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Willingness-to-pay for precautionary control of microplastics, a comparison of hybrid choice models*

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ABSTRACT

What are people willing to pay to reduce the uncertainty about the effects of microplastics? We examine this question in two ways. Firstly, using two contingent valuation questions, we elicit willingness to pay (WTP) to (a) reduce uncertainty about the potential adverse consequences of microplastic pollution, and (b) to reduce the release of microplastics to the marine environment. WTP was elicited from a representative sample of UK adults in 2020. Comparing WTP for these two scenarios suggests that respondents prefer resolving irreversibility over resolving uncertainty. Secondly, we use a hybrid choice model to show that latent precautionary attitudes exert a strong positive effect on WTP. Overall, respondents indicated a preference for resolving the uncertainty about microplastics by implementing abatement measures immediately. Given that policymakers are increasingly concerned about the potential for adverse environmental and health effects of microplastics in the marine environment, this paper suggests that the precautionary principle has strong support at the respondent level.

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KEYWORDS
Precaution; hybrid choice models; willingness-to-pay; microplastics

Key Policy Highlights

- Respondents preferred immediate restrictions on the release of microplastics.
- Respondents were not willing-to-pay as much for further research which could reduce the scientific uncertainty about the future effects of microplastics.
- Widespread awareness of microplastics drives high willingness-to-pay to tackle microplastics.

1. Introduction

Microplastics[1] are used in products as disparate as tyres, controlled release fertilisers, detergents, and cosmetics (ECHA, 2019). Once used, microplastics can easily be transported via wastewater to the marine environment. Microplastics small size implies that they are practically unrecoverable, and their release may, therefore, may be characterised as irreversible. As the stock of this unrecoverable pollutant is forecast to increase given growth in plastic production (Lebreton, Egger, and Slat 2019), the chance of microplastics being ingested by marine or even human life may increase. However, the current scientific evidence on the toxicity, concentration and effects of microplastic ingestion is uncertain. Although evidence suggests no effect on humans and minimal effect on most marine life, the increasing concentration may proxy for increased risk (Lusher, Hollman, and

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Mendoza-Hill 2017; Thompson et al. 2009). As such, policymakers may follow the precautionary principle in restricting microplastics despite the absence of scientific certainty.

There is uncertainty about the future environmental and health impacts of microplastic ingestion. Although there is no current evidence suggesting that levels of human ingestion of marine microplastics have deleterious consequences (Lusher, Hollman, and Mendoza-Hill 2017), a range of physical and chemical health effects have been hypothesised or observed in some marine life. For instance, microplastics could leach contaminants or translocate across bodily tissues when ingested (Duis and Coors 2016; Koelmans et al. 2016). There is also the possibility for the trophic transfer of microplastics through marine life to eventually affect human health via the ingestion of seafood or water (ECHA 2014; Kosuth, Mason, and Wattenberg 2018; Lusher, Hollman, and Mendoza-Hill 2017). However, Koelmans et al. (2016) disputes the leachate possibility as they found that ingestion of microplastics did not significantly increase contaminants' ingestion. While Thompson et al. (2009) acknowledged that humans might ingest microplastics, they note that it is at an extremely low level unlikely to lead to any adverse effects. Secondly, Burns and Boxall (2018) urged caution when describing the potential effects of microplastics as many studies had relied on potentially unrealistic laboratory conditions. Although no exact limit has not yet been identified, microplastics' ingestion may increase above a no-effect threshold, given the increasing release and concentration of microplastics (Lebreton et al. 2018). Given the potential for future adverse effects, the European Chemicals Agency proposed a restriction on microplastics. This restriction is underpinned by the precautionary principle, suggesting that the current absence of scientific certainty on the potential effects should not be a barrier to restrictions (Courbage, Rey, and Treich 2013). However, there has been a relatively scarce study of the support for precautionary policies at the individual level.

The objective of this study is to elicit preferences for different policy options for microplastics. Policymakers may prefer to delay any action in favour of action to resolve the scientific uncertainty, either through advent of time or via deliberate research. Alternatively, they may opt to resolve the irreversible release of microplastics by immediate precautionary action. Although policymakers commonly use the precautionary principle, there is little evidence regarding public preferences towards precautionary restrictions. Indeed, prior studies of precaution have been primarily theoretical (Aldred 2012; Ingham and Ulph 2003) or focused on precautionary behaviour (Svensson 2009). In this paper, we investigate preferences for precaution expressed in Willingness-To-Pay (WTP) terms. Expressed this way, preferences for different options are more easily compared. Furthermore, we also investigate how WTP is influenced by precautionary attitudes. Respondents' latent precautionary attitudes about the potential human health effects of microplastics were observed using three Likert scales. As attitudinal data in a choice model may give rise to potential measurement error and endogeneity (Buckell, Hensher, and Hess 2021), this paper uses the Hybrid Choice Model (HCM) to evaluate how latent precautionary attitudes influence preferences for precautionary control. This approach can illuminate how the benefits of pollution control vary with perceived subjective risk.

