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Abstract

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1. Introduction

Global plastics production has grown rapidly due to the versatility and wide range of applications in packaging, building and construction, electronics, transportation, and textiles. Annual plastic resin and fibre production reached 380 million tonnes in 2015 from just 2 million tonnes in 1950, equivalent to 8.4% compound annual growth rate (Geyer, et al, 2017).

Currently, plastics are mainly derived from oil and gas, both as chemical feedstocks and as fuel sources. About 4% of fossil fuels extracted yearly is used as raw materials for plastics (British Plastics Federation, 2014). Plastics become waste at the end of their service life, which can range from days to 50 years or more. Global production of mismanaged plastic waste was estimated between 60 and 99 million metric tonnes in 2015 and projected to generate 155-265 million metric tonnes by 2060 (Lebreton and Andrady, 2019). Increasing production of non-biodegradable plastics gives rise to serious waste problems, because of its persistence at a global scale, particularly in the oceans (Gross, 2015).

Apart from addressing concerns over single-use plastics and waste, shifting to bio-based plastics can offer substantial climate benefits. For instance, substituting annual world demand for fossil-based polyethylene (PE) with bio-based PE would yield 42 million tonnes in CO_2 savings (European Bioplastics, 2016). Research has identified a number of bio-based alternative raw materials, including palm oil, soybean oil, and castor oil as well as other plant-based biodegradable polymers such as starch and cellulose (Mooney, 2009).

Currently global bioplastics capacity is 4 Mt or roughly 1% of nonbiodegradable plastic production (Geyer, et al, 2017). Despite the availability of some ‘‘green’’ plastic products, consumer interest is currently limited by the limited range of bio-based plastic products available, minimal experience with "green" plastics, and high prices. Ottman (1998) argues that many customers continue to choose conventional products with higher environmental impacts because of price and performance considerations or ignorance and disbelief. For example, petroleum-based plastic polystyrene is currently more cost effective than its alternatives, making widespread adoption of biodegradable plastics challenging (Barnes et al. 2011), despite the substitution advocacy for the replacement of a fossil-based PE plastic with a bio-based polyethylene for (Vivien et al., 2019). To better understand the barriers to adoption and opportunities for reformulation of plastics, we seek to elicit preferences for bio-based attributes of plastics using a choice experiment with the aim of identifying the preferred characteristics for environmentally friendly plastic bottles.

Unlike past studies (e.g., Yue et al., 2010; Barnes et al., 2011, Kainz, 2016), we use discrete choice models based on random utility maximization, which are useful in determining consumer valuation of environmental goods for which there is no market price (McFadden, 2001). Specifically, we include a set of green plastic attributes that allows us to examine the effects of a consumer's environmental attitudes on individual choice decision-making. Attributes we consider in the discrete choice experiment (DCE) include: (i) national origin of raw materials; (ii) ecolabel certification; (iii) proportion of CO_2 captured; (iv) share of bio-based plastics; and (v) price. In addition, we explore the impact of specific demographic characteristics on respondents' stated choices including age, education, gender and income, which have previously been found to influence perceptions and willingness to pay.

The remainder of the paper proceeds as follows: in the next section, we provide a brief literature review. Section 3 describes the discrete choice experiment. The data collected is presented in Section 4 and empirical strategy are discussed in section 5. The results are reported and discussed in Section 6 while Section 7 offers some conclusions.

2. Related Literature

Consumer interest in environmentally sustainable products has grown substantially. This has prompted the design of policies to encourage such behaviour and studies that attempt to provide better information to policymakers on consumers' valuations, preferences, and behaviours. Increased consumer interest in greener products and a willingness to pay a premium for bio-based products has been confirmed in a range of contexts (Yue et al. 2010; Barnes et al. 2011; Hall et al. 2012; Kainz 2016; and Carus et al. 2014). Other studies examined the share of participants willing to pay more for bio-based plastics (Kurka and Menrad 2009; Scherer et al. 2017). However, the methods used to assess WTP in these studies vary considerably.

One of the most common stated preference techniques for measuring consumer preferences for environmental goods is contingent valuation, whereby people indicate the most they would be willing to pay for an improvement. The technique has been criticized (Kahneman and Knetsch 1992; Diamond and Hausman, 1994) because results of contingent valuation studies are theoretically inconsistent. Notably, Kahneman and Knetsch (1992) find willingness to pay for environmental amenities is remarkably unresponsive to the scope or scale of the amenity provided – WTP to clean one polluted lake in Ontario was not statistically different from WTP to clean all polluted lakes in the province.

The other widely used stated preference method to elicit consumers' WTP for products with different environmental attributes is choice modelling (e.g. conjoint choice experiment (CCE) and discrete choice experiment (DCE)). Past studies that examine consumer preferences and willingness to pay using conjoint choice experiment include Barnes et al. (2011); and Scherer et al. (2017; 2018). Barnes et al. (2011) find an increase in consumer willingness to pay for more environmentally friendly food containers, in Honolulu, Hawaii, which may allow businesses to offset the costs of substituting a petroleum-based plastic polystyrene for biodegradable materials. In a related study, Scherer et al (2017) investigate consumers' preferences on a set of sand toys made of bio-based plastic. Aside from a general interest of consumers in bio-based product alternatives, they identified consumer preferences for regionally grown raw materials, a reduction of CO_2 emissions and products without toxic additives. Scherer et al (2018) use a choice-based-conjoint analysis to analyze preferences for plastic drink bottles for bicycles and running shoes with a bio-based soles and find a clear preference for products using German, i.e. local raw materials, a high percentage of bio-based plastic, not requiring plastic softeners and leading to large reductions in CO_2 emissions. However, despite these stated preferences, respondents rejected paying a high price premium.

