

Lavee, D., 2010. A cost-benefit analysis of a deposit–refund program for beverage containers in israel. *Waste management*, 30(2), pp.338–345. Available from: https://www.sciencedirect.com/science/article/pii/S0956053X09003808.

Layard, R., Mayraz, G. and Nickell, S., 2008. The marginal utility of income. *Journal of Public Economics*, 92(8-9), pp.1846–1857. Available from: https://www.sciencedirect.com/science/article/pii/S0047272708000248.

Lebreton, L., Egger, M. and Slat, B., 2019. A global mass budget for positively buoyant macroplastic debris in the ocean. *Scientific reports*, 9(1), pp.1–10. Available from: https://www.nature.com/articles/s41598-019-49413-5.

Lebreton, L., Slat, B., Ferrari, F., Sainte-Rose, B., Aitken, J., R.Marthouse, S.Hajbane, Cunsolo, S., A.Schwarz, Levivier, A. and Noble, K., 2018. Evidence that the great pacific garbage patch is rapidly accumulating plastic. *Scientific reports*, 8(1), p.4666. Available from: https://www.nature.com/articles/s41598-018-22939-w.

Lee, J., 2015. Economic valuation of marine litter and microplastic pollution in the marine environment: An initial assessment of the case of the united kingdom. *SOAS-CeFiMS: London, UK*, pp.1–16. Available from: https://www.researchgate.net/profile/Jeo_Lee3/publication/283680054_Economic_valuation_of_marine_litter_and_microplastic_pollution_in_the_marine_environment_An_initial_assessment_of_the_case_of_the_United_Kingdom/links/564328df08ae451880a31e52/Economic-valuation-of-marine-litter-and-microplastic-pollution-in-the-marine-environment-An-initial-assessment-of-the-case-of-the-United-Kingdom.pdf.

Leggett, C.G., Scherer, N., Curry, M.S., Bailey, R. and Haab, T.C., 2014. *Assessing the economic benefits of reductions in marine debris: a pilot study of beach recreation in orange county, california*. Industrial Economics, Incorporated. Available from: http://marinedebris.noaa.gov/sites/default/files/publications-files/MarineDebrisEconomicStudy_0.pdf.

Lew, D.K. and Wallmo, K., 2011. External tests of scope and embedding in stated preference choice experiments: an application to endangered species valuation. *Environmental and Resource Economics*, 48(1), pp.1–23. Available from: https://link.springer.com/content/pdf/10.1007/s10640-010-9394-1.pdf.

Li, D., Zhao, L., Ma, S., Shao, S. and Zhang, L., 2019. What influences an individual's pro-environmental behavior? a literature review. *Resources, Conservation and Recycling*, 146, pp.28–34. Available from: https://www.sciencedirect.com/science/article/pii/S0921344919301302.

Lim, S.Y., Jin, S.J. and Yoo, S.H., 2017. The economic benefits of the dokdo seals restoration project in korea: A contingent valuation study. *Sustainability*, 9(6), p.968. Available from: https://www.mdpi.com/2071-1050/9/6/968/pdf.

Lindhjem, H. and Navrud, S., 2011. Are internet surveys an alternative to face-to-face interviews in contingent valuation? *Ecological economics*, 70(9), pp.1628–

1637. Available from: https://www.sciencedirect.com/science/article/pii/S0921800911001340.

Logar, I., Brouwer, R. and Campbell, D., 2020. Does attribute order influence attribute-information processing in discrete choice experiments? *Resource and Energy Economics*, 60, p.101164. Available from: https://www.sciencedirect.com/science/article/pii/S0928765518302409.

Logar, I., Brouwer, R., Maurer, M. and Ort, C., 2014. Cost-benefit analysis of the swiss national policy on reducing micropollutants in treated wastewater. *Environmental science & technology*, 48(21), pp.12500–12508. Available from: https://pubs.acs.org/doi/pdf/10.1021/es502338j.

Loomis, J.B., 2010. Importance of incorporating distributional issues in benefit-cost analysis. *paper commissioned by the Benefit-Cost Analysis Center, University of Washington*. Available from: https://evans.uw.edu/sites/default/files/public/Loomis_Distributional_Issues_21Apr2010.pdf.

Loomis, J.B., 2014. 2013 waea keynote address: Strategies for overcoming hypothetical bias in stated preference surveys. *Journal of Agricultural and Resource Economics*, pp.34–46. Available from: https://www.jstor.org/stable/pdf/44131313.pdf.

Luisetti, T., Turner, R.K., Bateman, I.J., Morse-Jones, S., Adams, C. and Fonseca, L., 2011. Coastal and marine ecosystem services valuation for policy and management: Managed realignment case studies in england. *Ocean & Coastal Management*, 54(3), pp.212–224. Available from: https://www.sciencedirect.com/science/article/pii/S0964569110001961.

Lusher, A., Hollman, P. and Mendoza-Hill, J., 2017. *Microplastics in fisheries and agriculture*. Food and Agriculture Office of the United Nations. Available from: http://www.fao.org/3/a-i7677e.pdf.

Manne, A.S., Manne, A.S., Richels, R.G. and Richels, R.G., 1992. *Buying greenhouse insurance: the economic costs of carbon dioxide emission limits*. MIT press. Available from: https://books.google.co.uk/books?hl=en&lr=&id=sLFdp89-dQcC&oi=fnd&pg=PR9&dq=buying+greenhouse+insurance+manne+and+richels&ots=LlT99GikXx&sig=p0JhCzbQjbCLlsgCzuO2TZCAMZc.

Mao, B., Ao, C., Wang, J., Sun, B. and Xu, L., 2020. Does regret matter in public choices for air quality improvement policies? a comparison of regret-based and utility-based discrete choice modelling. *Journal of Cleaner Production*, p.120052. Available from: https://www.sciencedirect.com/science/article/pii/S0959652620300998#sec3.

McFadden, D. et al., 1973. Conditional logit analysis of qualitative choice behavior. *Institute of Urban and Regional Development, University of California ...*. Available from: http://elsa.berkeley.edu/reprints/mcfadden/zarembka.pdf.

McIlgorm, A., Campbell, H.F. and Rule, M.J., 2011. The economic cost and control of marine debris damage in the asia-pacific region. *Ocean and Coastal Management*, 54(9), pp.643 – 651. Available from: http://www.sciencedirect.com/science/article/pii/S0964569111000688.

McIntosh, E. and Ryan, M., 2002. Using discrete choice experiments to derive welfare estimates for the provision of elective surgery: implications of discontinuous preferences. *Journal of Economic Psychology*, 23(3), pp.367–382. Available from: https://www.sciencedirect.com/science/article/pii/S0167487002000818?casa_token=jg98pEue0rMAAAAA:2lmctmgid0gFB3FDwx4Ub159yL47Yr31Ry0wBDM5s8-0pTEypWPFRsN7gUEJ3gTx3wymY3b7XhA#aep-section-id16.

Mensink, P. and Requate, T., 2005. The dixit–pindyck and the arrow–fisher–hanemann–henry option values are not equivalent: a note on fisher (2000). *Resource and Energy Economics*, 27(1), pp.83–88. Available from: https://doi.org/10.1016/j.reseneeco.2004.04.001.

Meulen, M. Van der, Devriese, L., Lee, J., Maes, T., Van Dalfsen, J., Huvet, A., Soudant, P., Robbens, J. and Vethaak, A., 2014. Socio-economic impact of microplastics in the 2 seas, channel and france manche region: an initial risk assessment. *MICRO Interreg project IVa*. Available from: https://archimer.ifremer.fr/doc/00287/39834/38359.pdf.

Milani, P., França, D., Balieiro, A.G. and Faez, R., 2017. Polymers and its applications in agriculture. *Polímeros*, 27(3), pp.256–266. Available from: https://www.scielo.br/scielo.php?pid=S0104-14282017005006108&script=sci_arttext.

Mitchell, R.C. and Carson, R.T., 2013. *Using surveys to value public goods: the contingent valuation method.* Rff Press. Available from: https://content.taylorfrancis.com/books/download?dac=C2011-0-05561-4&isbn=9781135887742&format=googlePreviewPdf.

Morrissey, K., 2019. Aligning ocean plastic pollution and human health a co-benefits approach. *Journal of Ocean and Coastal Economics*, 6(1), p.5. Available from: https://cbe.miis.edu/cgi/viewcontent.cgi?article=1090&context=joce.

Moser, M. and Lee, D., 1992. A fourteen-year survey of plastic ingestion by western north atlantic seabirds. *Colonial Waterbirds*, 15, pp.83–94. Available from: https://www.jstor.org/stable/pdf/1521357.pdf.

Mouat, J., Lozano, R.L. and Bateson, H., 2010. *Economic impacts of marine litter.* Kommunenes Internasjonale Miljøorganisasjon. Available from: http://www.kimointernational.org/wp/wp-content/uploads/2017/09/KIMO_Economic-Impacts-of-Marine-Litter.pdf.

Murphy, F., Ewins, C., Carbonnier, F. and Quinn, B., 2016. Wastewater treatment works (wwtw) as a source of microplastics in the aquatic environment. *Environmental science & technology*, 50(11), pp.5800–5808. Available from: https://pubs.acs.org/doi/abs/10.1021/acs.est.5b05416.

Murphy, J.J., Allen, P.G., Stevens, T.H. and Weatherhead, D., 2005. A meta-analysis of hypothetical bias in stated preference valuation. *Environmental and Resource Economics*, 30(3), pp.313–325. Available from: https://link.springer.com/content/pdf/10.1007/s10640-004-3332-z.pdf.

Nick, J. and Ysé, S., 2006. *The distributional effects of environmental policy.* OECD Publishing. Available from: https://books.google.co.uk/books?hl=en&lr=&id=jB3WAgAAQBAJ&oi=fnd&pg=PR5&dq=The+Distributional+Effects+of+Environmental+Policy+edited+by+Johnstone+Nick,+Serret+Ys%C3%A9&ots=5OA_rfpCjv&sig=vhym0AgMeg0gs_hXlz--QAhe3v0.

Nixon, H. and Saphores, J.D.M., 2007. Financing electronic waste recycling californian households' willingness to pay advanced recycling fees. *Journal of Environmental Management*, 84(4), pp.547–559. Available from: https://cloudfront.escholarship.org/dist/prd/content/qt19p943dz/qt19p943dz.pdf.

OECD, 2004. Addressing the economics of waste. *Addressing the Economics of Waste*, pp.7–21. Available from: https://www.oecd-ilibrary.org/docserver/9789264106192-en.pdf?expires=1542298100&id=id&accname=ocid56018429&checksum=8F538A7A5323ADC60F02494763ACA282.

OECD, 2006. *Cost-benefit analysis and the environment: Recent developments.* OECD. Available from: 'http://www.oecd.org/environment/tools-evaluation/36190261.pdf'.

Oosterhuis, F., Papyrakis, E. and Boteler, B., 2014. Economic instruments and marine litter control. *Ocean and coastal management*, 102, pp.47–54. Available from: https://www.sciencedirect.com/science/article/pii/S096456911400249X.

Orme, B., 2010. *Getting started with conjoint analysis: Strategies for product design and pricing research.* 2nd ed. Research Publishers LLC. Available from: https://www.sawtoothsoftware.com/download/techpap/samplesz.pdf.

Orset, C., Barret, N. and Lemaire, A., 2017. How consumers of plastic water bottles are responding to environmental policies? *Waste management*, 61, pp.13–27. Available from: https://www.sciencedirect.com/science/article/pii/S0956053X16307693.

Ortega, D.L., Wang, H.H. and Olynk Widmar, N.J., 2015. Effects of media headlines on consumer preferences for food safety, quality and environmental attributes. *Australian Journal of Agricultural and Resource Economics*, 59(3), pp.433–445. Available from: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1467-8489.12097.

Pawar, P., Sanket, S., Shirgaonkar, S. and Patil, R., 2016. Plastic marine debris: Sources, distribution and impacts on coastal and ocean biodiversity. *Oceanography.* Available from: https://www.researchgate.net/profile/Prabhakar_Pawar/publication/295919494_Plastic_marine_debris_Sources_distribution_and_impacts_on_coastal_and_ocean_biodiversity/links/56d09cde08ae4d8d64a392aa/Plastic-marine-debris-Sources-distribution-and-impacts-on-coastal-and-ocean-biodiversity.pdf.

Pearce, D., 1998. Cost benefit analysis and environmental policy. *Oxford review of economic policy*, 14(4), pp.84–100. Available from: https://academic.oup.com/oxrep/article-pdf/14/4/84/9915932/84.pdf.

Pearce, D., 2003. The social costs of carbon and its policy implications. *Oxford Review of Economic Policy.* Available from: http://citeseerx.ist.psu.edu/images/pdf_icon.png;jsessionid=DA51AB5F953183CF8CFD7F2807CF86B3.

Perchard, D. and Bevington, G., 2016. A discussion of the uk prn/pern system for packaging waste and possible alternatives. Available from: http://www.esauk.org/application/files/3515/3589/6447/20161018_A_discussion_of_the_UK_PRN_PERN_system_for_packaging_waste_and_possible_alternatives.pdf.

Phillips, A., 2014. *The usefulness of'think-aloud'for evaluating questionnaires in use in the health domain.* Ph.D. thesis. University of Manchester. Available from: https://www.research.manchester.ac.uk/portal/files/54556341/FULL_TEXT.PDF.

Rakib, M.R.J., Torre, G.E. De-la, Pizarro-Ortega, C.I., Dioses-Salinas, D.C. and Al-Nahian, S., 2021. Personal protective equipment (ppe) pollution driven by the covid-19 pandemic in cox's bazar, the longest natural beach in the world. *Marine Pollution*

Bulletin, p.112497. Available from: https://doi.org/10.1016/j.marpolbul.2021.112497.

Rakotonarivo, O.S., Schaafsma, M. and Hockley, N., 2016. A systematic review of the reliability and validity of discrete choice experiments in valuing non-market environmental goods. *Journal of environmental management*, 183, pp.98–109. Available from: https://www.sciencedirect.com/science/article/pii/S0301479716305709.

Ray, A., Hughes, L., Konisky, D.M. and Kaylor, C., 2017. Extreme weather exposure and support for climate change adaptation. *Global Environmental Change*, 46, pp.104–113. Available from: https://doi.org/10.1016/j.gloenvcha.2017.07.002.