2. Background

Traditional policy appraisal tools may be complicated by uncertainty about the severity of health effects and the irreversibility of microplastic releases (ECHA, 2019). Cost–benefit analysis may omit the option to delay a decision and wait until the impacts are known with greater certainty. Delaying would, however, lead to more microplastics irreversibly released to the environment.[2] Gollier and Treich (2003) describes the 'irreversibility effect', enunciated by (Arrow and Fisher 1974; Henry 1974), as biasing a decision towards option preservation. For instance, if development is irreversible, the potential to resolve uncertainty through learning is lost. Therefore, the irreversibility effect argues in favour of delaying such a development. However, in the unique context of this paper, the irreversibility effect does not argue for a delay. As the release of microplastics irreversibly alters the marine environment, the option to preserve the status quo is lost. Therefore, the irreversibility effect in this context favours an immediate restriction. Evidently, a trade-off exists between an immediate decision to resolve the irreversibility or delaying a decision to resolve the uncertainty.

The tension between resolving uncertainty via learning, and resolving irreversible release, by acting, has been characterised as an act-then-learn or learn-then-act approach (Ingham and Ulph 2003) Although these have been commonly used in the debate over appropriate climate change policy, ECHA (2019) noted some clear parallels between climate change and marine pollution, including the increasing irreversible release of pollutants and the uncertainty about the long-term impacts In either case, Hanemann (1989) noted that the availability of future knowledge might change the optimal decision process. For instance, the value of delaying a decision to undertake learning, a learn-then-act approach, is always positive according to Traeger (2014). The value of learning first has substantial implications for the magnitude of abatement undertaken (Ha-Duong 1998; Ingham and Ulph 2003; Manne et al. 1992). However, while Traeger (2014) finds that the value of learning is positive, Ha-Duong (1998) notes that the option value of early abatement, an act-then-learn approach, may be significant. Although an act-then-learn approach may preserve option value which would otherwise be lost to irreversible changes, Kuntz-Duriseti (2004) debated the economic value of precaution (Gollier and Treich 2003). Precaution may broadly be defined as a prudent activity in the face of uncertainty (Courbage, Rey, and Treich 2013). Precaution is distinct to prevention, which reduces the probability of a loss, as it concerns uncertain rather than risky outcomes (Gollier and Treich 2003). The precautionary principle suggests that in the presence of uncertainty, the appropriate policy response is preservation (ECHA, 2019; Gollier and Treich 2003). The presence of uncertainty in a decision typically reduces welfare (Kuntz-Duriseti (2004); Riddel 2011; Cameron 2005; Faccioli, Kuhfuss, and Czajkowski 2019). Therefore, an act-then-learn approach in the context of marine microplastic pollution may be valuable in preserving option value.

Precaution is, however, a relatively limited topic in environmental economics with most literature focusing on risk perceptions and avoidance as distinct from precaution.[3] For instance, Svensson (2009) compared WTP for risk reductions and precautionary behaviours in the context of mortality risks such as seat belt usage. Moreover, Sereenonchai, Arunrat, and Kamnoonwatana (2020) and Arunrat et al. (2017) discussed risk perceptions in the context of climate change. In the context of a pollutant with uncertain effects, public preferences for precautionary policies are less clear. We do, however, have some information on public perceptions on the potential effects of microplastics which has often found respondents to be more pessimistic than the scientific uncertainty may warrant (Kramm et al. 2022). Catarino et al. (2021) suggested that this could partially be due to the conflation of microplastics with larger plastics, while Kramm et al. (2022) argued for the role of the media on negative perceptions of microplastics. However, these studies did not elicit WTP to reduce the potential effects of microplastics and thus did not quantify the value of precautionary restrictions. To summarise, there is little evidence on the value respondents attach to treating uncertainty with precautionary restrictions despite the common usage of the precautionary principle in policymaking.

3. Methodology

This paper follows Abate et al. (2020) two-step method. Firstly, we elicit WTP values using two CV questions. Eliciting the CV values is an instructive exercise to reveal the degree of public support for precautionary policies relating to microplastics. Secondly, we analyse responses using HCMs.