Another technique that complements traditional stated preference methods is experimental auctions. Michaud and Llerena (2011) examine whether consumers are willing to pay for remanufactured products, especially when they are informed that these products are 'green' using experimental auctions to elicit consumers' WTP for specific characteristics of remanufactured products. They find no evidence consumers are willing to pay a premium for green products.

Ellison et al. (2015) elicit consumers' willingness to pay for an environmentally sustainable good by using an auction design in a market setting and find consumers are willing to pay a \$0.67–\$1.12 premium for a bioplastic plant container over a traditional plastic one.

Comparing both hypothetical conjoint analysis and non-hypothetical experimental auctions to elicit WTP for biodegradable plant containers among consumers in the United States, Yue et al. (2010) show participants were willing to pay a price premium for biodegradable containers, but the premium varies for different types of containers. Similarly, Khachatryan et al. (2014) used conjoint analysis to show through a mixed-ordered probit model that consumers were willing to pay a premium for non-plastic containers, with the highest premium for compostable containers (\$0.227) and locally grown plants (\$0.222) and slightly lower WTP for plantable (\$0.122), and recyclable (\$0.155) containers. Other studies examine willingness to pay for bio-based replacements for specific plastic products. Kainz (2016) analyzed respondents' WTP for bio-based toothbrushes and sunglasses in Germany and found a higher WTP for products made of bio-based plastic. Kurka and Menrad (2009) investigated bio-based orange juice bottles and cell phone cases and concluded that consumers interest in bio-based products and a higher willingness to pay were identified, depending on characteristics such as home country, environmental attitude and health consciousness.

Although the relatively sparse literature suggests mixed findings on consumer preferences and willingness to pay for green plastic, to date, studies do not offer any evidence from discrete choice experiments. Choice modelling may be particularly preferable in situations where alternative choices differ across multiple dimensions and the focus is on assessing trade-offs (Hanley et al, 2001). Furthermore, Louviere et al (2010) argue CCE does not naturally yield willingness to pay (WTP) and should be used with caution in economic applications.[2] Thus, we adopt discrete choice models based on random utility maximation. Discrete choice experiments have been used in a growing number of studies to understand consumers' willingness to pay for products with environmental benefits[3] (Achtnicht, 2011; Daziano and Achtnicht, 2014; Völker and Lienhoop, 2016; Galassi and Madlener, 2017 ; Wensing et al., 2020 ; Zandersen et al., 2020), as well as education (Walsh et al., 2019), energy (Richter and Pollitt, 2018; Morrissey et al., 2018), health (Hole and Kolstad, 2012; Riise, et al., 2016; Grépin et al., 2018), outdoor recreation (Scarpa et al., 2008; Thiene and Scarpa, 2009), transportation (Greene and Hensher, 2010) and water services (Hensher, et al., 2005)[4].

To our knowledge, the paper represents the only study to provide a concrete and detailed evidence on the potential willingness to pay for "green" plastics using a discrete choice experiment. Second, it examines consumers revealed heterogeneity in WTP to infer their price sensitivity in the context of green plastics. Third, while Greene and Hensher (2010) show that the WTP space model can be expressed as a special case of the GMNL model, we implement this extension by specifying a GMNL model. Thus, our study is the first to investigate the heterogeneities in WTP of plastic attributes using both preference space and WTP approaches while comparing the results of the estimated models based on selection criteria to arrive at the preferred model.

[2] While both DCE and CCE are choice modelling techniques widely used to elicit stated preferences from individuals' preferences for "alternatives" expressed in a survey context, CCE evolved out of a more mathematical approach not studies of human behaviour. DCE is based on random utility theory which is a well-tested theory strongly associated with error components whose properties play key roles in parameter estimates and welfare measures derived from DCE data (Louviere, et al., 2010).

[3] Hoyos (2010) reviews past studies on environmental valuation with discrete choice experiments

[4] See Kanninen (2002), Campbell et al. (2008) and Johnson et al., (2013) for a detailed discussion of experimental designs for discrete choice experiments.

3. Discrete choice experiment (DCE)

Our discrete choice modelling is carried out in the following stages: (i) selection of green plastic attributes; (ii) assignment of attribute levels; (iii) experimental design; (iv) construction of choice sets presented to respondents; (v) measurement of preferences as choice; and (vi) estimation using a mixed logit approach.

The empirical analysis is based on original data from a stated choice experiment conducted online with 3085 respondents in Great Britain from 21 September to 6 October 2018 to elicit customer willingness to pay for green plastic bottles. The demand for green plastic depends largely on price, green plastic attributes and on socio-economic and demographic consumer characteristics. Green plastic bottles are relatively novel to consumers as a result of the renewed advocacy by environmental organisations across the world for reduction in carbon footprint due to emission of greenhouse gas.

Thus, the number of attributes presented was limited to those likely to determine the substitution patterns between the three options. The attributes and their levels in the choice experiment were chosen based on previous consumer research (e.g., Scherer et al., 2017, 2018) on bio-based plastics in specific end uses. The five attributes were: (1) the origin of raw materials, (2) eco-certification, (3) proportion of CO_2 captured, (4) fraction of bio-based plastic contained, (5) price of green plastic bottles. The price is expected to be paid by the consumers in exchange for the hypothetical attribute combinations that guarantee little or no carbon emission in the production of the plastic bottles. The green plastic attributes and levels are summarised in Table 1 and explained in more detail below.