Regier, D.A., Watson, V., Burnett, H. and Ungar, W.J., 2014. Task complexity and response certainty in discrete choice experiments: an application to drug treatments for juvenile idiopathic arthritis. *Journal of Behavioral and Experimental Economics*, 50, pp.40–49. Available from: https://www.sciencedirect.com/science/article/abs/pii/S221480431400038X.

Riddel, M., 2011. Uncertainty and measurement error in welfare models for risk changes. *Journal of Environmental Economics and Management*, 61(3), pp.341–354. Available from: https://doi.org/10.1016/j.jeem.2010.11.004.

Robards, M., Piatt, J. and Wohl, K., 1995. Increasing frequency of plastic particles ingested by seabirds in the subarctic north pacific. *Marine Pollution Bulletin*, 30, pp.151–157. Available from: https://www.researchgate.net/profile/Martin_Robards/publication/222483960_Increasing_Frequency_of_Plastic_Particles_Ingested_by_Seabirds_in_the_Subarctic_North_Pacific/links/5a820ae80f7e9bda869f4fa1/Increasing-Frequency-of-Plastic-Particles-Ingested-by-Seabirds-in-the-Subarctic-North-Pacific.pdf.

Røine, K. and Lee, C.Y., 2006. With a little help from epr?: Technological change and innovation in the norwegian plastic packaging and electronics sectors. *Journal of Industrial Ecology*, 10(1-2), pp.217–237. Available from: https://onlinelibrary.wiley.com/doi/pdf/10.1162/108819806775545448.

Ryan, M., Gerard, K. and Amaya-Amaya, M., 2007. *Using discrete choice experiments to value health and health care*, vol. 11. Springer Science & Business Media. Available from: https://link.springer.com/content/pdf/10.1007%2F978-1-4020-5753-3.pdf.

Sandorf, E.D., Persson, L. and Broberg, T., 2020. Using an integrated choice and latent variable model to understand the impact of "professional" respondents in a stated preference survey. *Resource and Energy Economics*, p.101178. Available from: https://www.sciencedirect.com/science/article/pii/S0928765518304548#bib0065.

Scarpa, R. and Alberini, A., 2005. *Applications of simulation methods in environmental and resource economics*, vol. 6. Springer Science & Business Media. Available from: https://pdfs.semanticscholar.org/999d/5116a01106a88a50bfd68d8117a1a9163448.pdf.

Scasny, M. and Zvěřinová, I., 2014. *Stated-preference study to examine the economic value of benefits of avoiding selected adverse human health outcomes due to exposure to chemicals in the european union: Part ii: Fertility and developmental toxicity*. European Chemicals Agency. Available from: https://echa.europa.eu/documents/10162/13630/study_economic_benefits_avoiding_adverse_health_outcomes_2_en.pdf.

Schaafsma, M., Brouwer, R., Liekens, I. and De Nocker, L., 2014. Temporal stability of preferences and willingness to pay for natural areas in choice experiments: a test–retest. *Resource and Energy Economics*, 38, pp.243–260. Available from: https://www.sciencedirect.com/science/article/pii/S0301479716305709.

Schwartz, S.H., 1977. Normative influences on altruism. *Advances in experimental social psychology*, Elsevier, vol. 10, pp.221–279. Available from: https://www.researchgate.net/profile/Shalom-Schwartz/publication/319507233_NORMATIVE_INFLUENCES_ON_ALTRUISM/links/59b005cf458515563dd2faf6/NORMATIVE-INFLUENCES-ON-ALTRUISM.pdf.

Shalizi, C., 2012. Conditional logit model. *Carnegie Melon University*. Available from: https://www.stat.cmu.edu/~cshalizi/uADA/12/lectures/ch12.pdf.

Shen, M., Huang, W., Chen, M., Song, B., Zeng, G. and Zhang, Y., 2020. (micro) plastic crisis: Un-ignorable contribution to global greenhouse gas emissions and climate change. *Journal of Cleaner Production*, p.120138. Available from: https://www.sciencedirect.com/science/article/pii/S0959652620301852.

Sherrington, C., Hogg, D., Darrah, C. and Hann, S., 2013. *Exploring the indirect costs of litter in scotland. report to zero waste scotland*. Eunomia. Available from: https://www.zerowastescotland.org.uk/sites/default/files/Exploring%20the%20Indirect%20Costs%20of%20Litter%20in%20Scotland.pdf.

Sifringer, B., Lurkin, V. and Alahi, A., 2018. Enhancing discrete choice models with neural networks. *hEART*. Available from: https://pdfs.semanticscholar.org/5cc5/2c482db27510f9fca080a3982814d4139660.pdf.

Sparkman, G., Lee, N.R. and Macdonald, B.N., 2021. Discounting environmental policy: The effects of psychological distance over time and space. *Journal of Environmental Psychology*, 73, p.101529. Available from: https://www.sciencedirect.com/science/article/pii/S0272494420306940.

Spash, C.L., 2006. Non-economic motivation for contingent values: Rights and attitudinal beliefs in the willingness to pay for environmental improvements. *Land Economics*, 82(4), pp.602–622. Available from: https://www.jstor.org/stable/pdf/27647736.

Sudhakar, M., Trishul, A., Doble, M., Kumar, K.S., Jahan, S.S., Inbakandan, D., Viduthalai, R., Umadevi, V., Murthy, P.S. and Venkatesan, R., 2007. Biofouling and biodegradation of polyolefins in ocean waters. *Polymer Degradation and Stability*, 92(9), pp.1743–1752. Available from: https://www.sciencedirect.com/science/article/pii/S0141391007001267.

Takehama, S., 1990. Estimation of damage to fishing vessels caused by marine debris, based on insurance statistics. *Proceedings of the second international conference on marine debris*, Hawaii. pp.792–809. Available from: https://ci.nii.ac.jp/naid/10011369890/.

Thaler, R., 1981. Some empirical evidence on dynamic inconsistency. *Economics letters*, 8(3), pp.201–207. Available from: http://nobel.zufe.edu.cn/uploads/1/file/public/201712/20171207185435_1sfueu8i2x.pdf.

Thalmann, P., 2004. The public acceptance of green taxes: 2 million voters express their opinion. *Public Choice*, 119(1-2), pp.179–217. Available from: https://link.springer.com/content/pdf/10.1023/B:PUCH.0000024165.18082.db.

The Economist, 2019. The inflexibility of plastic. *The Economist*. Available from: https://www.economist.com/business/2019/07/25/the-inflexibility-of-plastic.

Thompson, R.C., Moore, C.J., Vom Saal, F.S. and Swan, S.H., 2009. Plastics, the environment and human health: current consensus and future trends. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1526), pp.2153–2166. Available from: https://dx.doi.org/10.1098%2Frstb.2009.0053.

Tinelli, M., 2019. *Applying discrete choice experiments in social care research*. NIHR School for Social Care Research. Available from: http://www.lse.ac.uk/business-and-consultancy/consulting/assets/documents/applying-discrete-choice-experiments-in-social-care-research.pdf.

Tol, R.S., 2001. Equitable cost-benefit analysis of climate change policies. *Ecological Economics*, 36(1), pp.71–85. Available from: https://www.sciencedirect.com/science/article/pii/S0921800900002044.

Traeger, C.P., 2014. On option values in environmental and resource economics. *Resource and Energy Economics*, 37, pp.242–252. Available from: https://www.sciencedirect.com/science/article/pii/S0928765514000360.

Train, K., 2009. *Discrete choice methods with simulation.* Cambridge University Press. Available from: https://eml.berkeley.edu/books/choice2.html.

Train, K. and Weeks, M., 2005. Discrete choice models in preference space and willingness-to-pay space. *Applications of simulation methods in environmental and resource economics*, Springer, pp.1–16. Available from: https://www.repository.cam.ac.uk/bitstream/handle/1810/131583/cwpe0443.pdf?sequence=1.

Treasury, H., 2018. *Tackling the plastic problem summary of responses to the call for evidence.* London: HM Treasury. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/734837/Plastics_call_for_evidence_summary_of_responses_web.pdf.

Trivedi, R.H., Patel, J.D. and Savalia, J.R., 2015. Pro-environmental behaviour, locus of control and willingness to pay for environmental friendly products. *Marketing Intelligence & Planning*, 33(1), pp.67–89. Available from: https://core.ac.uk/download/pdf/156963474.pdf.

Turpie, J.K., 2003. The existence value of biodiversity in south africa: how interest, experience, knowledge, income and perceived level of threat influence local willingness to pay. *Ecological Economics*, 46(2), pp.199–216. Available from: https://doi.org/10.1016/S0921-8009(03)00122-8.

Tyllianakis, E. and Skuras, D., 2016. The income elasticity of willingness-to-pay (wtp) revisited: A meta-analysis of studies for restoring good ecological status (ges) of water bodies under the water framework directive (wfd). *Journal of environmental management*, 182, pp.531–541. Available from: https://www.sciencedirect.com/science/article/pii/S0301479716305503#bib3.

UNEP, 2005. *Marine litter: An analytical overview.* United Nations Environment Programme. Available from: http://wedocs.unep.org/bitstream/handle/20.500.11822/8348/-Marine%20Litter%2c%20an%20analytical%20overview-20053634.pdf?sequence=3&isAllowed=y.

VALPAK, 2017. *Packaging for people, planet and profit - a sustainability checklist.* Food and Drink Federation. Available from: http://www.wrap.org.uk/sites/files/wrap/Business%20case%20using%20recycled%20polymers%20in%20new%20products.pdf.

Vegter, A.C., Barletta, M., Beck, C., Borrero, J., Burton, H., Campbell, M.L., Costa, M.F., Eriksen, M., Eriksson, C., Estrades, A. et al., 2014. Global research priorities to mitigate plastic pollution impacts on marine wildlife. *Endangered Species Research*, 25(3), pp.225–247. Available from: https://www.int-res.com/articles/esr_oa/n025p225.pdf.

Vigsø, D., 2004. Deposits on single use containers-a social cost-benefit analysis of the danish deposit system for single use drink containers. *Waste management & research*, 22(6), pp.477–487. Available from: https://journals.sagepub.com/doi/pdf/10.1177/0734242X04049252.

Vij, A. and Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B: Methodological*, 90, pp.192–217. Available from: https://doi.org/10.1016/j.trb.2016.04.021.

Voltaire, L., Pirrone, C. and Bailly, D., 2013. Dealing with preference uncertainty in contingent willingness to pay for a nature protection program: A new approach. *Ecological Economics*, 88, pp.76–85. Available from: https://www.sciencedirect.com/science/article/pii/S0921800913000189.

Vossler, C.A. and Watson, S.B., 2013. Understanding the consequences of consequentiality: Testing the validity of stated preferences in the field. *Journal of Economic Behavior & Organization*, 86, pp.137–147. Available from: https://www.sciencedirect.com/science/article/pii/S0167268112002661.

Waste and Resource Action Programme, 2011. *Plastic packaging composition report.* Waste and Resource Action Programme. Available from: http://www.wrap.org.uk/sites/files/wrap/Plastics%20Composition%202011%20Report.pdf.

Watson, V. and Ryan, M., 2007. Exploring preference anomalies in double bounded contingent valuation. *Journal of Health Economics*, 26(3), pp.463–482. Available from: https://doi.org/10.1016/j.jhealeco.2006.10.009.

Weng, W., Morrison, M.D., Boyle, K.J., Boxall, P.C. and Rose, J., 2020. Effects of the number of alternatives in public good discrete choice experiments. *Ecological Economics*, p.106904. Available from: https://www.sciencedirect.com/science/article/pii/S0921800920321959.

Whitehead, J.C. and Blomquist, G.C., 2006. The use of contingent valuation in benefit-cost analysis. *Handbook on contingent valuation*, pp.92–115. Available from: http://www.appstate.edu/~whiteheadjc/ECO4660/PDF/Whitehead%20and%20Blomquist%20CH04.pdf.

Wit, W. de and Bigaud, N., 2019. No plastic in nature: Assessing plastic ingestion from nature to people. *World Wildlife Fund*. Available from: https://d2ouvy59p0dg6k.cloudfront.net/downloads/plastic_ingestion_web_spreads.pdf.

Zambrano-Monserrate, M.A. and Ruano, M.A., 2020. Estimating the damage cost of plastic waste in galapagos islands: A contingent valuation approach. *Marine Policy*, 117, p.103933. Available from: https://www.sciencedirect.com/science/article/pii/S0308597X19309820.

Zhuang, J., Liang, Z., Lin, T. and De Guzman, F., 2007. *Theory and pwractice in the choice of social discount rate for cost-benefit analysis: a survey*. ERD working paper series. Available from: https://www.econstor.eu/bitstream/10419/109296/1/ewp-094.pdf.

Appendices

8.1 Appendix One: Sample Truncation

The sample of 670 can be truncated according to five different rules. The following section reports the theoretical justification for the five rules before Table 8.1 reports whether mean fitted WTP is statistically different between included and excluded respondents.