3.1. Survey design

A stated preference survey is appropriate in this context where no market exists to reveal individual preferences for microplastic reductions. Indeed, given that this paper is ex-ante any policy measures, WTP can only be estimated using the stated preference approach. Although the final survey design included both the Contingent Valuation (CV) and Choice Experiment (CE) stated preference methods, discussion of the CE, which aimed to describe the trade-offs implicit in reformulating cosmetic products to substitute out microplastics, is omitted from this paper in favour of greater exploration of the CV modelling. The survey questions were designed following expert consultation, interviews with respondents, and a small pilot survey; this pre-testing process is consistent with Johnston et al. (2017) guidelines.[4] The two pre-tested CV questions in this research are described in Section 3.1.1.

3.1.1. Valuation questions

Two CV questions were included to elicit sample WTP for two different public-good policy options. The two public goods were resolving uncertainty (referred to as 'Question One') and resolving irreversible releases (referred to as 'Question Two').

Question One elicited WTP for research into microplastics. The public good valued is, therefore, the provision of greater information that may resolve the current scientific uncertainty about the potential for adverse effects of microplastics. Question Two instead elicited WTP for investment into Wastewater Treatment Plants (WWTP) that would reduce the irreversible release of microplastics to the environment. This question values the prevention of future releases of microplastics to the marine environment. The motivation for these two scenarios is to explore different options for microplastic policy. For instance, if respondents prefer to resolve uncertainty, no immediate restrictions must be imposed. However, if respondents prefer to immediately resolve the irreversible release, despite highly uncertain effects, precautionary control may be more justified.

The first CVM question (referred to as 'Question One') represents the value of hypothetically resolving the scientific uncertainty about microplastics' environmental and health impacts. The status quo is that research may occur, but it is uncertain when and if it resolves the scientific uncertainty. The adopted question text following pre-testing is:

Question One:

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 was extra annual water bills at the household level. Water bills were chosen instead of income tax, given evident tax-aversion in the pre-testing. The bid vector was randomly varied with eight levels (in £GBP): 5, 10, 20, 40, 60, 80, 90, 100. Eight levels were used to provide greater information on the WTP distribution while maintaining a relatively high number of responses at each bid level. However, future research may increase the magnitude of the bid levels as the lowest levels were highly supported. The question format was the incentive-compatible Single-Bound Dichotomous Choice (SBDC).[5] The SBDC format simply asks respondents a yes or no question as to whether they are willing to pay a given bid level for the described scenario (Abate et al. (2020); Cameron (2005)). Responses are thus binary and can be evaluated in a probit model. The SBDC is a very commonly used CV format given its incentive compatibility and simplicity (Arrow et al. 1993; Johnston et al. 2017). 364/670 respondents answered Question One first, while 306/670 answered it second. All respondents answered all the CV questions before the choice experiment and the attitudinal questions.

The second CV question (henceforth referred to as 'Question Two') elicited WTP for a public-good measure to restrict the release of microplastics, although no uncertainty would be resolved.

This question used the same bid levels: 5, 10, 20, 40, 60, 80, 90, 100 (annual £GBP in water bills) to facilitate comparison with Question One.

Question Two

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 order of the two CV questions (Question One and Question Two) was randomised to control for ordering effects (Day et al. 2012) In the reversed order, minimal changes to the wording of the two questions were used to stress that the policies are substitutes and not complements; respondents were also informed that the two policies would not run consecutively. Respondents can thus be assumed to have valued the two scenarios independently. Respondents were provided with some descriptions of microplastics and the uncertainty surrounding their environmental and health effects prior to either CV question. This information was added to ensure that respondents knew about the goods being valued.

3.1.2. Additional questions

Three attitudinal questions were included to indicate a latent attitude. This attitude may be interpreted as the respondent's subjective concern about the perceived threat of microplastics to human health; this may provide a precautionary motivation for respondents' WTP. The three questions are Likert scales (range 1–5). A Cronbach's Alpha of 0.81 (0.80–0.82) is reported for the three indicators, suggesting that they all indicate the same attitude. Table 1 reports the percentage of the full sample choosing each level. The mean scores suggest that respondents were most concerned about the current threat to the environment, then the future threat to themselves with the least concern for their current exposure to microplastics.