Table 1: Attributes and levels

		Variable
Origin of raw material		
Level 1 (base)	Soybean oil from the USA	
Level 2	Palm oil from Indonesia	IndoPalm
Level 3	Castor oil from China	ChiCast
Eco-certification		
Level 1 (base)	Fairtrade	
Level 2	Certified sustainable palm oil	CertCSPO
Level 3	USDA Organic certification	CertOrg
CO_2 captured		
Level 1 (base)	1%	
Level 2	50%	CCS50
Level 3	100%	CCS100
Bio-plastic fraction		
Level 1 (base)	20%	
Level 2	80%	BIO80
Level 3	100%	BIO100
Price per bottle (£)		
3 levels	1.05, 1.20, 2.00	Price

Prior to the DCE, each respondent was provided with background information on the different attributes and associated levels of green plastics via written and graphic explanations. For all attributes and levels, hover-buttons were provided for participants to refresh their memory about the meaning of the different attributes and levels. In each choice set, respondents were asked to choose between three unlabelled options that differed along the five dimensions. Participants are shown the choice sets in succession and asked which option they prefer in each.

A questionnaire accompanying the choice experiment included further questions as to how certain consumers were about their choices, whether they are able to make comparisons between options that were presented and whether each of the levels presented were easy to understand. In addition, a variety of questions socio-economic, demographic, household size, financial state, and involvement in environmental organisations were used to better characterize customers.

3.1 Experimental design

The design approach is based on a search algorithm to obtain as statistically efficient a design as possible given prior values for the ultimate model to be estimated. Discrete choice experimental design is usually expressed in terms of some form of error (e.g., D-error, A-error) derived from the asymptotic variance-covariance matrix (Scarpa and Rose, 2008). The target measure of efficiency was the *D*-error, calibrated on the basis of sign-based priors. Neutral (zero) priors were assigned to 'Origin of raw materials' and 'Eco-certification' attribute levels on the basis that there was no strong prior reason to expect any level to be more or less attractive to participants than any others. The CO_2 Captured and Bio-plastic Fraction attributes were both specified as having positive priors as higher values were expected to be more attractive to participants. Finally, the 'Amount to pay (£)' attribute was specified as having a negative prior as people prefer lower prices to higher prices all else equal. Ngene, a software programme that allows users to generate designs for a wide variety of discrete choice model specifications was used including implementation of a swapping algorithm (Huber and Zwerina, 1996). In this design, levels were approximately, although not exactly, balanced across the design. Table A.1 in the appendix shows an example of the choice card presented to respondents, which contains randomly varying levels for each attribute. Each respondent was presented with eight such cards, i.e., each respondent was asked to make eight choices.

4. Data

Discrete choice modelling is useful for estimating WTP for goods and services, to derive demand and consumer surplus as well as for optimum pricing. Indeed, the exploration of customer preferences and estimation of WTP via stated choice experiments has become vitally important in the price review processes for environmentally friendly products. To explore our random coefficient models for the estimation WTP distributions of green plastic bottle, we use the stated preference survey. The discrete choice experiment was conducted with a representative sample of 3058 consumers in Great Britain. The questionnaire was administered by Accent, a London-based market research firm that has carried out similar discrete choice experiments on large, nationally representative samples.

The sample was chosen to be representative of the British population in terms of age, gender, education, household income and region and the survey covered a number of green plastics-specific questions. Respondents were asked the extent to which they are willing to pay a bit more for products that are environmentally friendly. Only 10% claimed they always paid a bit more compared to almost a quarter (24%) of respondents who said they were willing to pay a bit more most of the time, some of the time (39%), or seldom (15%), while only 9 per cent of respondents said they never paid more. When asked to what extent, if at all, they believed "green" plastics (bioplastics) are more environmentally friendly than conventional plastics, about 42% of respondents believed bioplastics to be more environmentally friendly including almost 28% who claimed bioplastics are much more environmentally friendly. Asked whether they support or oppose capturing the CO_2 used in producing plastic and storing that CO_2 below the North Sea to reduce the carbon footprint associated with the plastics they buy, about 58% of respondents supported the option (including 23% strong support(and 28% neither supported nor opposed CO_2 being captured in the production of green plastics.

We also confirmed respondents were able to make comparisons between the options that were presented to them in the choice questions. 87% of respondents reported that they were able to make comparisons between the options while only 13% could not compare the options. Furthermore, 82% of respondents claimed they found each of the service levels described easy to understand compared to 18% who claimed otherwise. Table A.2 in the Appendix provides the demographic and socio-economic characteristics of respondents.

We also employ data from the survey to model interactions of the price attribute variables with other variables such as donations to environmental organisations and the amount donated to good causes. To measure respondents' donations, we exploit the responses to 'are you involved in any environmental organisation'? The variable is coded "1" if the response is yes, I donate and "0" otherwise. The amount donated by respondents to good causes was measured using the survey question "Approximately, how much money, if any, did you donate to good causes, in pounds , in the past year? (e.g. donating to a charity)". The amount variable is coded as: 1, nothing; 2, £1-£50; 3, £51 -£100; 4, £101-£250; 5, £251-£500; 6, £500 or more. Table A.2 in the appendix also reports the percentage share of the different types in the sample.

5. Empirical Strategy

Our DCE empirical framework is based on random utility maximation theory in which consumers' probability of choice is estimated using random utility models. Given the limitations associated with some widely used probability choice models, we employ different model specifications, ranging from multinomial logit to mixed logit and finally generalised multinomial logit, and conduct diagnostic tests to reveal their explanatory powers.

In the baseline multinomial (or conditional) logit, the utility U that consumer *n* obtains from alternative *j* in choice situation *t* is expressed as:

$$U_{njt} = \beta x_{njt} + \varepsilon_{njt} \qquad (1)$$

x_{njt} denotes a vector of observed attributes of alternative j, β is a vector of utility weights, which are homogeneous across consumers, and ε_{njt} is the error term, which is distributed extreme value i.i.d. The multinomial logit (MNL) model has choice probabilities given as:

$$P(j|X_{nt}) = \frac{\exp(\beta x_{njt})}{\sum_{k=1}^{J} \exp(\beta x_{nkt})} \qquad (2)$$

However, an important drawback of employing MNL is the underlying property of independence of irrelevant alternatives (IIA)[5] also known as binary independence which can lead to unrealistic predictions in a mixed logit.