Rule: 1 Survey Understanding

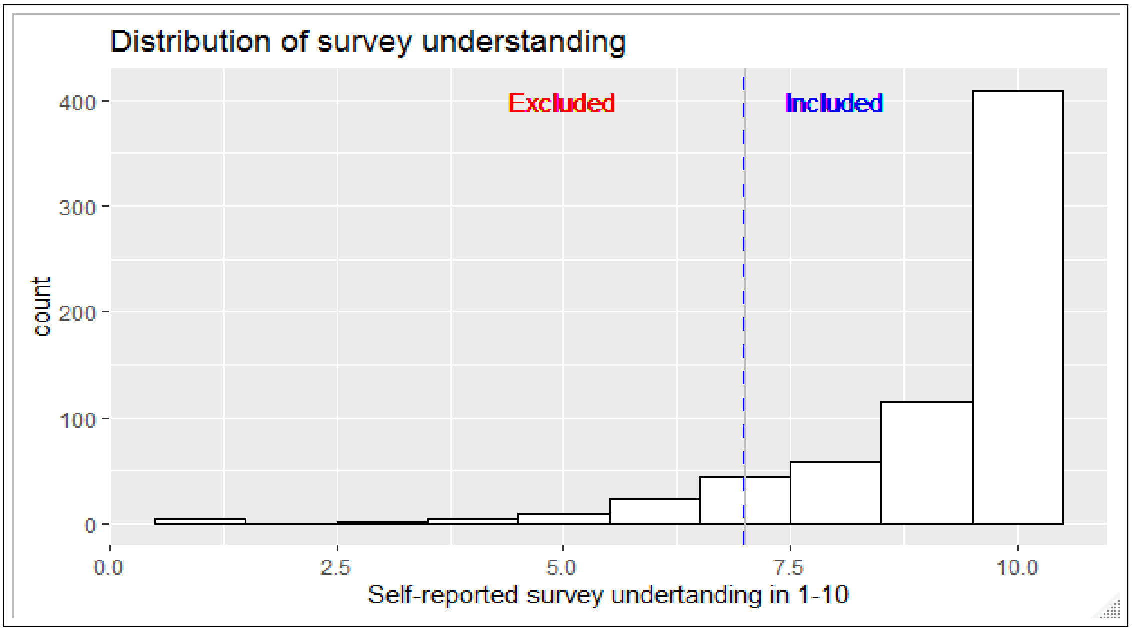
Question: 25

Respondents failing: 88, remaining: 582. Rate: 13%

The first truncation rule used respondents self-reported understanding of the survey post-completion. The understanding was assessed on a scale of 1 - 10 (incomprehensible - wholly understood). The level of respondent understanding and comprehension of the survey has been stressed as a critical factor in the SP literature, especially for more complex DCE designs (Arrow et al., 1993; Lancsar and Louviere, 2008; Rakotonarivo, Schaafsma and Hockley, 2016). Low levels of understanding may be associated with random responses, choice heuristics, or insensitivity to scope (Johnston et al., 2017; Scasny and Zvěřinová, 2014). In this research, respondents reporting that their understanding of the survey was less than 7/10 were excluded from the survey. There is no prior justification for arbitrarily choosing the seventh level, but it appears from Figure 8.1 to be an appropriate threshold given the majority of the sample reported a higher level of understanding. Indeed, the median level of understanding was nine, which suggests a high level of comprehension of the survey information and design. However, one flaw in this approach is that the understanding regards the whole survey rather than each question, and thus respondents may misunderstand the critical valuation questions. To handle this, certainty levels were elicited for the critical tasks. The responses may also be truncated according to self-reported certainty. Finally, it should also be noted that survey completion length could be used to truncate the sample, but there are three issues. Firstly, excluding respondents based on their timing involves using an arbitrary exclusion threshold which is less reliable. Secondly, purely using time is less informative of respondents comprehension than survey understanding. Finally, as timing and understanding are positively correlated, there is a potential collinearity problem. The collinearity should also be contrasted with any omitted variable bias if the endogenously determined timing is excluded. To summarise, the high level of understanding of this survey design suggests an encouraging degree of content validity.

Figure 8.1: Full survey understanding.

A histogram of the answers to Q25 about how well respondents understood the survey on a scale of 1-10. Those below 7/10 were excluded as in ECHA (2016).



Rule: 2 Dominance test

Question: 8.

Respondents failing: 192, remaining: 478. Rate: 28%

Question Eight (Q8) of the survey deliberately included a test of respondents understanding of the CE. The question featured a scenario where one alternative is unambiguously superior as it was lower cost and more effective, and thus 'dominates', the other scenario. Respondents who chose the dominated alternative thus completed the CE irrationally. Foster and Mourato (2002) motivates the use of this test as a test of the non-satiation axiom underpinning the rational choice model. In this research, Table 8.1 reports that there is a statistically significant difference in fitted mean WTP between those passing and failing the dominated test scenario, robust to both CE and CV questions. Furthermore, Figure 8.2 indicates that mean sample MWTP was higher for those who failed the dominated scenario test. This finding of exaggerated MWTP supports the exclusion of respondents who failed the dominated scenario test of rationality and comprehension.

Figure 8.2: Effect of dominated scenario on MWTP.

Rule: 3 Protest Votes

Question: 6, 7D, 8, 25

Respondents failing: 90, remaining: 580. Rate: 13%

The third truncation rule excluded protest votes from the sample. Analysis of the protest votes is provided in section 3.3.2.

Rule: 4 Consequentiality

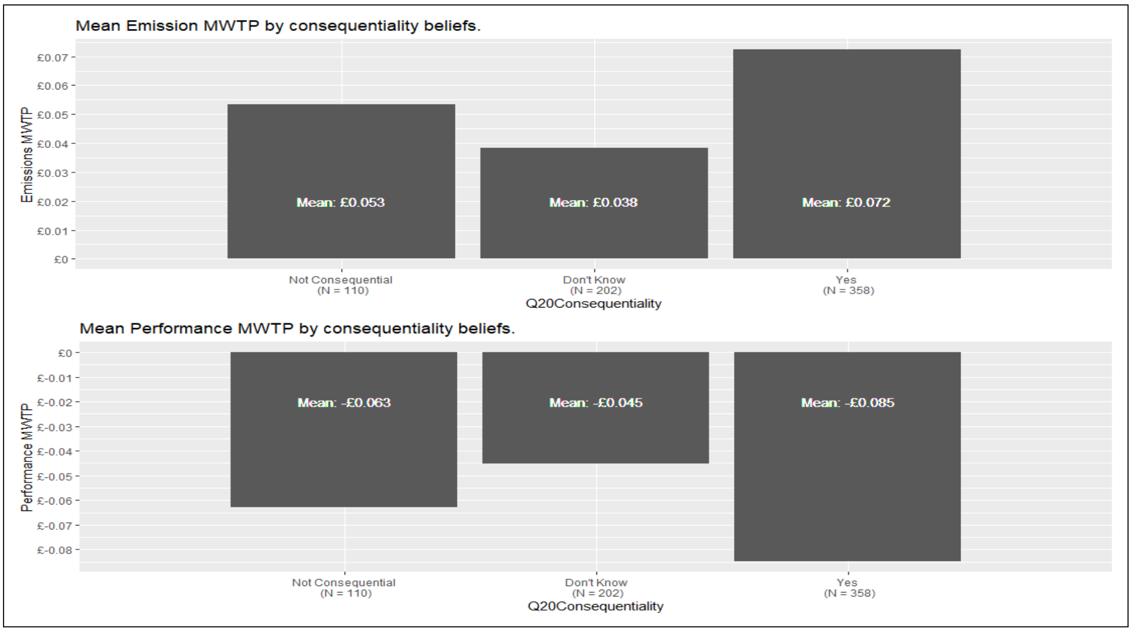
Question: 20

Respondents failing: 110, remaining: 560. Rate: 16%

This rule removed those who believed their survey participation to be inconsequential. Consequentiality is a necessary, albeit not sufficient, condition for responses to be incentive-compatible and *"describes a condition in which an individual faces or perceives a nonzero probability that their responses will influence decisions related to the outcome in question and they will be required to pay for that outcome if it is implemented."* (Johnston et al., 2017, p.323-333). Johnston et al. (2017) notes that ensuring that the survey design is incentive-compatible is critical for the validity of both CV and CE responses. Reporting respondents consequentiality beliefs is an instructive method of demonstrating the incentive-compatibility of the survey design (Vossler and Watson, 2013; Brouwer et al., 2017; Bateman and Langford, 1997; Loomis, 2014). This research asked respondents in Question twenty (Q20) whether they believed their participation to be consequential to policymaking. Payment consequentiality was not assessed in this research, although recent literature suggests that future work should assess both payment and policy consequentiality (Dugstad et al., 2021). The results of Q20 were 110 respondents reporting that they did not believe their participation to be consequential. The inconsequential rate was 16% (110/670 excluded), although other studies have not reported their rates. A stricter truncation rule would exclude both 'No' and the 'Don't Know' option provided by the survey company for respondents who did not understand the policymaking process. However, the stricter exclusion is rejected for two reasons. Firstly, the 'do not know' responses are typically more similar to the consequential respondents than the inconsequential and, therefore, it appears unnecessary to exclude them. Secondly, the exclusion rate of 54% (364/670 excluded) is far higher and, combined with the other rules, radically reduces the sample size. Therefore, the 110 inconsequential responses were excluded from the sample. The difference in WTP between consequential and inconsequential beliefs is evident in Table 8.1, which reports highly significant statistical differences in mean fitted WTP, and in Figures 8.3 and 8.4 which plot WTP by consequentiality beliefs.

Figure 8.3: Difference in mean CV WTP by consequentiality beliefs.

Figure 8.4: Difference in mean CE MWTP by consequentiality beliefs.



Rule: 5 Certainty

Question: 6C, 7B, 12B.

Respondents failing: 70, remaining: 600. Rate: 10.50% (For Q6)

The final possible truncation rule is to use respondent self-reported certainty of their valuations. There is a rich debate in the SP literature on the appropriate measurement strategy for including respondent certainty (Johnston et al., 2017). For instance, Blomquist, Blumenschein and Johannesson (2009); Loomis (2014); Voltaire, Pirrone and Bailly (2013) in the CV literature discuss ex-post calibration CV WTP of using certainty scales. Examples in the DCE literature include Regier et al. (2014) who discussed the effect of certainty and complexity on responses and Dekker et al. (2016) who used the ICLV approach to model preference uncertainty. Although the literature has previously used five to ten levels for self-reported certainty, this research used only three levels, 'Unsure', 'Quite Sure', and 'Very Sure' for simplicity (Blomquist, Blumenschein and Johannesson, 2009; Watson and Ryan, 2007). Therefore, the sample can be truncated using either a 'strong' condition, allowing only 'Very Sure' responses, or a 'weak' condition, using 'Very Sure' and 'Quite Sure' responses. The weak condition was adopted in this research as 'quite sure' respondents reported WTP closer to the 'very sure' respondents compared to the unsure respondents; see Figures 8.5 and 8.6. Additionally, many of the 'Unsure' responses were largely from those with protest votes or believed the survey to be inconsequential and may already be excluded. This may be due to the general nature of the certainty questions.

There are two effects of greater certainty; greater status quo aversion and higher WTP. Unsure respondents chose the status quo option far more often than very sure respondents; see Table 8.4 in the Appendix. This finding of greater certainty leading to status quo aversion is robust to question and corroborates Dekker et al. (2016). Indeed, it suggests that unsure respondents are more likely to choose the status quo when faced with a hypothetical scenario. The fewer unsure respondents in the CE suggests that it was not too complex for respondents. Alternatively, the greater certainty may be due to the CV questions being first, and thus respondents were more familiar with the context (Regier et al., 2014). The relationship between WTP and certainty is reported in Figures 8.5 and 8.6. The small positive effect of greater certainty on WTP suggests that hypothetical bias leads to reduced WTP, contrary to Murphy et al. (2005), but consistent with ECHA (2019). To summarise, compared to 'certain' respondents, uncertain ones were biased towards the status quo and reported statistically different WTP, thus were excluded.

Figure 8.5: Greater response certainty influenced CV WTP.

Figure 8.6: Greater response certainty influenced CE MWTP.

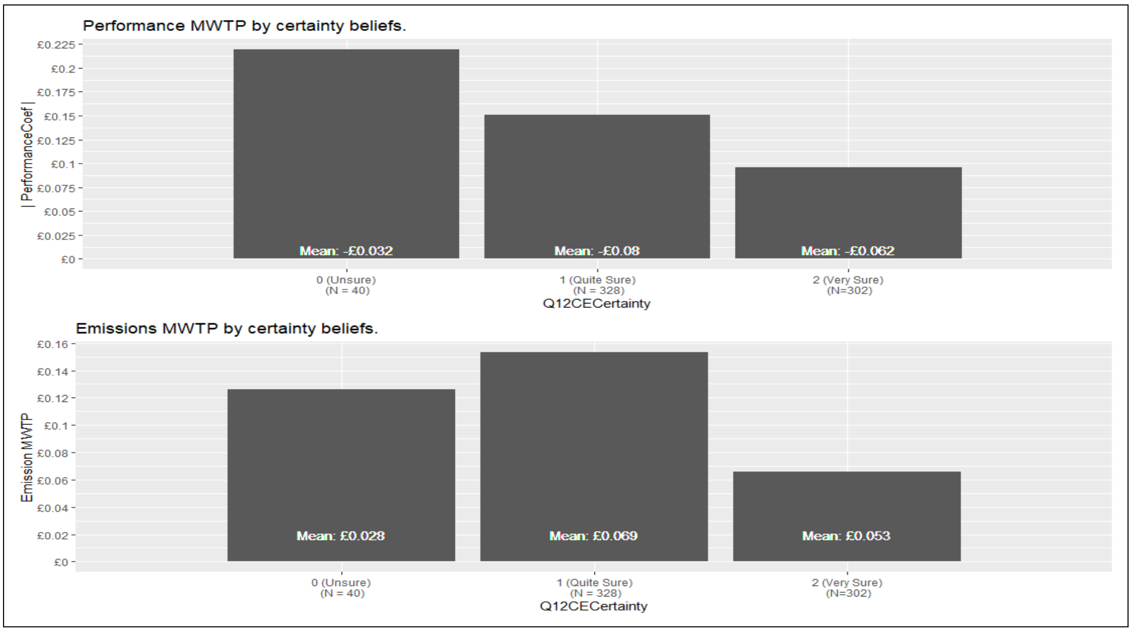


Table 8.1 reports the p-values for nonparametric Mann-Whitney (Wilcoxon Rank Sum) tests of equality of mean fitted WTP between included and excluded respondents under each truncation rule. The nonparametric approach is appropriate where the data is not normally distributed. The first three rules report statistically significant differences in mean fitted WTP between the included and excluded rules. Therefore, the Mann-Whitney tests support their use of understanding and the dominated test to truncate the sample. For the consequentiality rule, the 'Don't Know responses were statistically different from the 'No' responses, which supports their inclusion under Truncation Strategy Two. Moreover, the 'Quite Sure' respondents were statistically significant from both the 'Unsure' and 'Very Sure' respondents, with the exception of the CE, where there were no statistically significant differences in mean fitted WTP. Therefore, the support for including or excluding 'Quite Sure' respondents is weaker. The insignificant difference in Q6 mean fitted WTP for both 'No' and 'Yes' consequentiality and 'Unsure' and 'Very Sure' respondents does not conform to theoretical explanations or the graphical evidence and is thus believed to be anomalous. Additionally, there are statistically significant differences in means between protest voters and others, as explored in Section 3.3.2. Curiously, there is no statistical difference in most of the SP tasks except for Q6; this challenges the existence of an ordering effect in this research. Finally, the table also reports mixed results about the differences between no truncation, truncation rule one and truncation rule two, which generally support the weaker and more inclusive truncation rule. To summarise, the Mann-Whitney tests indicate that there are statistically different WTP values when truncating the sample.