3.2. Data collection

The distribution of the final survey design to 670 nationally representative adults (approximately 65% response rate) in the UK in April 2020 was supported by funding from the United Kingdom Environment Agency (EA). The United Kingdom was chosen as the study site given that a UK REACH restriction on microplastics was being considered following the European Chemicals Agency (ECHA) proposal for a restriction on intentionally added microplastics. The target

Table 1. Percentage of respondents choosing level of Likert scale per question.

Question	1	2	3	4	5	Mean	Std.Dev
(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	1.01
(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	0.98
(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	0.97

Table 2. Sample characteristics.

Category	Sample	Population
Gender	Male: 46%	Male: 49%
	Female: 53%	Female: 51%
Age	Mean: 42 years old	Mean: 38 years old
Education	Below graduate: 50.75%	Below graduate: 40.4%
	Graduate or more: 49.25%	Graduate or more: 42%
Gross monthly income	Mean: £2193	Mean: £2340[a]

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

population was UK adults who would potentially pay for any restriction. A representative sample was recruited using an online marketing firm; DJS Ltd. Ethical approval for the data collection was granted by the University of Bath, Department of Economics.

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; per the best-practice guidance in Arrow et al. (1993) and Johnston et al. (2017). The survey instrument consisted of five sections; socioeconomic questions, CV questions (See Section 3.1.1), a choice experiment (discussion in forthcoming research), environmental indicators, and finally, debriefing questions. The median completion length was 7.5 min. Table A1 in the Appendix details all the questions from the survey. Table 2 indicates that the sample was broadly representative of the UK adult population. This paper presents the results from the full sample in-text, but results using a truncated sample are available in the appendix. Sample truncation was used to preserve only the most valid responses, and while the estimates do not alter the final conclusions, they are provided for completeness.

4. Econometric methods

We recover sample WTP using standard probit models before using HCMs to elucidate the effect of latent attitudes on respondents' valuation of subjective risks. The probit model is chosen for consistency with Abate et al. (2020) although results are robust to using the alternative logit model. The HCM has been used previously to model latent concepts including addiction (Buckell, Hensher, and Hess 2021), professionalism (Sandorf, Persson, and Broberg 2020), certainty (Dekker et al. 2016), consequentiality beliefs (Czajkowski et al. 2017), environmental attitudes (Faccioli et al. 2020) and concerns about plastics (Abate et al. 2020). The choice model component of the HCM is used in both standard and hybrid approaches.

CV data is traditionally analysed using Random Utility Models (RUM), which assumes respondents are rational utility maximisers (McFadden et al. 1973). In the RUM, the individual utility ($U_{a,n}$) respondent n gains from choice a is a function of deterministic ($V_{a,n}$) and stochastic components ($\varepsilon_{a,n}$) distributed i.i.d extreme value; see Equation (1) (Hess and Beharry-Borg 2012; Train 2009). The deterministic component is a function of the vector (X_n) which are choice specific characteristics. We can include respondent-specific variables including income (Y_n), socioeconomic characteristics, and later a latent variable (α_n) which we describe as latent precautionary attitudes. Equation (2) reports an indirect utility function where the (β) represent the effect of characteristics on the probability of a respondent's choice.

Utility:

$$Ua, n = Va, n + \varepsilon a, n \tag{1}$$

Indirect Utility:

$$V_{a,n} = f(\beta, X_{a,\, n}) \tag{2}$$

Probit Model:

$$P(Answer_{\{n\}} = Yes|X_{\{n\}}) = \phi\left(\frac{\beta X_{\{n\}}}{\sigma}\right) \tag{3}$$

In Equation (3), (P) is the probability of a respondent n answering 'Yes' to the given CV question, is conditional on the vector of respondent specific characteristics ($X_{\{n\}}$) which includes the bid level. As we use a probit model, the probability is expressed using the cumulative normal distribution (ϕ) (Abate et al. 2020). Sample mean WTP can be calculated using Equation (4). Sample WTP:

$$WTP = -\frac{C}{\beta_{Bid}} \tag{4}$$

Although probit analysis suffices to evaluate the magnitude of WTP, a more complex treatment of attitudes may be necessary. To correct for potential measurement bias when using attitudinal data, Hess and Beharry-Borg (2012) argued that a hybrid approach is required. As attitudes are not directly observed, they can be treated as latent variables. Only indicators of latent variables are observed, and thus there is the potential for measurement error.[6] Czajkowski et al. (2017) noted that the HCM has also been called an Integrated Choice-Latent Variables (ICLV) model, which illustrates how latent variables can be used to explain choices.