[5] The IIA assumption states that the ratio of the probabilities of choosing any two options is independent of the attributes or the availability of any additional alternatives in the choice set (McFadden, et al.,1977).

In the mixed logit model, the utility U that consumer n obtains from alternative j in choice situation t can be written as[6]

$$U_{njt} = (\beta + \eta_n)x_{njt} + \varepsilon_{njt} \qquad (3)$$

Here, β is the vector of mean attribute utility weights and η_n is the vector of consumer n-specific deviations from the mean. The error term ε_{njt} is assumed to be i.i.d. Since we are interested in obtaining estimates of WTP, we let utility be separable in price and non-price attributes following Train and Weeks (2005), hence utility can be written:

$$U_{njt} = \alpha_n p_{njt} + \beta_n' x_{njt} + \varepsilon_{njt} \qquad (4)$$

Where p_{njt} represents the price and x_{njt} denotes a vector of non-price attributes of green plastics. The coefficients $\alpha_n$and β_n vary randomly over consumers and ε_{njt} are distributed extreme value i.i.d. with variance $\sigma_n^2\ (\pi^2/6)$, where σ_n is a consumer-specific scale parameter. Since utility is ordinal, the utility function in Eq. (4) can be divided by the individual-specific scale parameter to obtain its scale-free equivalent without affecting behaviour. This results in a utility function with a new error term with constant variance $\pi^2/6$ for all consumers.

$$U_{njt} = (\alpha_n/\sigma_n)p_{njt} + (\beta_n/\sigma_n)' x_{njt} + \varepsilon_{njt} \qquad (5)$$

[6] Examples of empirical application of this utility specification include studies such as Scarpa et al. (2008); Thiene and Scarpa (2009), Hole and Kolstad (2012), Walsh et al. (2019).

where ε_{njt} is i.i.d. type-1 extreme value. The utility coefficients are defined as $\lambda_n = (\alpha_n/\sigma_n)$ and $c_n = (\beta_n/\sigma_n)$, such that utility may be written:

$$U_{njt} = \lambda_n p_{njt} + c_n' x_{njt} + \varepsilon_{njt} \tag{6}$$

Eq. (6) is referred to as the model in preference space (Train and Weeks, 2005). Eq. (3) reveals that λ_n and c_n will be correlated in as much as the scale parameter, σ_n , appears in the denominator for both coefficients, except if the scale parameter does not vary over consumers. Independent coefficients implicitly constrain σ_n to be constant, indicating that the randomness is homoscedastic, which might not be a realistic assumption (Louviere et al, 2002).

Defining WTP for a green plastic attribute as the ratio of the attribute's coefficient to the price coefficient: $\omega_n = c_n/\lambda_n = \beta_n/\alpha_n$

The utility expression can be rewritten as:

$$U_{njt} = \lambda_n [p_{njt} + \omega_n' x_{njt}] + \varepsilon_{njt} \tag{7}$$

Eq. (7) describes the model in WTP space (Train and Weeks, 2005). Equations (6) and (7) are behaviourally equivalent, but standard assumptions regarding the distribution of λ_n and c_n in Eq. (6) can lead to abnormal distribution of the random estimated WTP parameters . For instance, in the event that λ_n and c_n are normally distributed, it means that ω_n is a ratio of two normals, without defined moments.[7] The preference space approach involves the following steps – specify distributions for random coefficients of the preference Eq.(6); obtain the estimates of the hyper-parameters of the underlying distributions; and derive the distributions of WTPs by simulation from the estimated distributions of the random coefficients in preference space.

Re-parameterising the utility function in WTP space in Eq.(7) as:

$$U_{njt} = \underbrace{(\alpha_n/\sigma_n)}_{\lambda_n}\left[p_{njt} + \underbrace{(\boldsymbol{\beta}'_n/\alpha_n)}_{\boldsymbol{\omega}'_n}\, x_{njt}\right] + \varepsilon_{njt} \tag{8}$$

where σ_n captures scale heterogeneity, and ε_{njt} still follows extreme value type-1 distribution, with constant variance $\pi^2/6$, which allows for estimation as a mixed logit model. The WTP coefficients are independent of scale parameter σ_n, since the scale parameter cancels out in the expression but the price coefficient in WTP space λ_n incorporates scale (Hole and Kolstad, 2012; Train and Weeks, 2005).

Greene and Hensher (2010) show that the WTP space model can be specified as a special case of the generalised multinomial logit (GMNL) model (Fiebig et al., 2010). The GMNL model incorporates a separate random scale parameter in addition to the random preference parameters while imposing distributions on both preference and scale coefficients. Following Fiebig et al. (2010), the utility *U* that consumer *n* obtains from alternative *j* in choice situation *t* is given by:

[7] To avoid the unusual distribution of WTP, we assume that the non-price coefficients have a normal distribution and price coefficient is assumed to be non-random.

$$U_{njt} = [\sigma_n\beta + \gamma\eta_n + (1-\gamma)\sigma_n\eta_n]x_{njt} + \varepsilon_{njt}$$

$$\sigma_n = \exp(\bar{\sigma} + \tau\varepsilon_{0n}) \quad (9)$$

where $\gamma \in [0, 1]$, the parameter σ_n can be interpreted as a lognormally distributed price parameter. Thus, the assumption of homoscedastic errors is relaxed. Since only relative scale difference can be identified, $\bar{\sigma} = -\tau^2/2$, and $\theta = 0$, which implies that $E(\sigma_n) = 1$. If the parameter τ is significantly different from zero that indicates significant heterogeneity in σ_n. If $\gamma = 0$, the specification gives the GMNL-II;

$$U_{njt} = \sigma_n(\beta + \eta_n)x_{njt} + \varepsilon_{njt} \quad (10)$$

Thus, the GMNL model is a specific form of the mixed logit specification with flexible mixing distributions[8]. When the scale factor is assumed constant ($\sigma_n = 1$), the GMNL model reduces to the standard mixed logit model.