Table 8.3 in the Appendix reports the effect on sample size and mean fitted WTP when implementing the five possible rules using the weaker or stronger conditions. While Strategy One is the closest to theory, the minimal sample size reduces the precision and validity of econometric modelling. By contrast, Strategy Two relaxes rules four and five and produces a larger and more reasonable sample of 304. This research, therefore, uses truncation strategy two given the economic and statistical justification for each rule. The high truncation rate (45% remaining) reduces the validity of the survey design as it suggests that a majority of the sample did not adequately understand the survey. Indeed, the WTP was statistically different between the full and truncated samples.

Table 8.1: P-values of Mann-Whitney (Wilcox Rank Sum) test of mean WTP values between subsamples.

Rule	Q6WTP	Q7WTP	Performance MWTP	Emissions MWTP
1) Understanding	0.124	0.000***	0.046**	0.046**
2) Q8 Dominated	0.000***	0.000***	0.000***	0.000***
3) Protest votes	0.298	0.000***	0.000***	0.000***
4) Q20 Consequentiality No vs Yes	0.2353	0.000***	0.007***	0.007***
4) Q20 Consequentiality No vs Don't Know	0.000***	0.000***	0.000***	0.000***
4) Q20 Consequentiality Don't Know vs Yes	0.000***	0.000***	0.000***	0.000***
5) Certainty Unsure vs Very Sure	0.334	0.001***	0.0359	0.0359
5) Certainty Unsure vs Quite Sure	0.000***	0.000***	0.672	0.672
5) Certainty Quite Sure vs Very Sure	0.000***	0.000***	0.168	0.168
Full vs Truncation1	0.049*	0.003***	0.001***	0.000***
Full vs Truncation2	0.041*	0.680	0.619	0.619
Truncation1 vs Truncation2	0.002***	0.159	0.010**	0.010**
Order 0 Consecutive vs Order 1 Reverse	0.000***	0.325	0.207	0.207

Table 8.2: Included and excluded sample characteristics.

Category	Full Sample	Included	Excluded
N	670	304	358
Gender	Male: 53% Female: 46%	Male: 56% Female: 44%	Male: 51% Female: 48%
Age	43	44.68	41.10
Mean Gross monthly income	£2192	£2229	£2098
Q6 WTP	£23.75	£23.72	£23.79
Q7 WTP	£44.74	£45.33	£44.25
CE MWTP	Performance: -0.069 Emission: 0.059	Performance: -0.053 Emission: 0.045	Performance: -0.083 Emission: 0.070
Environmental Concern	Q13: 3.42 Q14: 3.74 Q15: 4.01	Q13: 3.46 Q14: 3.77 Q15: 4.06	Q13: 3.39 Q14: 3.72 Q15: 3.97

8.2 Appendix Two: Supplementary Tables

This section provides further detail on the survey responses. Firstly, Table 2.2 reports the coding, expectations, and summary statistics for the variables available to this research given the survey design. Table 8.3 reports the sample size by truncation strategy. Table 8.4 tabulates the self-reported response certainty for each valuation question; most respondents were somewhat sure of their responses, although the effect on status quo bias and WTP is question-specific. Table 8.5 is produced for Section 3.3.2 to indicate the common reasons used by protest responses. Table 8.6 disentangles the income and distance-decay effects by question and measure for Section 6.2.2.1, while Table 8.7 details Q17 for Section 6.2.2.5 and Table 8.8 tabulates fitted WTP by brackets of self-reported gross monthly income for Section 6.2.3.1. Finally, Table 8.9 is produced to show that the CV bid levels were randomly varied across respondents. Some bid levels were less common than others due to the random nature of the allocation. Similarly, Table 8.10 reports the number and proportion of respondents per task block. In both tables, the totals may not sum to 100.00 due to rounding the frequency to only two decimal places. Finally, Table 8.11 extends Table 7.10 by including group-specific WTP.

Table 8.3: Comparison of WTP and sample size across both truncation strategies .

Truncation Strategy	Strategy One: Stricter	Stategy Two: Weaker
Rules	1-5 strictly	1,2,3: Same. 4: Exclude 'Inconsequential' 5: Exclude 'Very Unsure'
Sample Size	105	304
Exclusion Rate	85%	53%
Mean fitted Q6 WTP	£23.75	£23.75
Mean fitted Q7 WTP	£44.74	£44.74
Mean Performance MWTP	-0.069	-0.069
Mean Emissions MWTP	0.059	0.059

Table 8.4: Tabulating self-reported response certainty.

Question	Level	N	Proportion	Percent choosing status quo	Fitted WTP
Q6Certainty	Unsure	70	10.45%	61.43%	22.66
	Quite Sure	277	41.34%	50.18%	22.56
	Very Sure	323	48.21%	45.20%	25.02
Q7Certainty	Unsure	54	8.06%	66.67%	44.27
	Quite Sure	269	40.15%	29.37%	43.38
	Very Sure	347	51.79%	35.45%	45.87
Q12CECertainty	Unsure	40	5.97%	48.12%	Emission: 0.028 Performance: -0.032
	Quite Sure	328	48.96%	42.07%	Emission: 0.069 Performance: -0.080
	Very Sure	303	45.07%	43.13%	Emission: 0.053 Performance: -0.062

Table 8.5: Tabulation of Protest responses.

Type	Q6 Count	Q7 Count
Use “The benefits I receive are not worth my rates increase”, ‘It is not feasible to stop the release of microplastics’	27	3
Principle ‘I pay enough water rates already’, ‘It is the governments responsibility’, ‘Others should pay’, ‘Fat Cat Syndrome’ Water company profits salaries too high’	45	15
Cost ‘I cannot afford the payment’	166	75
Don’t Know ‘Insufficient information’ ‘Other reasons’	0	36
Total protests:	72	18

Table 8.6: Tabulation of WTP by measure and distance.

WTP	Income: Below Median Distance: Below Median	Income: Below Median Distance: Above Median	Income: Above Median Distance: Below Median	Income: Above Median Distance: Above Median
Q6	22.352	24.936	23.127	25.640
Q7	42.201	46.324	44.161	47.777
Emissions	0.044	0.059	0.063	0.067
Performance	-0.052	-0.069	-0.074	-0.079

Table 8.7: Q17 Responsibility Question Responses.

Stakeholder	**Chosen as part**	**Chosen as only**
Firms	510	88
Consumers	384	34
Government	471	68
Local Authority	269	9
Other	28	12

Stakeholder	**Q6 (Chosen)**	**Q6 (not chosen)**	**Q7 (Chosen)**	**Q7 (not chosen)**	**Performance (chosen)**	**Emission (chosen)**	**Performance (not chosen)**	**Emission (not chosen)**
Firms	£24.18	£23.62	£44.74	£44.74	-£0.08	£0.06	-£0.07	£0.04
Consumers	£23.71	£23.79	£45.20	£44.40	-£0.07	£0.07	-£0.06	£0.06
Government	£23.48	£23.87	£44.82	£44.71	-£0.06	£0.10	-£0.05	£0.09
Local Authority	£23.53	£24.08	£44.86	£44.57	-£0.07	£0.06	-£0.07	£0.06
Other	£23.72	£24.45	£44.73	£44.94	-£0.05	£0.07	-£0.04	£0.06

Table 8.8: WTP by income bracket.

Income bracket	**Q6 WTP**	**Q7 WTP**	**Precaution**	**Emissions MWTP**	**Performance MWTP**	**N**
£0 - £500	£24.65	£42.87	£18.22	£0.019	- £0.022	68
£501 - £1000	£22.29	£43.09	£20.80	£0.087	-£0.102	69
£1000 - £1500	£23.55	£44.49	£20.94	£0.082	-£0.096	113
£1501 - £2000	£23.41	£44.53	£21.12	£0.051	-£0.060	94
£2001 - £2500	£24.08	£44.69	£20.61	£0.034	-£0.040	103
£2501 - £3000	£23.05	£44.21	£21.16	£0.125	-£0.146	71
£3001 - £4000	£24.33	£46.62	£22.28	£0.011	£0.013	61
£4001 - £5000	£24.32	£45.78	£21.46	£0.031	-£0.036	46
£5000+	£24.88	£48.55	£23.67	£0.114	-£0.134	45
Mean: £2192	£23.75	£44.74	£20.99	£0.059	-£0.069	670

Table 8.9: Random allocation of CVM bid levels.

Bid level	Count	Percentage	Bid level	Count	Percentage
Q6Bid			**Q7Bid1**		
£5	79	11.79	£5	94	14.03%
£10	73	10.90%	£10	73	10.90%
£20	71	10.60%	£20	87	12.99%
£30	13	1.94%	£30	14	2.09%
£40	82	12.24%	£40	82	12.24%
£50	19	2.84%	£50	14	2.09%
£60	97	14.48%	£60	73	10.90%
£70	18	2.69%	£70	13	1.94%
£80	75	11.19%	£80	72	10.75%
£90	71	10.60%	£90	82	12.24%
£100	72	10.75%	£100	66	9.85%
Totals:	670	100.02%	Totals:	670	100.02%
Q7Bid2					
£2	21	3.13%	£50	33	4.93%
£5	9	1.34%	£60	9	1.34%
£10	96	14.33%	£80	52	7.76%
£15	5	0.75%	£100	8	1.19%
£20	94	14.03%	£120	41	6.12%
£25	6	0.90%	£140	10	1.49%
£30	32	4.78%	£160	37	5.52%
£35	3	0.45%	£180	41	6.12%
£40	99	14.78%	£200	33	4.93%
£45	41	6.12%	Total:	670	100.01%

Table 8.10: Random allocation of CE task blocks.

CE Block	Number of respondents	Frequency
Q9 Block	Block 1: 110 Block 2: 229 Block 3: 216 Block 4: 115	Block 1: 16% Block 2: 34% Block 3: 32% Block 4: 17%
Q10 Block	Block 1: 105 Block 2: 231 Block 3: 226 Block 4: 108	Block 1: 15% Block 2: 34% Block 3: 34% Block 4: 16%
Q11 Block	Block 1: 104 Block 2: 208 Block 3: 251 Block 4: 107	Block 1: 16% Block 2: 31% Block 3: 37% Block 4: 16%
Q12 Block	Block 1: 119 Block 2: 215 Block 3: 220 Block 4: 116	Block 1: 18% Block 2: 32% Block 3: 33% Block 4: 17%

Table 8.11: Benefits, Net Benefits, and Implicit Weights, by income.

Policy	Q6: Research			Q7: Treatment			Emissions: Source Control		
Category	**Low**	**Point**	**High**	**Low**	**Point**	**High**	**Low**	**Point**	**High**
WTP: (CV WTP: £/hh/py, CE MWTP: £/pp)									
Sample:	72.35	77.10	82.83	83.23	88.43	93.92	3.40	3.60	3.90
Low-Income:	53.05	58.81	67.03	77.5	84.57	93.64	2.82	3.86	3.96
High-Income:	75.90	82.67	90.72	107.23	122.35	143.16	2.20	2.52	2.83
NPV: £bn									
Sample:	17.26	18.26	18.94	11.31	9.37	-20.56	-1.16	-7.98	-20.75
Low-Income:	18.11	19.59	20.83	9.94	8.44	-20.63	-1.28	-7.91	-20.85
High-Income:	25.61	29.09	33.37	17.05	17.49	-8.78	-1.40	-8.19	-20.96
Implicit Weight	0.71	0.67	0.62	0.58	0.48	2.35	0.91	0.96	0.99

8.3 Appendix Three: Robustness Checks

This section reports several alternative possible specifications for the CE and CV models and illustrates that the WTP is relatively robust. For the CE data, Table 8.12 reports that the attribute-specific MWTP is relatively stable to the number of random draws used for the MXL models, which were also used for the ICLV models (which were hybrid mixed logits). Section 8.3.2 then reports the same MNL as Table 4.2 but with the income variable β_{Income} in levels rather than as a dummy. Section 8.3.3 reports five different specifications to account for the flexibility of the MXL approach while Section 8.3.4 details the LCM specification search and Section 8.3.5 varies the ICLVs measurement model. Models using the full sample instead are all presented in Section 8.3.6.2. For the CV data, Section 8.3.6.1 reports full sample versions of all the models available in-text. Finally, a copy of the final adopted survey design is reprinted for completeness. To summarise, the aim here is to demonstrate that both CE and CV WTP were robust to specification.

8.3.1 Draws

All MXL models were estimated using 1,000 Halton draws. Halton draws were introduced by Bhat (2001) as a quasi-random alternative to pseudo-Monte Carlo draws with the advantage of increased estimation speed and enhanced stability, a result widely confirmed and applied in the literature (Scarpa and Alberini, 2005; Brouwer et al., 2017; Badura et al., 2019). The debate in the literature concerns the appropriate type of random draw, with candidates including Halton, Sobol and MHLS, and the appropriate number of draws. In this research, the MXLs used 1,000 draws which exceeded the number of draws other research has reported as sufficient (Bujosa, Riera and Hicks, 2010; Badura et al., 2019; Scarpa and Alberini, 2005; Bhat, 2001). Therefore, this research uses 1,000 Halton draws, although the conclusions are robust to the number and type of draws. While Halton draws may not be appropriate with high numbers of dimensions, this concern is not relevant to even the most complex ICLV specification in this research.

Table 8.12: MWTP when changing the number of random Halton draws for the three normally-distributed attributes WTP-space model (N = 670).

Number of random draws	Emission	Performance
100	0.03786	-0.04404
500	0.03838	-0.04456
1,000	0.03846	-0.04465
5,000	0.03848	-0.04466
10,000	0.03849	-0.04467

8.3.2 Alternative MNL specifications

Table 8.13: MNL model with all covariates with income in levels (N = 304).