The HCM has three components; a choice model similar to non-hybrid models, measurement equations linking observed Likert scale indicators to unobserved latent attitudes, and finally, structural equations using socioeconomic variables to understand determinants of the latent attitudes (Ben-Akiva et al. 2002; Czajkowski et al. 2017; Hess and Beharry-Borg 2012; Vij and Walker 2016). The interaction of each component is illustrated in Figure 1.

W link utility to choices using a probit model. Our simple specification of the probit model in Equation (5) includes a respondent-specific latent variable α_n. The effect of this latent precautionary attitude on choices is estimated by the parameter λ_{LV}. The (β) represent the effect of a matrix of individual-specific socioeconomic variables(X_N) on choices.

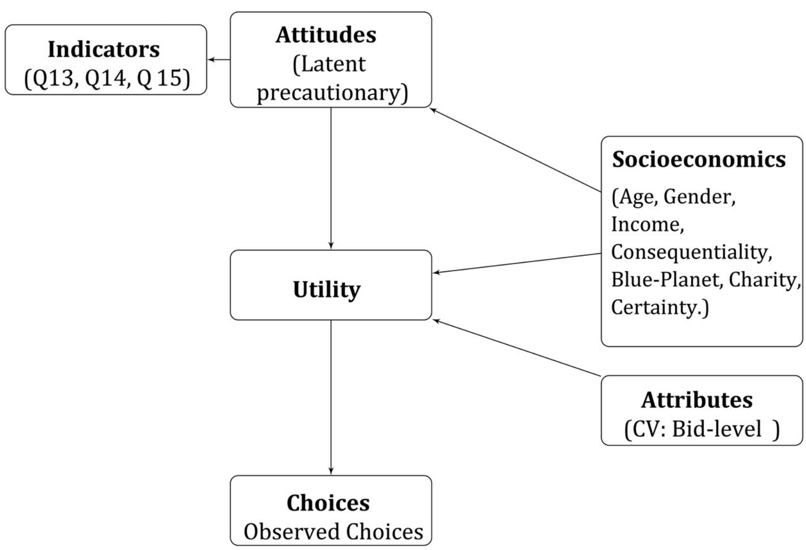

Figure 1. Hybrid choice model structure, adopted from Ben-Akiva et al. (2002).

HCM: Choice Component

$$QuestionResponse_{\{n\}} = \phi\left(\frac{C + \beta X_{\{n\}} + \lambda_{\{n\}}\alpha_{\{n\}}}{\sigma}\right) \tag{5}$$

A challenge to specifying the HCMs is whether to include socioeconomic variables in the choice or structural models (or both or neither). Socioeconomic characteristics recovered from the survey included age, gender, distance, income, experts, consequentiality, blue-planet viewership, charity, certainty. For the choice model, we included six covariates (Age, Gender, Income, Distance, Certainty, Consequentiality) which are more likely to affect choices directly rather than indirectly through the latent variable (Abate et al. 2020; Faccioli et al. 2020). We then decided to use just three of the socioeconomic variables in the structural equation (Blue-Planet, Charity, Experts) which are thought to influence the latent variable of precautionary attitudes directly. For instance, watching pro-environmental media may influence a respondents' latent attitudes which then influence their choices. The appendix presents models where alternatively all socioeconomic variables are included in the choice model, the structural model, or not at all.

The structural equations in Equation (6) link the latent variable to respondents' characteristics. Respondent's n latent attitude α_n is a function of socioeconomic characteristics Z and an error term η distributed $(0, \sigma_{\alpha})$. The effect of socioeconomic variables on latent attitudes is estimated by the parameter γ. Three of these gamma parameters are included in the matrix Z. The variance of the error term is fixed to one to permit identification (Czajkowski et al. 2017; Raveau, Yáñez, and de Dios Ortúzar 2012). One structural equation is estimated for each latent variable.

HCM: Structural Equation

$$\alpha_n = \gamma Z_n + \eta_n \tag{6}$$

A measurement equation links unobserved latent variables, observed responses, and attitudinal questions. This component is necessary as the latent variable cannot be directly observed, only respondents' responses to the attitudinal questions. These questions are detailed in Section 3.1.2. Following Faccioli et al. (2020), we used an ordered probit model for the measurement equation. Ordinal models are appropriate for Likert scales with discrete levels where respondents may interpret the differences between levels differently (Faccioli et al. 2020). The Ordered Probit model in Equation (7) adopted from Train (2009); Hess and Palma (2019) estimate the probability P of respondent n in alternative a choosing ordered Likert scale level s. The model compares respondent indirect utility (Equation 2) with a Likert scale level τ_s and the one below it τ_{s-1} (Hess and Palma 2019). As this is an ordered probit, Φ is the cumulative normal distribution function (Czajkowski et al. 2017). Ordered probit estimates the thresholds between likert scale levels (Train 2009).