5.1 Model specification

In our empirical specification, we use dummy variables to indicate the levels of the non-price attributes; *origin of raw material, eco-certification, bio-plastic fraction and CO_2 capture.* Level 1 of each attribute serves as the base level. The *price* attribute is included as a continuous monetary variable. We did not include alternative specific constants for the alternatives in the model as our choice experiment was not labelled[9]

[8] See Keane and Wasi (2013) for a comparison of six alternative models of heterogeneity.

[9] When data are derived from an unlabelled choice experiment, the alternatives have no utility beyond the characteristics attributed to them in the experiment, hence the usual practice entails excluding the alternative-specific constants from the model (Hole, 2007). Besides, the choice experiment did not take the status-quo or no choice option

$$
\begin{aligned}
U_{njt} = \; & \alpha_n Price_{jt} + \beta_{1n} IndoPalm_{jt} + \beta_{2n} ChiCast_{jt} + \beta_{3n} CertCSPO_{jt} \\
& + \beta_{4n} CertOrg + \beta_{5n} CCS50 + \beta_{6n} CCS100_{jt} \\
& + \beta_{7n} Bio80 + \beta_{8n} Bio100 \qquad (11)
\end{aligned}
$$

where $Price_{jt}$ is the price per green plastic bottle (£) and $IndoPalm_{jt}. . . , Bio100_{jt}$ are the variables representing the attribute levels as described in Table 1.

We present results for four model specifications. Model 1 is the standard MNL model, Model 2 is the mixed logit model in preference space in which the price coefficient is fixed, Model 3 is a mixed logit model with constant scale parameters and random preference parameters. In both estimated mixed logit models, all non-price coefficients are specified as random and independently normally distributed. The price coefficient is assumed to be random but follow a log-normal distribution in Model 3 while the price coefficient is fixed in Model 2, which simplifies derivation of the distribution of WTP. The price coefficient is fixed across consumers such that the distribution of the calculated post-estimation WTP for each attribute in the preferences space model have the same distribution as the attribute's coefficient (Revelt and Train, 1998). Model 4 is the generalized multinomial logit (GMNL-II) with random preference and random scale parameters. We estimate preference space and WTP space models using maximum simulated likelihood.[10]

into account, which can be considered labelled or identifiable by the respondents. We multiply price by -1 to obtain a price coefficient that is lognormally distributed and positive for all individuals.

[10] An alternative approach of estimating the preference space and WTP space models is to specify a hierarchical Bayesian model with priors for all model parameters (Train, 2009).

6. Results and discussion

Drawing on the discrete choice experiment to derive consumers' willingness to pay for green plastic bags, we estimate four models: the baseline standard MNL model, two mixed logit models – one in preference space and one in WTP space – and a GMNL model. The models are well specified and the mean estimates have the expected signs with respect to the price attribute coefficient across the models. In this section we compare and discuss results of the different model specifications.

Table 2: Results from models in Preference Space

	Model 1-Multinomial logit		**Model 2-Mixed logit**	
Variable	Coefficient	Standard error	Coefficient	Standard error
Mean				
Price	-0.777***	(0.0162)	-1.006***	(0.0222)
IndoPalm	-0.113***	(0.0234)	-0.319***	(0.0345)
ChiCast	-0.133***	(0.0148)	-0.181***	(0.0193)
CertCSPO	-0.365***	(0.0242)	-0.717***	(0.0404)
CertOrg	-0.0805***	(0.0147)	-0.103***	(0.0188)
CCS50	0.498***	(0.0264)	0.561***	(0.0332)
CCS100	1.002***	(0.0257)	1.142***	(0.0347)
Bio80	0.385***	(0.0285)	0.376***	(0.0362)
Bio100	0.700***	(0.0205)	0.831***	(0.0272)
SD				
IndoPalm			0.779***	(0.0518)
ChiCast			0.470***	(0.0325)
CertCSPO			1.410***	(0.0421)
CertOrg			0.282***	(0.0440)
CCS50			0.654***	(0.0491)
CCS100			1.002***	(0.0329)
Bio80			-0.449***	(0.0672)
Bio100			0.633***	(0.0308)
Log-Likelihood	-26829.02		-25216.77	
AIC	53676.04		50647.55	
BIC	53760.31		50626.55	
# of respondents	3085		3085	
# of observations	86,040		86,040	

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In Table 2, the estimate of the MNL model is reported as Model 1 – the choice of MNL is usually recommended as the first step in the empirical investigation of discrete choice models in order to determine the right attributes and ensure sensible results in terms of parameter sign and significance (see Louviere et al, 2000).

Model 2 is a mixed logit preference-space model where only the price coefficient is fixed (non-random) in the estimation and is included as a benchmark specification (see Scarpa et al., 2008; Hole and Kolstad, 2012; Morrissey et al., 2018)[11]. Table 2 reports estimates of the price variable and the estimated non-price attribute level coefficients, which are indicated by dummy variables. We report the goodness-of-fit measures along with coefficient estimates and estimated standard errors are in parentheses. Although mixed logit models do not provide direct estimates of willingness to pay in the preference space model, given the linearity of price in the utility function, marginal willingness to pay for an attribute is estimated as the ratio between the attribute's coefficient and the price coefficient. As the price coefficient is fixed, this ratio follows the same distribution as attribute-level coefficients, which implies that WTP is normally distributed in the preference space model. Corresponding WTP estimates for the models in Table 2 are reported in Table 3.