Coefficient	**Estimate**	**Bootstrap.s.e.**	**Bootstrap.p-val(0)**
β_{ASC}	-0.071	1.068	0.463
β_{Price}	-0.298***	0.041	0.000
$\beta_{Performance}$	0.018***	0.003	0.000
$\beta_{Emission}$	0.010***	0.002	0.000
β_{Gender}	-0.015	0.197	0.456
β_{Age}	-0.001	0.008	0.460
$\beta_{Distance}$	-0.002	0.006	0.283
β_{Trips}	0.071	0.114	0.162
β_{BP}	-0.110	0.153	0.137
$\beta_{Charity}$	0.051	0.227	0.356
$\beta_{Education}$	0.066	0.098	0.160
$\beta_{Employment}$	0.015	0.055	0.339
β_{Income}	-0.000*	0.000	0.078
β_{Order}	0.175*	0.188	0.087
β_{Task}	0.013	0.048	0.410
$\beta_{Consequentiality}$	0.637***	0.207	0.000
$\beta_{Experts}$	0.243***	0.131	0.002
$\beta_{Understanding}$	-0.106*	0.094	0.051
$\beta_{Q12Certainty}$	-0.194*	0.195	0.072
Estimation Statistics			
Estimation method	bfgs	LL(start)	-790.1878
Convergence	Successful	LL(final, whole model)	-712.4413
Number of individuals	304	AIC	1462.88
Number of observations	1216	BIC	1558.62
Estimated parameters	19	Iterations	29
WTP			
Performance MWTP	-0.060	Emission MWTP	0.0327

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

8.3.3 Alternative MXL specifications

Four alternative specifications to the adopted MXL model in Section 4.3.1 are estimated in this section. Table 8.14 reports an income in levels model, Table 8.16 reports an attributes-only model, Table 8.17 relaxes the non-constant marginal utility of income model described in Buckell, Hensher and Hess (2021), while Table 8.18 estimates an MXL with correlated attributes as in Train (2009). The attributes-only model has marginally improved AIC and R^2, but an LR test that it is superior to the covariates model is rejected (test value: 20.94, p.value: 0.138). To summarise, the MWTP is shown to be robust to specification, and econometric alternatives would not significantly alter the MXL results.

Although the MXL allowed the price coefficient to be randomly distributed across respondents, income effects could be explicitly included in the parameterisation of the price attribute. Buckell, Hensher and Hess (2021) illustrated that the price coefficient could be scaled using respondents income; see Equation (8.3.1). The standard price parameter in the previous MXL may be scaled using respondent income ($income_i$) divided by mean sample income ($\bar{income}$) to the power of the elasticity of the marginal utility of income (λ). The λ takes values between zero and one from no income effect to marginal utility being extremely elastic with regards to the income effect.

$$\beta_{Price_i} = -exp\left(\mu_{log(\beta_{Price})} + \sigma_{log(\beta_{Price})} * \xi_{Price,i}\right) * \left(\frac{income_i}{\bar{income}}\right)^{\lambda} \tag{8.3.1}$$

Table 8.17 reports the MXL in WTP-space with the three negative lognormally distributed attributes and no covariates. However, the price attribute now relaxes the constant marginal utility of income. It is doubtful whether relaxing this assumption improves the model. Specifically, the λ is not statistically significant at any level, while the coefficient magnitude is extremely small. Moreover, the MWTP is still comparable with the previous MXL models, while the goodness-of-fit criteria are inferior. Therefore, the Buckell, Hensher and Hess (2021) suggestion of non-constant marginal utility of income is estimated without improving the prior models. Moreover, the low magnitude of the prices used in the CE and the weak income marginal effect in the results indicate that including income effects in this way would make a minimal difference to the MWTP.

Another extension would re-estimate the MXL with correlations and thus incorporate heterogeneity at the inter and intra-respondent level. Equations (8.3.2) and (8.3.3) illustrate how the β are now functions of the inter-attribute correlations (Hess and

Palma, 2019). Table 8.18 estimates this model, and all the standard deviations are highly statistically significant. However, the goodness-of-fit statistics and LR test indicate that it is inferior to the MXL with uncorrelated attributes.

$$\begin{aligned}\beta_{Performance_i} = -exp(\mu_{log(\beta_{Performance})} + \sigma_{Price,Performance} * \xi_{Price,i} + \\ \sigma_{Performance} * \xi_{Performance,i})\end{aligned} \tag{8.3.2}$$

$$\begin{aligned}\beta_{Emission_i} = \\ -exp(\mu_{log(\beta_{Emission})} + \sigma_{Performance,Emission} * \xi_{Performance,i} + \\ \sigma_{Price,Emission} * \xi_{Price,i} + \sigma_{Emission} * \xi_{Emission,i})\end{aligned} \tag{8.3.3}$$

Table 8.14: MXL model income in levels (N = 304).

Variable	**Estimate**	**Bootstrap.std.err.**	**Bootstrap.p-val(0)**
ASC_B	-0.370	2.465	0.427
μ_{Price}	-0.228***	0.237	0.000
σ_{Price}	1.544***	0.444	0.000
$\mu_{Performance}$	-3.651***	0.235	0.000
$\sigma_{Performance}$	-1.406***	0.092	0.000
$\mu_{Emission}$	3.591***	0.087	0.000
$\sigma_{Emission}$	2.519***	0.095	0.000
β_{Gender}	-0.219	0.413	0.265
β_{Age}	0.014	0.021	0.185
$\beta_{Distance}$	-0.006	0.013	0.300
β_{Trips}	-0.082	0.312	0.358
β_{BP}	-0.246	0.361	0.188
$\beta_{Charity}$	-0.125	0.517	0.366
$\beta_{Education}$	0.142	0.319	0.247
$\beta_{Employment}$	0.174**	0.123	0.045
β_{Income}	-0.000*	0.000	0.096
β_{Order}	0.084	0.447	0.405
β_{Task}	0.035	0.103	0.353
$\beta_{Consequentiality}$	0.798**	0.422	0.017
$\beta_{Experts}$	0.516**	0.302	0.014
$\beta_{Understanding}$	-0.229	0.222	0.107
$\beta_{Q12CECertainty}$	-0.360	0.408	0.160
Estimation Statistics			
AIC:		1290.48	
Log-Likelihood:		-623.2379	
Adjusted R^2:		0.1834	
Likelihood ratio test:		Chi.Sq = 579.29 (p.v = 0.000)	
WTP			
Attribute	**Lower bound**	**Median**	**Upper bound**
Emission	£0.034	£0.036	£0.039
Performance	-£0.043	-£0.037	-£0.057

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.15: MXL Covariates model (N = 670).

Variable	**Estimate**	**Bootstrap.std.err.**	**Bootstrap.p-val(0)**
ASC_B	-1.212**	0.789	0.047
μ_{Price}	-0.702***	0.169	0.000
σ_{Price}	2.024***	0.390	0.000
$\mu_{Performance}$	-4.124***	0.076	0.000
$\sigma_{Performance}$	-2.248***	0.026	0.000
$\mu_{Emission}$	-3.529***	0.014	0.000
$\sigma_{Emission}$	-3.386***	0.037	0.000
β_{Gender}	0.016	0.250	0.470
β_{Age}	0.019**	0.012	0.026
$\beta_{Distance}$	-0.007	0.008	0.150
β_{Trips}	-0.020	0.199	0.445
β_{BP}	0.070	0.222	0.352
$\beta_{Charity}$	-0.218	0.250	0.144
$\beta_{Education}$	-0.012	0.165	0.461
β_{Income}	-0.440**	0.291	0.032
β_{Order}	-0.017	0.254	0.469
β_{Task}	-0.067	0.062	0.127
$\beta_{Consequentiality}$	0.591***	0.163	0.000
$\beta_{Experts}$	0.458***	0.152	0.000
$\beta_{Understanding}$	-0.015	0.061	0.398
$\beta_{Q12Certainty}$	-0.220	0.245	0.136
Estimation Statistics			
Estimation method	bfgs	LL(start)	-1841.217
Convergence	Successful	LL(final, whole model)	-1461.192
Number of individuals	670	AIC	2964.38
Number of observations	2680	BIC	3088.15
Adjusted R^2	0.202	Iterations	104
WTP			
Performance	-£0.041	Emission	£0.035

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.16: MXL Attributes-only model (N = 304).

Variable	Estimate	Bootstrap.std.err.	Bootstrap.t.ratio(0)	Bootstrap.p-val(0)
ASC_B	1.167	0.213	5.475	0.000***
μ_{Price}	-0.103	0.254	-0.407	0.318
σ_{Price}	1.690	0.348	4.855	0.000***
$\mu_{Performance}$	-3.370	0.568	-5.931	0.000***
$\sigma_{Performance}$	-0.303	0.249	-1.217	0.220
$\mu_{Emission}$	-4.028	0.065	-61.516	0.000***
$\sigma_{Emission}$	2.764	0.132	20.888	0.000***
Estimation Statistics				
AIC:		1281.43	BIC	1628.21
Log-Likelihood:		-633.7128	Adjusted R^2:	0.189
WTP				
Performance MWTP		-3.369	Emission MWTP	-4.028

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.17: MXL with non-constant marginal utility of income. (N = 304).

Coefficient	Estimate	Bootstrap.std.err.	Bootstrap.t.ratio	Pr(>|z|)
ASC_B	1.165	0.254	4.593	0.000***
μ_{Price}	-0.348	0.245	-1.418	0.051
σ_{Price}	1.107	0.532	2.081	0.004***
λ_{Income}	0.087	0.188	0.461	0.317
$\mu_{Performance}$	-3.862	0.557	-6.938	0.000***
$\sigma_{Performance}$	-2.990	0.139	-21.562	0.000***
$\mu_{Emission}$	-3.314	0.316	-10.490	0.000***
$\sigma_{Emission}$	2.377	0.160	14.861	0.000***
Estimation Statistics				
AIC:		1279.18	BIC:	1362.57
Log-Likelihood:		-631.588	McFadden R^2:	0.201
WTP				
Performance MWTP		-3.862	Emission MWTP	-3.314

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.18: MXL with correlated attributes. (N = 304).

Coefficient	Estimate	Bootstrap.std.err.	Bootstrap.t.ratio	Pr(>|z|)
ASC_B	1.036	0.278	3.730	0.000***
μ_{Price}	-0.183	0.444	-0.412	0.275
σ_{Price}	-0.923	0.888	-1.039	0.053*
$\sigma_{Performance,Price}$	-2.071	0.283	-7.321	0.000***
$\sigma_{Emission,Performance}$	-2.055	0.486	-4.228	0.000***
$\sigma_{Emission,Price}$	-1.204	0.260	-4.639	0.000***
$\mu_{Performance}$	-4.135	0.659	-6.278	0.000***
$\sigma_{Performance}$	2.107	0.587	3.589	0.000***
$\mu_{Emission}$	-3.616	0.299	-12.083	0.000***
$\sigma_{Emission}$	1.132	0.047	24.135	0.000***
Estimation Statistics				
AIC:		1283.28	BIC:	1561.43
Log-Likelihood:		-631.6411	McFadden R^2:	0.188
WTP				
Performance MWTP	-4.135	Emission MWTP	-3.616	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

8.3.4 Alternative LCM specifications

Section 4.3.2 reports that 16 LCM specifications were estimated to reveal the appropriate one. Table 8.20 reports the details and diagnostics of each specification.

Table 8.19: LR test of LC models.

Model	**LogLik**	**#Df**	**Test Value**	**Pr(>Chi.Sq)**
LCM 2 vs 3-class				
Model 9	-737.32	8		
Model 10	-627.35	12	219.94	0.000***
LCM 3 vs 4-class				
Model 10	-627.35	12		
Model 11	-622.03	16	10.64	0.031**

Table 8.20: Class shares and MWTP by LCM specification. One class per row.

Model	Performance	Emissions	Shares
Model 1 (Full Sample): 2-classes, no-socioeconomics	-0.042	0.021	57.01%
	-0.059	0.692	42.93%
Model 2 (Full Sample): 2-classes, all-socioeconomics	-0.058	0.692	43.32%
	-0.041	0.020	56.68%
Model 3 (Full Sample): 3-classes, no-socioeconomics	-0.018	0.000	16.83%
	-0.061	0.601	36.95%
	-0.039	0.030	46.23%
Model 4 (Full Sample): 3-classes, all-socioeconomics	-0.046	0.087	0.14%
	-0.038	0.051	75.64%
	-0.012	0.001	24.22%
Model 5 (Full Sample): 4-classes, no-socioeconomics	-0.061	0.568	37.62%
	0.554	0.298	16.20%
	-0.032	0.012	37.44%
	-0.077	0.059	08.75%
Model 6 (Full Sample): Mixed within 2 classes, no-socioeconomics	-16.120	2.783	41.29%
	-16.118	3.739	58.71%
Model 7 (Full Sample): Mixed within 2 classes, all-socioeconomics	-14.226	0.658	0.00%
	-14.172	3.207	1.00%
Model 8 (Full Sample): Mixed within 3 classes, all-socioeconomics	-3.084	2.387	100.00%
	-2.893	3.251	0.00%
	-3.307	5.000	0.00%
Model 9 (Truncated Sample) 2-classes, no-socioeconomics	-0.061	0.033	50.00%
	-0.061	0.033	50.00%
Model 10 (Truncated Sample): 3-classes, no-socioeconomics	-0.046	0.025	51.41%
	-0.543	0.174	16.42%
	-0.067	0.046	32.16%
Model 11 (Truncated Sample) 4-classes, no-socioeconomics	-0.068	0.423	32.77%
	-0.038	0.020	47.29%
	0.088	0.024	02.43%
	-0.837	0.047	17.50%
Model 12 (Truncated Sample) 2-classes, all-socioeconomics	-0.061	0.033	50.00%
	-0.061	0.033	50.00%
Model 13 (Truncated Sample): 3-classes, all-socioeconomics	-3.551	2.625	02.81%
	0.013	0.112	0.00%
	-0.059	0.033	97.19%
Model 14 (Truncated Sample): Mixed within-classes, 2-classes, no-socioeconomics	-3.394	-0.968	96.14%
	3.707	13.953	03.86%
Model 15 (Truncated Sample): Mixed within-classes, 2-classes, all-socioeconomics	-3.394	-0.968	96.14%
	3.707	13.953	03.86%
Model 16 (Truncated Sample): Mixed within-classes, 3-classes, all-socioeconomics	-3.342	3.728	0.00%
	-3.692	3.121	100.00%
	-3.310	3.806	0.00%

8.3.5 Alternative ICLV specifications

Two modifications are estimated here. Firstly, models using income in levels demonstrate why the income dummy was used instead. Secondly, an Ordered Logit measurement model is estimated to complement the Ordered Probit in the text.