HCM: Measurement Equation

$$\zeta_{\{Indicator\}} = P_{\{n,\, t=s\}} = \phi(\tau_{\{s\}} - V_{\{n,\, a\}}) - \phi(\tau_{\{s-1\}} - V_{\{n,\, a\}}) \tag{7}$$

A measurement equation is estimated for each of the three indicator questions described in Table 1 (referred to as Q13, Q14, Q15). The question-specific (ζ) parameter represents the effect of the latent variable on each indicator question (Figure 1).

The three HCM components are combined in the log likelihood for a full information estimation (Vij and Walker 2016). Five types of parameters are thus estimated: the β and λ from the choice model (Equation 4.7), the γ from the structural model (Equation 7), and the ζ and τ from the measurement models (Equation 4.9). The parameter λ represents the effect of the latent variable on utility, γ for the effect of socioeconomic variables on latent attitudes, ζ for the effect of specific indicators on the latent variable, and τ parameters for the interaction between the latent variable and the betas. Results are reported in Tables 4 and 5.

Table 3. WTP in per household per year value by question and specification using Krinsky-Robb bootstrap.

Specifications	WTP	95% confidence interval	*N*	AIC	*R2*	Log-likelihood
Question one						
Question One Bid-Only	£53.37	(£42.75 – £63.98)	670	891.38	0.04	−443.69
Question One Covariates[a]	£53.17	(£42.77 – £63.24)	670	795.40	0.14	−384.70
Question One Order1 Sample	£50.84	(£39.23 – £61.75)	306	395.09	0.07	−195.55
Question One Order2 Sample	£56.42	(£35.25 – £82.36)	364	496.72	0.02	−246.36
Question One Hybrid Choice	N/A	N/A	670	5798.77	NA	−2872.38
Question two						
Question Two Bid-Only	£88.43	(£76.00 – £109.92)	670	833.23	0.04	−414.62
Question Two Covariates[b]	£91.76	(£78.65 – £114.06)	670	773.93	0.11	−373.96
Question Two Order1 Sample	£89.55	(£74.02 – £122.46)	306	370.53	0.05	−183.26
Question Two Order2 Sample	£87.31	(£68.48 – £123.96)	364	465.21	0.03	−230.60
Question Two Hybrid Choice	N/A	N/A	670	5780.50	NA	−2863.35

Note: [a]Model results in Tables A2 and A3 in the Appendix. [b]A plot of the distribution of the estimated latent variable from both models is available in the Appendix.

5. Results

The results are presented in two parts: the more common probit approach first before the hybrid choice analysis. Although probit models are common in the CV literature (Abate et al. 2020; Zambrano-Monserrate and Ruano 2020), the results are shown to be robust to alternatively estimating using logits.[7]

Table 4. Question one hybrid choice model ($N = 670$).

Coefficient	Estimate	Std. Err.	*P*. Value
$\beta_{Intercept}$	−46.335***	4.683	<0.001
β_{BID}	−26.631***	4.024	<0.001
λ	26.167***	0.688	<0.001
β_{Age}	−0.136	0.116	0.121
β_{Gender}	5.131**	3.106	0.049
$\beta_{Distance}$	0.103*	0.077	0.092
β_{Income}	5.977**	2.962	0.022
$\beta_{Certainty}$	−1.447	2.949	0.311
$\beta_{Consequential}$	−2.197	2.130	0.151
$\gamma_{Experts}$	0.544***	0.041	<0.001
γ_{BP}	0.319***	0.075	<0.001
$\gamma_{Charity}$	0.352***	0.072	<0.001
ζ_{Q13}	0.660***	0.059	<0.001
ζ_{Q14}	0.689***	0.066	<0.001
ζ_{Q15}	0.577***	0.057	<0.001
$\tau_{Q13,1}$	−0.561***	0.159	<0.001
$\tau_{Q13,2}$	0.155	0.158	0.162
$\tau_{Q13,3}$	1.767***	0.186	<0.001
$\tau_{Q13,4}$	2.809***	0.215	<0.001
$\tau_{Q14,1}$	−0.812***	0.166	<0.001
$\tau_{Q14,2}$	−0.116	0.164	0.238
$\tau_{Q14,3}$	1.272***	0.190	<0.001
$\tau_{Q14,4}$	2.501***	0.220	<0.001
$\tau_{Q15,1}$	−1.166***	0.171	<0.001
$\tau_{Q15,2}$	−0.463***	0.148	<0.001
$\tau_{Q15,3}$	0.700***	0.159	<0.001
$\tau_{Q15,4}$	1.715***	0.178	<0.001
Estimation statistics			
Iterations	105	LL (start)	−4414.92
AIC	5801.89	LL (final, whole model)	−2873.94
BIC	5961.01	LL (Choice)	−423.74

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5. Question two hybrid choice model ($N = 670$).