[11] We tried to estimate a random coefficient model in preference-space where all the variable coefficients are random to allow for preference heterogeneity in term of price. However, the model failed to converge with our dataset.

Table 3: Mean WTP implied by estimated parameter in Preference Space

	Model 1 - Multinomial logit		Model 2 - Mixed Logit	
Variable	Coefficient	Standard error	Coefficient	Standard error
IndoPalm	-0.145***	(0.0308)	-0.317***	(0.0354)
ChiCast	-0.171***	(0.0191)	-0.180***	(0.0192)
CertCSPO	-0.470***	(0.0315)	-0.712***	(0.0412)
CertOrg	-0.104***	(0.0189)	-0.102***	(0.0185)
CCS50	0.641***	(0.0343)	0.558***	(0.0330)
CCS100	1.290***	(0.0384)	1.135***	(0.0382)
Bio80	0.495***	(0.0368)	0.374***	(0.0368)
Bio100	0.901***	(0.0308)	0.826***	(0.0317)
# of respondents	3085		3085	
# of observations	86,040		86,040	

Mean WTP implied by estimated parameter in Preference Space reported in Table 2. Standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Standard errors are calculated using the delta method.

Table 4 presents estimates of models in WTP space in which the attributes, as well as the marginal WTPs are all random i.e. preference parameters vary randomly over consumers. Model 3 is the mixed logit and Model 4 is a GMNL model. The WTP coefficients in the WTP space model can be obtained directly from the estimated coefficients of the attributes. Thus, the coefficient estimates of both WTP-space models can be interpreted in monetary terms. Although, one rationale for reparametrizing the preference space model into WTP space is that the WTP distribution might be unrealistic or difficult to describe if we estimate the model in preference space, we conducted model selection tests to carefully choose the most appropriate model for our dataset, Table 5 summarizes the goodness-of-fit measures for the four models i.e. log likelihood, Akaike information criterion (AIC) and Bayesian information criterion (BIC).

Table 4: Results from models in WTP space

	Model 3 - Mixed Logit		Model 4 - GMNL-II	
Variable	Coefficient	Standard error	Coefficient	Standard error
Price	1		1	
IndoPalm	-0.145***	(0.0308)	-0.208***	(0.0255)
ChiCast	-0.172***	(0.0191)	-0.137***	(0.0143)
CertCSPO	-0.470***	(0.0315)	-0.777***	(0.0482)
CertOrg	-0.104***	(0.0189)	-0.0599***	(0.0171)
CCS50	0.640***	(0.0343)	0.566***	(0.0297)
CCS100	1.290***	(0.0384)	1.093***	(0.0326)
Bio80	0.495***	(0.0368)	0.348***	(0.0311)
Bio100	0.901***	(0.0308)	0.798***	(0.0258)
[Het] const	-0.252***	(0.0208)	0.804***	(0.0566)
Tau (τ)	0	-	1.404***	(0.0520)
SD				
IndoPalm	0.0119	(0.0236)	0.133**	(0.0567)
ChiCast	-0.0186	(0.0171)	0.0223	(0.0280)
CertCSPO	-0.0136	(0.0215)	1.223***	(0.0485)
CertOrg	-0.0205	(0.0169)	0.458***	(0.0237)
CCS50	-0.0199	(0.0220)	0.125***	(0.0418)
CCS100	-0.0135	(0.0171)	0.705***	(0.0250)
Bio80	-0.00965	(0.0234)	-0.0550	(0.0338)
Bio100	-0.0202	(0.0172)	0.397***	(0.0262)
Log-Likelihood	-26826.15		-24731.09	
AIC	53686.3		49498.19	
BIC	53845.47		49666.71	
# of respondents	3085		3085	
# of observations	86,040		86,040	

The WTP models are random parameter models using GMNL specification.
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

A good model is one with the largest log-likelihood value and minimum AIC and BIC values are used as model selection criteria. Hence, in comparing models vis-à-vis the selection criteria, we find the WTP-space Model 4, GMNL-II model, outperforms all other models.

Table 5: Measures of Fit

Test	Model 1	Model 2	Model 3	Model 4
Log-Likelihood	-26829.02	-25216.77	-26825.9	-24731.09
AIC	53676.04	50647.55	53685.79	49498.19
BIC	53760.31	50626.55	53844.96	49666.71
Observations	86,040	86,040	86,040	86,040

The goodness-of-fit measure also supports our preferred model in that the WTP-space models have been found to result in more realistic estimates of WTP given that the WTP distributions are specified directly in the estimation process (Scarpa et al., 2008, Hole and Kolstad, 2012) and consistent with Walsh et al. (2019) who found that GMNL models outperform mixed logit models.

In our chosen model reported in Table 4, Model 4- GMNL-II, the coefficients of the non-price attributes i.e. *IndoPalm, ChiCast, CertCSPO, CertOrg, CCS50, CCS100, Bio80 and Bio100* are assumed to be normally distributed. However, the price parameter is assumed to follow a log-normal distribution, and since the model is specified in WTP space, the coefficients of the attributes can be interpreted as WTP estimates. Estimated means of coefficients distribution of the attributes are significant at the 1% level.

Willingness to pay for reducing CO_2 emissions via capture and storage of CO_2 during plastic bottle manufacturing is positive and statistically significant. To capture and store 50% of the CO_2, consumers would be willing to pay about £0.57 extra on a £1 plastic bottle (*CC50*) relative to a bottle where only 1% of CO_2 was captured. They are also willing to pay almost twice as much for 100% capture and storage, on average an extra £1.09 per £1 plastic bottle (*CC100*), which is the highest premium recorded across all attributes and levels. This finding is consistent with Achtnicht (2011) who concludes that WTP for carbon reduction relates to consumers' awareness of their responsibility for environmental protection and consumers are willing to pay substantial amounts of money to fulfil that responsibility. Willingness to pay for more bio-based plastic bottles is also significant although somewhat lower in magnitude. Consumers would pay an extra £0.35 per £1 plastic bottle for plastic bottles containing 80% of bio-based materials (*Bio80*) and an extra £0.80 for 100% bio-based plastic bottles (*Bio100*). Although, the description in the choice experiment indicated that 100% bio-based plastic materials may not necessarily be biodegradable, consumers appear willing to pay a much higher premium for a fully bio-based plastic bottle.