Table 8.21: ICLV CE Model income in levels (N = 304).

Coefficient	Estimate	Bootstrap.std.err.	Bootstrap.t.ratio(0)	Bootstrap.p-val(0)
ASC_B	-0.371*	0.229	-1.617	0.055
μ_{Price}	-0.336*	0.240	-1.400	0.084
σ_{Price}	1.520***	0.533	2.851	0.001
$\mu_{Performance}$	-3.652***	0.034	-108.038	0.000
$\sigma_{Performance}$	3.878***	0.035	109.524	0.000
$\mu_{Emission}$	-3.233***	0.058	-55.693	0.000
$\sigma_{Emission}$	-2.072***	0.041	-50.301	0.000
λ	-1.107***	0.082	-13.538	0.000
γ_{Age}	-0.004	0.005	-0.755	0.217
γ_{Gender}	-0.152	0.139	-1.095	0.132
$\gamma_{Distance}$	-0.003	0.004	-0.640	0.238
γ_{Income}	0.000***	0.000	1.274	0.091
$\gamma_{Experts}$	0.379***	0.092	4.101	0.000
$\gamma_{Consequentiality}$	0.498	0.127	3.914	0.000
γ_{BP}	0.092	0.116	0.791	0.178
$\gamma_{Charity}$	0.353***	0.157	2.246	0.008
$\gamma_{Q12CECertainty}$	0.257**	0.167	1.536	0.039
ζ_{Q13}	1.496***	0.202	7.392	0.000
ζ_{Q14}	2.461***	0.727	3.385	0.000
ζ_{Q15}	0.842***	0.109	7.701	0.000
τ_{Q13_1}	-0.102	0.547	-0.187	0.427
τ_{Q13_2}	1.742***	0.545	3.199	0.001
τ_{Q13_3}	4.152***	0.684	6.066	0.000
τ_{Q13_4}	5.877***	0.807	7.279	0.000
τ_{Q14_1}	-0.556	0.851	-0.653	0.275
τ_{Q14_2}	2.144**	1.051	2.041	0.016
τ_{Q14_3}	5.597***	1.757	3.185	0.000
τ_{Q14_4}	8.493***	2.441	3.479	0.000
τ_{Q15_1}	-1.527***	0.492	-3.104	0.002
τ_{Q15_2}	-0.213	0.296	-0.719	0.264
τ_{Q15_3}	1.352***	0.320	4.230	0.000
τ_{Q15_4}	2.627***	0.357	7.350	0.000

Estimation Statistics

Estimation method	bfgs	LL(start)	-1956.529
Convergence	Successful	LL(final, whole model)	-1500.133
Number of individuals	304	LL(final,indic_Q13)	-350.4322
Number of observations	2680	LL(final,indic_Q14)	-336.1917
Number of inter-person draws	1000 Halton	LL(final,indic_Q15)	-322.07
AIC	3064.27	LL(0,choice)	-790.1878
BIC	3225.51	LL(final,choice)	-620.8917

WTP

Performance MWTP	-2.778	Emission MWTP	-3.308

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.22: ICLV CE Model using ordered logit (N = 304).

Coefficient	**Estimate**	**Bootstrap.std.err.**	**Bootstrap.p-val(0)**
ASC_B	-0.282	0.196	0.068
μ_{Price}	-0.151	0.312	0.324
σ_{Price}	1.996	0.709	0.002
$\mu_{Performance}$	-3.112	0.027	0.000
$\sigma_{Performance}$	3.221	0.030	0.000
$\mu_{Emission}$	-3.573	0.027	0.000
$\sigma_{Emission}$	2.422	0.019	0.000
λ	-1.228	0.021	0.000
γ_{Age}	-0.005	0.002	0.000
γ_{Gender}	-0.159	0.114	0.033
$\gamma_{Distance}$	-0.003	0.003	0.054
γ_{Income}	0.000	0.000	0.101
$\gamma_{Experts}$	0.375	0.016	0.000
$\gamma_{Consequentiality}$	0.449	0.088	0.000
γ_{BP}	0.068	0.078	0.181
$\gamma_{Charity}$	0.359	0.107	0.000
$\gamma_{Q12CECertainty}$	0.264	0.166	0.055
ζ_{Q13}	2.800	0.385	0.000
ζ_{Q14}	4.611	1.572	0.000
ζ_{Q15}	1.513	0.183	0.000
τ_{Q13_1}	-0.750	0.654	0.139
τ_{Q13_2}	2.693	0.603	0.000
τ_{Q13_3}	7.165	0.978	0.000
τ_{Q13_4}	10.347	1.291	0.000
τ_{Q14_1}	-2.100	1.137	0.043
τ_{Q14_2}	3.023	1.540	0.010
τ_{Q14_3}	9.509	3.311	0.000
τ_{Q14_4}	14.931	4.919	0.000
τ_{Q15_1}	-3.499	1.059	0.000
τ_{Q15_2}	-0.833	0.405	0.033
τ_{Q15_3}	2.150	0.399	0.000
τ_{Q15_4}	4.373	0.499	0.000
Estimation Statistics			
Estimation method	bfgs	LL(start)	-2021.298
Convergence	Successful	LL(final, whole model)	-1494.781
Number of individuals	304	LL(final,indic_Q13)	-350.8294
Number of observations	2680	LL(final,indic_Q14)	-336.2635
Number of inter-person draws	1000 Halton	LL(final,indic_Q15)	-321.5834
AIC	3053.56	LL(0,choice)	-790.1878
BIC	3214.8	LL(final,choice)	-621.2083
WTP			
Performance MWTP	-2.853	Emission MWTP	3.409

8.3.6 Truncated-Sample Models

8.3.6.1 CV Models:

Table 8.23: Q6 Model bid-only (N = 304).

Variable	Estimate	Marginal Effect	Std. Error	Pr(>|z|)
(Intercept)	0.895***		0.081	0.000
Bid	-0.018***	-0.004	0.001	0.000
Estimation Statistics				
Convergence		Successful	LL(final, whole model)	-1482.45
Number of individuals		304	AIC	2968.90
Number of observations		2432	BIC	2980.36
Adjusted R^2		0.062	Prediction	50.66%
WTP				
Measure		Mean	Lower	Upper
Mean		£68.00	£61.83	£72.15
truncated Mean		£49.65	£47.81	£51.60
adjusted truncated Mean		£69.34	£64.16	£73.22
Median		£53.25	£45.03	£57.25

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.24: Q6 Model All Covariates (N = 304).

Variable	**Estimate**	**Marginal Effect**	**Std. Error**	**Pr(>|z|)**
(Intercept)	-1.878***		0.343	0.000
β_{BID}	-0.015***	-0.006	0.001	0.000
β_{Gender}	-0.140**	-0.056	0.061	0.020
β_{Age}	-0.006**	-0.002	0.002	0.020
$\beta_{Distance}$	-0.008***	-0.003	0.002	0.000
β_{Trips}	0.067**	0.027	0.030	0.025
β_{BP}	0.360***	0.144	0.048	0.000
$\beta_{Charity}$	0.469***	0.185	0.069	0.000
$\beta_{Education}$	0.012	0.005	0.030	0.691
β_{Income}	0.338***	0.134	0.062	0.000
β_{Order}	-0.106*	-0.042	0.060	0.076
$\beta_{Consequentiality}$	-0.319***	-0.127	0.064	0.000
$\beta_{Experts}$	0.516***	0.206	0.041	0.000
$\beta_{Understanding}$	0.098***	0.039	0.030	0.001
$\beta_{Q6Certainty}$	0.034	0.014	0.045	0.452
Estimation Statistics				
Convergence	Successful	LL(final, whole model)	-1220.99	
Number of individuals	304	AIC	2471.98	
Number of observations	2432	BIC	2558.93	
Adjusted R^2	0.267	Prediction	52.96%	
WTP				
Measure	Mean	Lower	Upper	
Mean	£59.55	£56.12	£63.72	
truncated Mean	£50.28	£48.18	£52.36	
adjusted truncated Mean	£65.59	£61.26	£70.52	
Median	£50.52	£46.63	£54.27	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.25: Q7 SBDC Model Bid-only (N=304).

Variable	**Estimate**	**Marginal Effect**	**Std. Error**	**Pr(>|z|)**
(Intercept)	1.893***		0.093	0.000
Bid	-0.022***	-0.004	0.001	0.000
Estimation Statistics				
Convergence		Successful	LL(final, whole model)	-1406.055
Number of individuals		304	AIC	2816.11
Number of observations		2432	BIC	2827.70
Adjusted R^2		0.086	Prediction	51.97%
WTP				
Measure		Mean	Lower	Upper
Mean		£94.07	£88.28	£101.46
truncated Mean		£67.79	£65.99	£69.75
adjusted truncated Mean		£119.62	£110.86	£130.90
Median		£87.58	£82.61	£94.14

Table 8.26: Q7 SBDC Model All Covariates (N = 304).

Variable	**Estimate**	**Marginal Effect**	**Std. Error**	**Pr(>|z|)**
(Intercept)	1.016*	0.000	0.548	0.064
β_{BID}	-0.023***	-0.005	0.002	0.000
β_{Gender}	-0.089	-0.014	0.102	0.384
β_{Age}	-0.022***	-0.004	0.004	0.000
$\beta_{Distance}$	-0.014***	-0.003	0.003	0.000
β_{Trips}	0.120**	0.025	0.049	0.015
β_{BP}	-0.106	-0.016	0.079	0.182
$\beta_{Charity}$	0.752***	0.143	0.123	0.000
$\beta_{Education}$	0.034	0.006	0.051	0.508
β_{Income}	0.171	0.029	0.105	0.103
β_{Order}	0.270***	0.049	0.101	0.007
$\beta_{Consequentiality}$	-0.574***	-0.116	0.105	0.000
$\beta_{Experts}$	0.460***	0.096	0.066	0.000
$\beta_{Understanding}$	0.122**	0.025	0.050	0.015
$\beta_{Q7Certainty}$	-0.126	-0.018	0.081	0.123
Estimation Statistics				
Convergence		Successful	LL(final, whole model)	-1257.925
Number of individuals		304	AIC	2545.85
Number of observations		2432	BIC	2632.79
Adjusted R^2		0.174	Prediction	52.30%
WTP				
Measure		Mean	Lower	Upper
Mean		£94.16	£88.76	£101.74
truncated Mean		£69.68	£67.68	£71.49
adjusted truncated Mean		£123.77	£114.12	£135.76
Median		£89.21	£84.28	£95.57

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.27: Q7 DBDC Model Bid-only (N=304).

Variable	Estimate	Marginal Effect	Std. Error	Pr(>|z|)
(Intercept)	1.698***		0.05	0.000
Bid	-0.019***	-0.01	0.000	0.000
Estimation Statistics				
Convergence		Successful	LL(final, whole model)	-3131.16
Number of individuals		304	AIC	6266.32
Number of observations		2432	BIC	6277.91
WTP				
Measure		Mean	Lower	Upper
Mean		£93.75	£89.78	£98.12
truncated Mean		£88.82	£85.70	£92.36
adjusted truncated Mean		£97.94	£93.22	£103.29
Median		£73.71	£72.56	£77.87

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.28: Q7 DBDC Model All Covariates (N = 304).

Variable	**Estimate**	**Marginal Effect**	**Std. Error**	**Pr(>|z|)**
(Intercept)	-0.173	0.000	0.280	0.536
β_{BID}	-0.014***	-0.005	0.000	0.000
β_{Gender}	-0.141***	-0.014	0.050	0.005
β_{Age}	-0.013***	-0.004	0.002	0.000
$\beta_{Distance}$	-0.006***	-0.003	0.001	0.000
β_{Trips}	0.086***	0.025	0.025	0.001
β_{BP}	-0.019	-0.016	0.040	0.641
$\beta_{Charity}$	0.671***	0.143	0.061	0.000
$\beta_{Education}$	0.040	0.006	0.026	0.121
β_{Income}	0.303***	0.029	0.052	0.000
β_{Order}	0.048	0.049	0.050	0.336
$\beta_{Consequentiality}$	-0.314***	-0.116	0.053	0.000
$\beta_{Experts}$	0.340***	0.096	0.033	0.000
$\beta_{Understanding}$	0.077***	0.025	0.025	0.002
$\beta_{Q7Certainty}$	0.080	-0.018	0.040	0.043
Estimation Statistics				
Convergence		Successful	LL(final, whole model)	-2822.77
Number of individuals		304	AIC	5675.54
Number of observations		2432	BIC	5762.48
WTP				
Measure		Mean	Lower	Upper
Mean		£93.19	£90.05	£96.92
truncated Mean		£91.41	£88.53	£94.68
adjusted truncated Mean		£97.12	£93.25	£101.82
Median		£89.81	£86.29	£93.66

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.29: ICLV CV Model Q6 (N = 304).

Coefficient	Estimate	Bootstrap.std.err.	Bootstrap.p-val(0)
$\beta_{intercept}$	-67.439***	6.692	0.000
β_{Q6BID}	-32.326***	8.302	0.000
λ	23.704***	1.982	0.000
γ_{Age}	-0.001	0.005	0.409
γ_{Gender}	-0.122	0.174	0.242
$\gamma_{Distance}$	-0.002	0.004	0.328
γ_{Income}	0.220	0.189	0.122
$\gamma_{Experts}$	0.670***	0.140	0.000
$\gamma_{Consequentiality}$	0.279***	0.098	0.002
γ_{BP}	0.443**	0.189	0.010
$\gamma_{Charity}$	-0.005	0.192	0.489
$\gamma_{Q6ResearchCertainty}$	0.470*	0.343	0.086
ζ_{Q13}	0.591***	0.083	0.000
ζ_{Q14}	0.620***	0.090	0.000
ζ_{Q15}	0.624***	0.084	0.000
τ_{Q13_1}	-0.361	0.368	0.164
τ_{Q13_2}	0.673**	0.355	0.029
τ_{Q13_3}	2.262***	0.398	0.000
τ_{Q13_4}	3.349***	0.431	0.000
τ_{Q14_1}	-0.740**	0.421	0.040
τ_{Q14_2}	0.316	0.372	0.198
τ_{Q14_3}	1.803***	0.408	0.000
τ_{Q14_4}	3.058***	0.455	0.000
τ_{Q15_1}	-1.290***	0.498	0.005
τ_{Q15_2}	0.062	0.355	0.431
τ_{Q15_3}	1.441***	0.362	0.000
τ_{Q15_4}	2.585***	0.384	0.000
Estimation Statistics			
Estimation method	bfgs	Iterations	98
Convergence	Successful	LL(start)	-1986.967
Number of individuals	304	LL(final, whole model)	-1224.107
Number of observations	1216	LL(final,indic_Q13)	-373.7579
Number of inter-person draws	1000 (Halton)	LL(final,indic_Q14)	-362.5498
AIC	2502.21	LL(final,indic_Q15)	-341.6773
BIC	2640	LL(final,choice)	-166.6572
WTP			
Measure	**Mean**	**Lower**	**Upper**
Median	£64.71	£49.99	£79.45

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.30: ICLV CV Q7 Model (N = 304).