Coefficient	Estimate	Std. Err.	*P.* Value
$\beta_{Intercept}$	−31.565**	15.161	0.019
β_{BID}	−31.558***	5.341	<0.001
λ	31.339***	1.259	<0.001
β_{Age}	−0.278**	0.158	0.039
β_{Gender}	5.232*	3.706	0.079
$\beta_{Distance}$	0.186**	0.095	0.026
β_{Income}	1.242	3.8	0.372
$\beta_{Consequential}$	−3.057	2.679	0.127
$\beta_{Certainty}$	−0.301	3.129	0.462
$\gamma_{Experts}$	0.509***	0.187	0.003
γ_{BP}	0.252**	0.126	0.023
$\gamma_{Charity}$	0.331**	0.175	0.029
ζ_{Q13}	0.624***	0.069	<0.001
ζ_{Q14}	0.704***	0.072	<0.001
ζ_{Q15}	0.678***	0.063	<0.001
$\tau_{Q13,1}$	−0.693**	0.323	0.016
$\tau_{Q13,2}$	−0.008	0.316	0.490
$\tau_{Q13,3}$	1.555***	0.311	<0.001
$\tau_{Q13,4}$	2.564***	0.323	<0.001
$\tau_{Q14,1}$	−0.906***	0.379	0.008
$\tau_{Q14,\ 2}$	−0.206	0.368	0.288
$\tau_{Q14,3}$	1.173***	0.365	<0.001
$\tau_{Q14,4}$	2.394***	0.379	<0.001
$\tau_{Q15,1}$	−1.203***	0.383	<0.001
$\tau_{Q15,2}$	−0.438	0.367	0.116
$\tau_{Q15,3}$	0.784**	0.368	0.017
$\tau_{Q15,4}$	1.834***	0.383	<0.001
Estimation statistics			
Iterations	104	LL (start)	−4146.73
AIC	5789.12	LL (final, whole model)	−2867.56
BIC	5934.28	LL (Choice)	−411.27

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

5.1. Probit results

We estimate sample WTP using a bid-only probit model. To control for socioeconomic factors, we also estimate a model with covariates. Table 3 reports WTP and diagnostics for each model type for each question. We also provide results of models estimated by sample order as the order of the CV questions was randomised. To answer the first question of what respondents are willing to pay for microplastic policies, the unit values of WTP are £53.37 for Question One and £88.43 for Question Two. The WTP is only marginally different when controlling for socioeconomic factors. Respondents clearly exhibited a preference for resolving the irreversible release of microplastics compared to resolving uncertainty. The finding of a positive difference in WTP by scenario is robust to alternatively estimating using logit models, randomising question order, or changing specification. Using the probit model with covariates, individual level simulated WTP can be estimated.[8] Respondents were clearly willing to pay substantially more for precautionary restrictions. Indeed, the distribution of the two WTP distributions only slightly overlap, and a Mann–Whitney non-parametric test of means suggests that the mean WTP is statistically different by question.

5.2. Hybrid choice results

The Question One HCM is reported in Table 4 with Question Two in Table 5. The specification for each model is identical with the exception of changing the outcome vector, and the certainty variable, which were question specific.

The hybrid choice results illustrate the effect of latent attitudes on choices and the determinants of those latent attitudes. We directly compare model components for Question One (Table 4) and

Question Two (Table 5). The bid level (β_{Bid}), was large, statistically significant, and negative sign is consistent with theoretical and empirical evidence. The negative sign indicates a downward sloping demand curve in both questions which suggests that respondents' choices were highly sensitive to the magnitude of the bid.