Whereas one would expect that capturing more CO_2 and increasing the fraction of bio-based materials would lead to greater WTP, there was no unambiguous *a priori* reason to assume one type of certification or country of origin would be favoured over another. We do find a statistically significant WTP for environmentally-friendly raw materials sourced from the USA versus Indonesia (*IndoPalm*), i.e., respondents required an additional 0.21 per £1 plastic bottle to accept green plastics produced with palm oil from Indonesia relative to plastics produced from sunflower oil from the USA. Similarly, they wanted significant, though slightly lower compensation to accept plastic bottles produced using castor oil from China relative to American sunflower oil. Willingness to accept (WTA) is, on average, £0.14 per £1 plastic bottle (*ChiCast*).

On product certification, consumers would want compensation if plastic bottles held environmental certifications such as Certified Sustainable Palm Oil or organic certification instead of Fairtrade. The average WTA for bottles labelled as Certified Sustainable Palm Oil is about £0.78 per £1 plastic bottle relative to a Fairtrade label (*CertCSPO*). By contrast, although the difference is significant, customers would only ask for compensation of about £0.06 per £1 plastic bottle for Organic certification (*CertOrg*).

To gain insights into drivers of revealed heterogeneity, we estimate models where we interact price attributes and respondent characteristics to test if the means of the random coefficients of the interaction terms are non-zero. Introducing an interaction between an estimate of the mean random parameter and a covariate is the same as revealing the presence or absence of preference heterogeneity around the mean parameter estimate and a lack of significance of the interaction would indicate the non-existence of preference heterogeneity around the mean on the basis of measured covariates[12] (Hensher and Greene, 2003). Given the large number of variables included, some models suffer from convergence problems and selecting appropriate interactions models becomes too difficult to estimate. Following Richter and Pollitt (2018), we employ multinomial logit model (MNL) models with interaction terms of attributes and respondent characteristics, which can provide insights into the drivers of heterogeneity in willingness to pay.

We test various model specifications using interaction terms between attributes and respondent characteristics in order to assess possible nonlinear effects of these variables. In particular, interactions of price with social economic factors and other variables can reveal the price sensitivity of different categories of consumers. In Table 6, we present the results of the MNL model with the interactions terms and price which indicate the heterogeneity in price sensitivities. The significant and negative coefficient of the price-gender interaction indicates that, *ceteris paribus*, male respondents are less likely to pay for green plastics relative to their female counterparts, whereas the price-education interaction (where education is defined as having completed tertiary education) does not differ significantly in price sensitivities and willingness to pay for green plastic. In terms of age, using respondents aged 18 to 24 as the reference group, the differences in price sensitivity for respondents between 25 and 34 is not significant. However, there is a significant and negative coefficient of the interaction term between price and other age categories (>35). Specifically, older respondents relative are less likely to pay for green plastics

[12] The lack of statistical significance does not signify there is no preference heterogeneity around the mean, but that its presence could not be revealed. See Hensher and Greene (2003) for a detailed discussion.

than younger ones. One possible reason is that older people are less worried about the environment, for example, Poortinga et al. (2011) find greater prevalence of climate scepticism among older respondents.

Table 6: Multinomial logit model with interaction terms

Variable	Coefficient	Standard error
Price	-0.869***	(0.0629)
IndoPalm	-0.112***	(0.0245)
ChiCast	-0.128***	(0.0154)
CertCSPO	-0.363***	(0.0253)
CertOrg	-0.0847***	(0.0154)
CCS50	0.506***	(0.0276)
CCS100	1.017***	(0.0269)
Bio80	0.395***	(0.0297)
Bio100	0.708***	(0.0215)
PriceXgender	-0.141***	(0.0330)
PriceXeducation	-0.0237	(0.0339)
PriceXage2 (25-34)	-0.0538	(0.0564)
PriceXage3(35-44)	-0.217***	(0.0572)
PriceXage4 (45-54)	-0.365***	(0.0591)
PriceXage5 (55-64)	-0.432***	(0.0619)
PriceXage6 (≥65)	-0.344***	(0.0596)
PriceXvolunteer	0.251***	(0.0501)
PriceXdonate	0.181***	(0.0410)
PriceXamount2(£1-£50)	0.190***	(0.0491)
PriceXamount3 (£51-£100)	0.344***	(0.0577)
PriceXamount4 (£101-£250)	0.330***	(0.0633)
PriceXamount5 (£251 or more)	0.280***	(0.0725)
PriceXknowledge2	0.141***	(0.0360)
PriceXknowledge3	0.299***	(0.0512)
Log-Likelihood	-24586.39	
AIC	49220.77	
BIC	49443.60	
# of respondents	3085	
# of Observations	79,584	

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
The reference group for age is 18-24 year olds, the reference group for amount donated are those who donated nothing to good causes in the past year and the reference group for knowledge are those not familiar with bio-based plastics.

Respondents actively involved in environmental organisations (e.g., via volunteering or donations) show greater willingness to pay for green plastics. The interaction term of price and volunteering is robust, which implies that respondents who have volunteered for an environmental organisation are less price sensitive and more willing to pay a premium. The interaction of price and donations is also significant, although respondents that volunteer are willing to pay a bit more for green plastics than those that donate. In addition, we explore how the amount donated to good causes by respondents reveals their willingness to pay for green plastics. For respondents who have donated different amounts to good causes in the past year, the price-amount interactions are significant with large coefficients relative to those who paid nothing. Consumers who donated £50-£100 are willing to pay the most for green plastics and price sensitivity is lowest for those who donated the least (£1-£50) .