Coefficient	**Estimate**	**Bootstrap.std.err.**	**Bootstrap.p-val(0)**
$\beta_{intercept}$	-33.033***	28.222	0.003
β_{Q7BID}	-42.867***	12.709	0.000
λ	28.685***	2.863	0.000
γ_{Age}	-0.005	0.017	0.260
γ_{Gender}	-0.070	0.337	0.335
$\gamma_{Distance}$	-0.004	0.007	0.135
γ_{Income}	0.149	0.148	0.121
$\gamma_{Experts}$	0.517***	0.202	0.000
$\gamma_{Consequentiality}$	0.058	0.157	0.297
γ_{BP}	0.438**	0.404	0.014
$\gamma_{Charity}$	-0.036	0.602	0.440
$\gamma_{Q7TreatmentCertainty}$	0.425***	0.236	0.001
ζ_{Q13}	0.677***	0.124	0.000
ζ_{Q14}	0.767***	0.129	0.000
ζ_{Q15}	0.739***	0.110	0.000
τ_{Q13_1}	-0.859**	0.799	0.012
τ_{Q13_2}	0.214	0.810	0.280
τ_{Q13_3}	1.812***	0.838	0.000
τ_{Q13_4}	2.912***	0.874	0.000
τ_{Q14_1}	-1.285***	0.881	0.002
τ_{Q14_2}	-0.102	0.877	0.400
τ_{Q14_3}	1.455***	0.907	0.000
τ_{Q14_4}	2.761***	0.932	0.000
τ_{Q15_1}	-1.838***	0.813	0.001
τ_{Q15_2}	-0.408	0.807	0.147
τ_{Q15_3}	1.002***	0.823	0.005
τ_{Q15_4}	2.177***	0.844	0.000
Estimation Statistics			
Estimation method	bfgs	Iterations	112
Convergence	Successful	LL(start)	-1834.244
Number of individuals	304	LL(final, whole model)	-1225.148
Number of observations	1216	LL(final,indic_Q13)	-375.8026
Number of inter-person draws	1000 (Halton)	LL(final,indic_Q14)	-363.0384
AIC	2504.3	LL(final,indic_Q15)	-343.701
BIC	2642.09	LL(final,choice)	-170.0473
WTP			
Measure	**Mean**	**Lower**	**Upper**
Median	£121.62	£107.01	£135.52

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

8.3.6.2 CE Models:

Table 8.31: Conditional logit model (N = 304).

Coefficient	**Estimate**	**Robust.std.err.**	**Robust.p-val(0)**
ASC_B	0.668***	0.134	0.000
β_{Price}	-0.267***	0.035	0.000
$\beta_{Performance}$	-0.015***	0.003	0.000
$\beta_{Emission}$	0.008***	0.002	0.000
Estimation Statistics			
AIC:			1598.70
Log-Likelihood:			-795.3503
Adjusted R^2:			0.052
Likelihood ratio test:			Chi.Sq = 129.62 (p.v = 0.000)
WTP			
Performance MWTP	-0.057	Emission MWTP	0.033

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.32: MNL model with all covariates (N = 304).

Variable	**Estimate**	**Bootstrap.std.err.**	**Bootstrap.p-val(0)**
ASC_B	-0.593	0.981	0.198
β_{Price}	-0.274***	0.039	0.000
$\beta_{Performance}$	0.015***	0.003	0.000
$\beta_{Emission}$	0.009***	0.002	0.000
β_{Gender}	-0.103	0.186	0.207
β_{Age}	-0.000	0.007	0.472
$\beta_{Distance}$	-0.000	0.006	0.478
β_{Trips}	0.066	0.108	0.171
β_{BP}	-0.075	0.147	0.220
$\beta_{Charity}$	-0.003	0.211	0.491
$\beta_{Education}$	0.061	0.096	0.168
β_{Income}	-0.243**	0.197	0.032
β_{Order}	0.263**	0.181	0.017
β_{Task}	-0.001	0.046	0.496
$\beta_{Consequentiality}$	0.775***	0.197	0.000
$\beta_{Experts}$	0.229***	0.124	0.002
$\beta_{Understanding}$	-0.079	0.092	0.107
$\beta_{Q12Certainty}$	-0.162	0.189	0.102
Estimation Statistics			
Estimation method	bfgs	LL(start)	-842.867
Convergence	Successful	LL(final, whole model)	-764.4971
Number of individuals	304	AIC	1564.99
Number of observations	1216	BIC	1656.85
Adjusted R^2	0.072	Iterations	26
WTP			
Performance MWTP	-0.056	Emission MWTP	0.032

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.33: MXL model in WTP-space with a truncated sample (N = 304).

Variable	**Estimate**	**Robust.std.err.**	**Robust.p-val(0)**
ASC_B	-0.753	2.162	0.331
μ_{Price}	-0.294*	0.244	0.096
σ_{Price}	1.940***	0.485	0.000
$\mu_{Performance}$	-3.563***	0.140	0.000
$\sigma_{Performance}$	0.823***	0.064	0.000
$\mu_{Emission}$	-3.976***	0.026	0.000
$\sigma_{Emission}$	2.538***	0.041	0.000
β_{Gender}	-0.326	0.357	0.141
β_{Age}	0.019*	0.016	0.084
$\beta_{Distance}$	-0.008	0.012	0.205
β_{Trips}	-0.114	0.284	0.284
β_{BP}	-0.151	0.294	0.268
$\beta_{Charity}$	-0.299	0.507	0.194
$\beta_{Education}$	0.093	0.267	0.308
β_{Income}	-0.295	0.474	0.207
β_{Order}	0.403	0.406	0.104
β_{Task}	0.013	0.092	0.442
$\beta_{Consequentiality}$	1.021***	0.408	0.001
$\beta_{Experts}$	0.371**	0.248	0.033
$\beta_{Understanding}$	-0.113	0.200	0.251
$\beta_{Q12Certainty}$	-0.299	0.432	0.193
Estimation Statistics			
Estimation method	bfgs	LL(start)	-828.967
Convergence	Successful	LL(final, whole model)	-673.8831
Number of individuals	304	AIC	1389.77
Number of observations	1216	BIC	1496.94
Adjusted R^2	0.176	Iterations	61
WTP			
Performance	- £3.559	Emission	£3.976

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.34: 3-class LCM (N = 304).

Variable	Estimate	Robust.std.err.	Robust.p-val(0)
ASC_2	0.736***	0.267	0.001
$\beta_{Price,Class1}$	-0.421***	0.071	0.000
$\beta_{Price,Class2}$	1.367	2.343	0.448
$\beta_{Price,Class3}$	-0.770***	0.340	0.006
$\beta_{Performance,Class1}$	0.018***	0.005	0.000
$\beta_{Performance,Class2}$	0.511	1.374	0.354
$\beta_{Performance,Class3}$	0.051***	0.020	0.007
$\beta_{Emission,Class1}$	0.010***	0.004	0.001
$\beta_{Emission,Class2}$	-0.821	1.702	0.389
$\beta_{Emission,Class3}$	0.381***	0.174	0.008
δ_{Class2}	-1.165***	0.204	0.000
δ_{Class3}	-0.511***	0.211	0.005
Estimation Statistics			
Estimation method	bfgs	LL(start)	-842.867
Convergence	Successful	LL(final, whole model)	-682.1171
Number of individuals	304	AIC	1388.23
Number of observations	1216	BIC	1449.47
Adj.Rho-square (0)	0.176	Iterations	55
WTP			
Performance	Class1: -0.042	Class2: -0.374	Class3: -0.066
Emission	Class1: 0.023	Class2: 0.600	Class3: 0.496

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8.35: ICLV CE Model Truncated Sample (N = 304).

Coefficient	**Estimate**	**Robust.std.err.**	**Robust.p-val(0)**
ASC_B	-0.286*	0.202	0.066
μ_{Price}	-0.161***	0.389	0.000
σ_{Price}	1.907***	0.928	0.005
$\mu_{Performance}$	-3.337***	0.018	0.000
$\sigma_{Performance}$	3.354***	0.017	0.000
$\mu_{Emission}$	-3.656***	0.022	0.000
$\sigma_{Emission}$	2.379***	0.015	0.000
λ	0.760***	0.032	0.000
γ_{Age}	-0.005***	0.001	0.000
γ_{Gender}	-0.146	0.112	0.101
$\gamma_{Distance}$	-0.002	0.002	0.117
γ_{Income}	0.165**	0.087	0.039
$\gamma_{Experts}$	0.367***	0.009	0.000
$\gamma_{Consequentiality}$	0.471***	0.018	0.000
γ_{BP}	0.063	0.050	0.120
$\gamma_{Charity}$	0.328***	0.093	0.001
$\gamma_{Q12CECertainty}$	0.263***	0.025	0.000
ζ_{Q13}	1.473***	0.198	0.000
ζ_{Q14}	2.611***	0.923	0.000
ζ_{Q15}	0.841***	0.103	0.000
τ_{Q13_1}	-0.493*	0.413	0.099
τ_{Q13_2}	1.342***	0.381	0.000
τ_{Q13_3}	3.720***	0.548	0.000
τ_{Q13_4}	5.419***	0.690	0.000
τ_{Q14_1}	-1.200*	0.714	0.050
τ_{Q14_2}	1.647**	0.923	0.017
τ_{Q14_3}	5.297***	1.925	0.000
τ_{Q14_4}	8.333***	2.860	0.000
τ_{Q15_1}	-1.739***	0.473	0.000
τ_{Q15_2}	-0.425**	0.226	0.042
τ_{Q15_3}	1.140***	0.236	0.000
τ_{Q15_4}	2.414***	0.285	0.000
Estimation Statistics			
Estimation method	bfgs	LL(start)	-1956.529
Convergence	Successful	LL(final, whole model)	-1499.673
Number of individuals	304	AIC	3063.35
Number of observations	1216	BIC	3224.59
Number of inter-person draws	1000 Halton	Iterations	109
WTP			
Performance MWTP	-2.841	Emission MWTP	3.298

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Participant Information Sheet

About this study:

This survey is part of a study to understand consumer understanding and beliefs about microplastics. As part of this, I am surveying a sample of the UK.

- The researchers who are conducting this study are based at the University of Bath.
- The survey should take no more than 15 minutes of your time.
- There are no right or wrong answers to these questions. Please remember that your honest opinion is the most valuable to us.
- The data will be held on a password-protected computer file.
- Your identity and those of other participants will be anonymous.
- If you agree to take part in this survey but feel at any stage that you would like to stop, you are free to do so at any time, and your data will be deleted.
- If, after the survey has taken place, you decide you do not want your responses used in the study, you are free to do so, and your data will be deleted.

If you have any questions about this study, feel free to contact us:

Mr Peter King
Department of Economics. University of Bath
Contact number: +44 (0) 7952 019756 Email address: P.M.King@bath.ac.uk

Dr Alistair Hunt
Department of Economics. University of Bath
Contact number: +44 (0) 1225 383244 Email address: A.S.P.Hunt@bath.ac.uk

1. **I agree to take part in this survey under the conditions explained to me above:** *Please select one*

Yes No

Section 1:

Please complete the following survey.

We are asking these questions to understand the survey responses better. Your data will be held securely and only used for research purposes.

Q1) **Please specify your gender:**

Please select one

- Man
- Woman
- Other

Q2) Please specify your current age:

Please select one

- 18-25
- 26-39
- 40-55
- 56-70
- 71+

Q3) **Approximately how far would you say you live from the coast?** *Please select one*

- 0 – 2 miles
- 3 – 10 miles
- 11 – 20 miles
- 21 – 50 miles
- 50+ miles

Q4) **On average, how many trips do you make to the coast annually?**

Please select one

- 0
- 1 - 2
- 3 - 5
- 6+

Q5) Please indicate your knowledge of microplastics and their effects on the environment and human health?

Please select one

	No knowledge	Little	Average	Good	Strong	
Low level						High level

Section 2:

A) Microplastics are small plastic particles, up to 5mm in diameter. Microplastics are some of the most commonly found types of plastic in the environment. The majority of microplastics in the environment come from larger plastics, such as packaging, that have broken down.

B) Some microplastics in the environment come from products, such as fertilisers, tyres, and personal care products that once used, may then be washed via sewage to the sea. As sewage sludge may be applied as fertiliser, some microplastics will stay in the environment and not reach the sea

C) Microplastics released to the environment cannot realistically be removed and may persist there for many thousands of years. A small amount of microplastics may be present in water and seafood, which is consumed by humans and animals. The potential for adverse effects is a cause of concern. However, it is not currently possible to determine the long-term impact of exposure on the environment and human and animal health.

D) The survey results will be useful for future microplastic policies so we would like you to answer all questions as realistically and accurately as you can.

Section 2A:
This section considers a policy to deal with the release of microplastics from wastewater sewage. It would be administered by water companies.

Q6) Suppose that the UK was going to introduce a policy that would fund research into the longterm environmental and health effects of microplastics in the environment. The research would definitely resolve the scientific uncertainty about any possible effects, though it would have no effect on the amount of microplastics currently entering the environment from wastewater sewage. An increase in your water bills would cover only the cost of this research. Any follow up action, depending on the research findings, would be funded separately.

Would your household be willing to pay £10 [Random value from: £5, £10, £20, £30, £40, £50, £60, £70] per year in extra water bills specifically for such research?

Please select one

- Yes
- No

Q6B) [If they answered no] You said you would not be willing to pay anything, could you please state why?

please elaborate.

Q6C) How sure are you of your choice?

Please select one

- Very Sure
- Quite Sure
- Unsure

Q7) An **alternative** possible policy option would stop microplastics from wastewater sewage entering the environment now, before waiting for the results of the research discussed in the previous question.

Suppose that the UK was going to introduce a policy that would pay to upgrade wastewater treatment plants filtering systems so that they would capture all the microplastics in sewage wastewater heading to the environment. An increase in your water bills would be used to pay for the cost of this investment.

Would your household be willing to pay £10 [Random value from: £5, £10, £20, £30, £40, £50, £60, £70] per year in extra water bills to implement this policy?

Please select one

- Yes
- No

Q7B) How sure are you of your choice?

Please select one

- Very Sure
- Quite Sure
- Unsure

Q7C) [If they answered yes] Would your household be willing to pay [Random value: £10, £20, £40, £60, £80, £100, £120, £140] per year in extra water bills to implement this policy?

Please select one

- Yes
- No

Q7C) [If they answered no] Would your household be willing to pay [Random value: £2.50, £5, £10, £15, £20, £25, £30, £35] per year in extra water bills to implement this policy?

Please select one

- Yes
- No

Q7D) [If they answered no] You said you would not be willing to pay anything, could you please elaborate on the reasons why?

Section 2B:

In this section we are interested in an alternative policy that would deal with the production of microplastics which are added to commonly used products. You are being asked about this as it is a different approach to controlling microplastics than those policies mentioned before.

Please note:

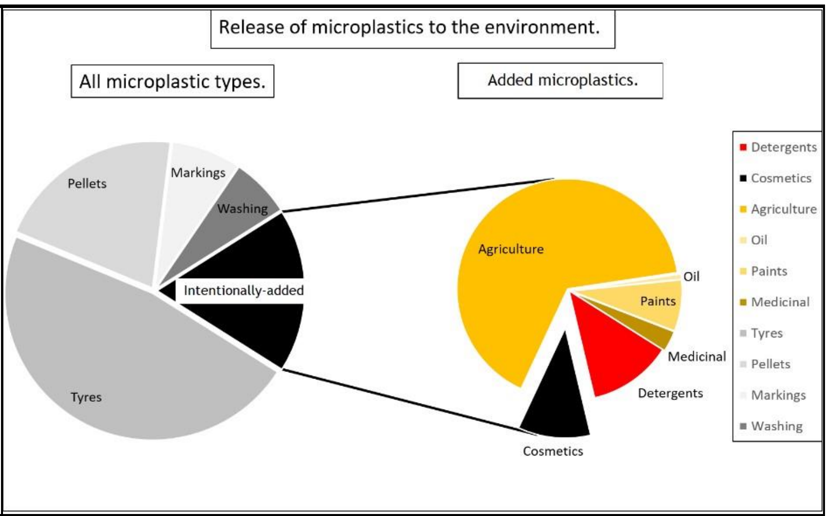
- Some types of microplastics added to personal care products, such as scrubs and exfoliators, were banned in the UK in 2018 as they were found to enter the environment. However, other types of microplastics added to personal care products have not been banned as there is limited evidence about their effects as discussed earlier in the survey.
- Although microplastics come from many sources, in this section we focus on those specifically added to personal care products, such as, toothpaste, shower gel, sunscreen and deodorant, as they are those most commonly used by consumers. See the following graph for context:

Microplastics by type:

This chart represents the proportion of microplastics entering the environment by type.

We are specifically interested in cosmetics as other policies exist for the other categories.

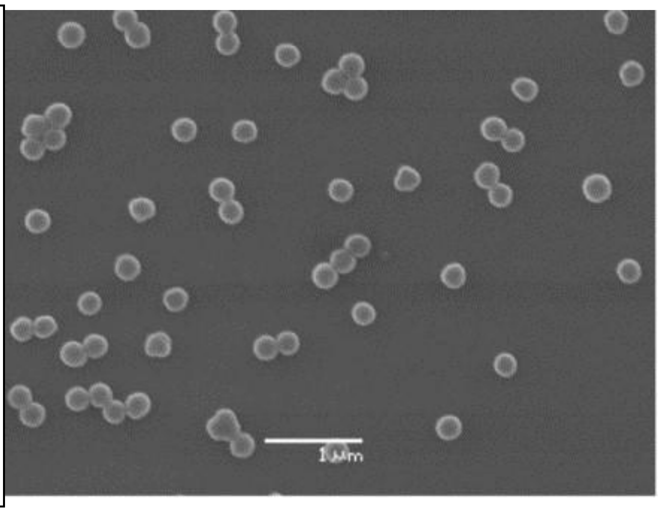
Source: https://echa.europa.eu/documents/10162/12414bc7-6bb2-17e7c9ec-652a20fa43fc



Example microplastics:

Microplastics in products such as sunscreen and toothpaste are tiny, in the micrometer size range, and visible only under the microscope.

Source: https://www.sacicfpa.com/site/upload/fiches/82597200447d539cc7d54e.pdf



Please Remember: As the existence and extent of environmental and health effects from microplastics are uncertain, paying more for a personal care product without microplastics is a *precautionary* choice, i.e., it guards against the possibility of any potential adverse effects on environment and health.

The next section presents options A and B - please choose whichever you prefer, there is no right or wrong.

This section uses a different question format where you will be presented two options; A and B, which are described in terms of 3 characteristics:

- **Product Performance:** How effective personal care products are with and without microplastics. ○ Without microplastics, personal care products would feel different or run out more quickly. e.g. sunscreen without microplastics may be heavier or greasier to apply
  - The values presented are the estimated change in effectiveness between 0% change (no change) and 90% (significant change).

- **Release**: How many microplastics from personal care products are annually released to the environment.
  ○ Approximately 500 tons of microplastics from personal care products are estimated to be released to the environment annually from the UK.
  - The values presented are the percentage reduction in the tonnage of microplastics coming from personal care products that may end up in the environment.

- **Price**: How costly personal care products are with and without microplastics.
  - Without microplastics, producers must find alternative, more expensive substitutes.
  - The values presented are the estimated increase in the price of a personal care product, such as an average bottle of SPF50 sunscreen if more expensive substitutes are used.

These characteristics will take different values for each option. We then ask you to carefully select which option you prefer – there is no right or wrong answer.

You will be given a table like this:

Then you will be asked which option you prefer:

Which option do you prefer?	**A**	**B**
Reduction in the performance of the personal care product.	0%	50%
Percentage reduction in the release of microplastics from personal care products.	0%	100%
Increase in product price.	£0	£1

EXAMPLE

Please select one

- Option A
- Option B

Option A represents current real levels.

- No change in price or quality.
- Some possibility of environmental and health effects.

Option B represents a proposed level.

- The Government would ban microplastics from being added to commonly used personal care products (toothpaste, shampoo, sunscreen etc).
- Prices would rise for products with lower quality.
- There would be a reduction in the likelihood of possible environmental and health impacts, although the existence and extent of these effects is uncertain in any case.
- You would have less money but would reduce the amount of microplastics going to the environment as a precaution against any potentially harmful effects.

We are interested only in which situation you prefer.

Q8) Do you prefer option A or B?

Please select one

- Option A
- Option B

	A	**B**
Reduction in the performance of the personal care product.	0%	90%
Percentage reduction in the release of microplastics from personal care product .	0%	0%
Increase in product price.	£0	£5

Q8B) You said you would choose Option [A or B], could you please elaborate what made you select that option?

Q9) Do you prefer option A or B?

Please select one

- Option A
- Option B

	A	B
Reduction in the performance of the personal care product.	0%	50%
Percentage reduction in the release of microplastics from personal care product.	0%	40%
Increase in product price.	£0	£5

BLOCK 2

	A	B
Reduction in the performance of the personal care product.	0%	50%
Percentage reduction in the release of microplastics from personal care product.	0%	90%
Increase in product price.	£0	£1

BLOCK 3

	A	B
Reduction in the performance of the personal care product.	0%	5%
Percentage reduction in the release of microplastics from personal care product.	0%	10%
Increase in product price.	£0	£5

BLOCK 4

	A	B
Reduction in the performance of the personal care product.	0%	10%
Percentage reduction in the release of microplastics from personal care product .	0%	10%
Increase in product price.	£0	£2.50

Q10) Do you prefer option A or B?

Please select one

- Option A
- Option B

	A	B
Reduction in the performance of the personal care product.	0%	10%
Percentage reduction in the release of microplastics from personal care product.	0%	10%
Increase in product price.	£0	£0.50

BLOCK 2

	A	B
Reduction in the performance of the personal care product.	0%	5%
Percentage reduction in the release of microplastics from personal care product.	0%	40%
Increase in product price.	£0	£2.50

BLOCK 3

	A	B
Reduction in the performance of the personal care product.	0%	5%
Percentage reduction in the release of microplastics from personal care product.	0%	40%
Increase in product price.	£0	£0.50

BLOCK 4

	A	B
Reduction in the performance of the personal care product.	0%	5%
Percentage reduction in the release of microplastics from personal care product .	0%	10%
Increase in product price.	£0	£1

Q11) Do you prefer option A or B?

Please select one

- Option A
- Option B

	A	**B**
Reduction in the performance of the personal care product.	0%	5%
Percentage reduction in the release of microplastics from personal care product.	0%	90%
Increase in product price.	£0	£2.50

BLOCK 2

	A	**B**
Reduction in the performance of the personal care product.	0%	5%
Percentage reduction in the release of microplastics from personal care product.	0%	10%
Increase in product price.	£0	£1

BLOCK 3

	A	**B**
Reduction in the performance of the personal care product.	0%	10%
Percentage reduction in the release of microplastics from personal care product.	0%	90%
Increase in product price.	£0	£5

BLOCK 4

	A	**B**
Reduction in the performance of the personal care product.	0%	5%
Percentage reduction in the release of microplastics from personal care product.	0%	90%
Increase in product price.	£0	£0.50

Q12) Do you prefer option A or B?

Please select one

- Option A
- Option B

	A	B
Reduction in the performance of the personal care product.	0%	50%
Percentage reduction in the release of microplastics from personal care product.	0%	10%
Increase in product price.	£0	£0.50

BLOCK 2

	A	B
Reduction in the performance of the personal care product.	0%	50%
Percentage reduction in the release of microplastics from personal care product.	0%	10%
Increase in product price.	£0	£2.50

BLOCK 3

	A	B
Reduction in the performance of the personal care product.	0%	10%
Percentage reduction in the release of microplastics from personal care product.	0%	40%
Increase in product price.	£0	£1

BLOCK 4

	A	B
Reduction in the performance of the personal care product.	0%	5%
Percentage reduction in the release of microplastics from personal care product .	0%	10%
Increase in product price.	£0	£5

Section 3:

This section specifically asks you about your attitude towards the environment.

The following section asks you how strongly you agree or disagree with the following statements.

Please answer these on a sliding scale of 1-5, thank you.

Q13) Please indicate the degree to which you think that microplastic pollution *currently* presents a threat to yourself. *Please select one*

	1	2	3	4	5	
Absolutely none	⬭	⬭	⬭	⬭	⬭	Absolutely critical

Q14) Please indicate the degree to which you think that microplastic pollution *will in the future* present a threat to yourself *Please select one*

	1	2	3	4	5	
Absolutely none	⬭	⬭	⬭	⬭	⬭	Absolutely critical

Q15) Please indicate the degree to which you think microplastic pollution currently presents a threat to *the environment* *Please select one*

	1	2	3	4	5	
Absolutely none	⬭	⬭	⬭	⬭	⬭	Absolutely critical

Q16) How much of 'Blue-Planet II' TV series have you seen?

Please select one

- ⬭ All of it
- ⬭ Some of it
- ⬭ None of it

Q17) Who do you think has the responsibility for reducing microplastics? Please select as many as you think.

- ⬭ Firms (who produce/use microplastics)
- ⬭ Consumers
- ⬭ Government
- ⬭ Local authorities:
- ⬭ Other:

Q18) Have you ever donated to or been a member of a charity/group dedicated to environmental causes? *Please select one*

- Yes
- No
- Prefer not to say

Final section

Q19) Please indicate your knowledge of microplastics and their effects on the environment and human health **following this survey?** *Please select one*

	No knowledge	Little	Average	Good	Strong	
Low level	◯	◯	◯	◯	◯	High level

Q20) Do you think the results of this survey will matter to how regulators change their policies?
Please select one

- ◯ Yes
- ◯ No

Q21) How confident are you in the ability of experts to provide reliable information? *Please select one*

	1	2	3	4	5	
Very unconfident	◯	◯	◯	◯	◯	Very confident

Q22) Please indicate your highest completed level of education

Please select one

- ◯ GCSE's / O levels
- ◯ A level or college equivalent
- ◯ Bachelor's degree
- ◯ Postgraduate degree

Q23) How would you describe your current employment status? *Please select one*

- ◯ Full-time employment
- ◯ Part-time employment
- ◯ Self-Employed
- ◯ Retired
- ◯ Not in education, employment, training
- ◯ Student

Q24) Has your income been affected by the coronavirus crisis this year? *Please select one*

- ◯ Yes
- ◯ No

Q24A) Please indicate your approximate average monthly income before tax and before coronavirus? *Please select one*

- £0 - £500
- £501 - £1000
- £1001- £1500
- £1501 - £2000
- £2001 - £2500
- £2501 - £3000
- £3001 - £4000
- £4001 - £5000
- £5000+
- Prefer not to say

Q25) On a scale of 1-10, how clear was this survey to complete? *Please select one*

	1	2	3	4	5	6	7	8	9	10	
Did not understand											Perfectly clear

If you have any further comments on the design or topic of this survey, please leave them here:

Your responses will remain confidential, but the results of this survey will be made publicly available. The results of this survey will be essential in developing future government programs to reduce the risks and severity of ingestion of microplastics. Your participation in this survey will be critical to its success.

For updates, withdrawals, questions and comments:

Researcher:
Mr Peter King
Department of Economics.
University of Bath
Contact number: 07952 019756
Email address: P.M.King@bath.ac.uk

That's all! Thank you for your time!