Table 7: Knowledge of bioplastic bottles

Response	% share
Have never heard this term before	37.2
I have heard this term before but could not explain what it means	48.8
I have heard this term before and can explain its meaning	14

Finally, consumers' knowledge of bioplastics can also help explain the revealed heterogeneity. To measure knowledge of bioplastics, we ask "how familiar are you with bioplastic bottles?" Three response categories were provided, and Table 7 shows the percentage share of the response categories. knowledge-price interaction in Table 6 suggests that respondents who are knowledgeable about bioplastic bottles are more willing to pay a premium for bioplastics. Indeed, consumers who had previously heard the term "bioplastic bottles" and can explain its meaning

(Knowledge3), are willing to pay more than twice the amount for a green plastic bottle compared to those who only heard the term before but could not explain its meaning (Knowledge2).

7. Conclusions

This study uses stated preference data to investigate British consumer preferences and WTP for green plastic bottles. We conducted a discrete choice experiment in which over 3000 respondents could choose from three options of environmentally-friendly plastics. In so doing, this can provide insight into the main attributes that influence consumer willingness to pay for green plastic bottles. We employ different models – multinomial logit, mixed logit specifications and generalised multinomial logit (GMNL) – to analyse the choice data. The goodness-of-fit measure indicates that the flexible mixed logit model in WTP space which considers consumer preferences and heterogeneity in valuations for green plastics best fits our data. The estimated GMNL model in WTP space also accounts for both scale and preference heterogeneity as well as direct estimation of WTP coefficients for the attributes, which is preferable to the post-estimation approach found in mixed logit preference space.

Several important results were found in this study using the GMNL model. On the one hand, we find that British consumers have substantial and positive WTP for plastic bottles in which a significant fraction of the CO_2 is captured during its production. Similarly, consumers show a clear preference for green plastic bottles with greater bio-based content and are willing to pay a premium for them. In particular, they are willing to pay an extra £1.10 for zero-carbon plastics where 100% of the CO_2 used to produce the plastic is captured and stored, representing the highest price premium for any attribute explored. We posit that consumers view complete CO_2 capture as the most important attribute because of growing interest in climate action, which is perhaps simpler than more nuanced debates over bio-based materials.

By contrast, certification and material/origin offer less obvious outcomes. WTP is negative for using raw materials for green plastic bottles sourced from China and Indonesia relative to the United States, which is perhaps unsurprising since British consumers may feel a greater affinity for the USA or that American products are of higher quality . Respondents also indicated a significant negative WTP for ecolabel certifications other than Fairtrade. They would require £0.78 and £0.06 compensation to accept bottles with Certified Sustainable Palm Oil and Organic Certification ecolabels respectively instead of a Fairtrade ecolabel. Therefore, plastic bottle manufacturers should carefully consider consumer preferences in relation to the origins of raw materials and the certification labels used. Looking at price sensitivity, we find that consumers involved in environmental organisations (e.g., through volunteering or donations) and those with knowledge of bioplastics have higher willingness to pay for green plastics. Thus, both policymakers and fast moving consumer good (FMCG) firms may consider targeted education programmes, to highlight the benefits of bioplastics and raise their profile to future consumers.

Most importantly for purposes of climate policy, our findings may inform the design of industrial decarbonisation. Addressing energy-intensive industries will be challenging for many reasons, most notably that as trade-exposed sectors, it is difficult for governments to impose high CO_2 prices on firms in these sectors for fear that they move abroad to jurisdictions with lower prices and overall emissions may actually increase rather than decrease (also known as carbon leakage, see Babiker 2005). However, our results indicate that despite concerns over other characteristics of plastic bottles, it is actually fully decarbonised plastics that entice consumers to pay the greatest amount and so there might be some scope for producers to market plastics produced without CO_2 and charge a significant premium. Our findings should be interpreted with caution, however, owing to the hypothetical nature of the discrete choice experiments since consumers are not under any obligation to demonstrate commitment to their choices and may overstate their preferences for certain attributes. Nevertheless, the results are illustrative of potential consumer WTP for decarbonised plastic bottles at a time when there is increased policy and firm-level attention to industrial decarbonisation, which suggests that more effort should go in to understanding the potential willingness of consumers to pay more for green industrial products.

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Appendix

Table A.1: Sample choice card

	Option A	**Option B**	**Option C**
Origin of raw material	Soybean oil from USA	Palm oil from Indonesia	Castor oil from China
Eco-certification	Fairtrade	Certified sustainable palm oil (RSPO)	USDA Organic certification
CO_2 captured (%)	1	50	100
Bio-plastic fraction (%)	20	80	100
Price per bottle (£)	1.05	1.20	2.0

Table A.2: Demographic and socio-economic characteristics of respondents

Survey question	
Gender	
Male	48.0%
Female	51.7%
Age	
18-24	14.5%
25-34	15.9%
35-44	16.5%
45-54	17.3%
55-64	15.2%
65+	20.4%
Education	
Below GCSE level/no formal qualifications	6.9%
GCSE level (GNVQ, ONC, etc)	28.2%
AS/A level (HND/HNC, etc)	23.9%
Undergraduate degree level or other professional qualification	27.2%
Postgraduate degree level or above	12.7%
Household annual income	
Under £5000	4.3%
£5000-£9999	6.7%
£10000-£14999	10.2%
£15000-£19999	12.1%
£20000-£24999	11.7%
£25000-£34999	15.4%
£35000-£59999	21.9%
£60000-£79999	5.9%
£80000+	3.8%
Prefer not to say	4.8%