The parameter of particular interest in this paper is λ, which represents the effect of latent precautionary attitudes on respondents' choices. Across both models, the parameter is large, positive and highly significant. However, the parameter is larger for Question Two, suggesting that precautionary concern exerted a stronger influence on the more precautionary policy. This is also evident in Figure 2, which plots WTP by percentiles of the latent variable. The positive sign indicates that respondents more concerned about microplastics were more likely to vote yes to the investment scenario. The interpretation of the positive and significant sign is that precautionary attitudes positively influenced the probability of respondents being willing to pay for the hypothetical scenario. The large magnitude indicates that more concerned respondents were more willing to pay for research into microplastics. This finding is consistent with previous hybrid choice literature, which finds that attitudes strongly influence choices (Buckell, Hensher, and Hess 2021; Faccioli et al. 2020).

The parameters represent the effect of socioeconomic variables on choices. Variables included in the choice model are those believed to directly influence choices rather than indirectly through the structural model. However, for robustness, we provide alternative specifications in the appendix. Age (β_{Age}) was statistically significant for Question Two only. The negative sign suggests that older respondents were less likely to vote 'yes' to the second CV question. Conversely, self-reported respondent gender (β_{Gender}) was a statistically significant influence on choices for both Question One and Two. The large positive sign suggests that male respondents were more likely to vote for the CV questions. This may be driven by an income effect, although the effect of being in a

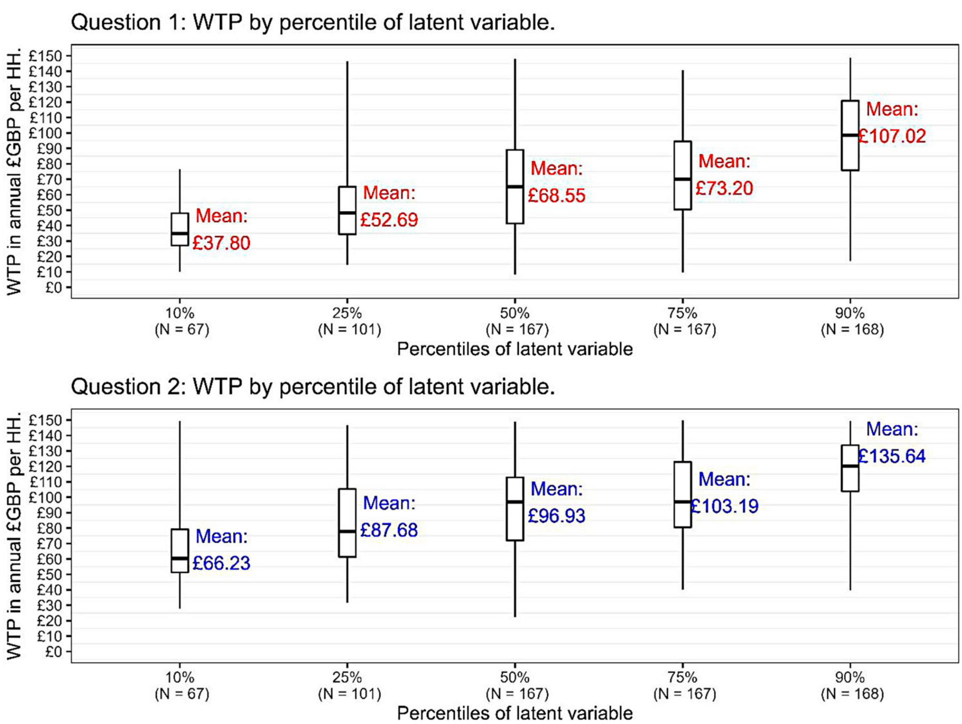

Figure 2. Box and whiskers plot (using interquartile range) of CV hybrid choice model WTP by percentiles of the latent precautionary attitude.

high-income household (β_{Income}) on choices was significant only for the Question One model (Table 4). Conversely, there were no statistically significant income effects for Question Two. Indeed, robustness tests indicate that the small magnitude of the income coefficient was robust to entering income as levels, in logs, or as a dummy on whether respondents were willing to report their income (Abate et al. 2020; Adamowicz et al. 2011). This finding is similar to Hess and Beharry-Borg (2012), who found no statistically significant income effect when included in their hybrid choice model. Finally, self-reported distance from the coast ($\beta_{Distance}$) was only statistically significant at the 5% level for Question Two. This, combined with the small positive magnitude, suggests that distance from the coast exerted minimal influence on respondents' choices for either CV question. As microplastics are spatially disparate and practically unobservable, a limited distance decay effect is no surprise.

The response certainty ($\beta_{Certainty}$) parameter merits further consideration. Certainty was included in the choice models as it was question-specific and thus may directly influence choices. However, certainty may indirectly influence choices too as in Dekker et al. (2016). We report no statistically significant effect of question certainty on choices in both our models. This suggests that being highly certain or highly uncertain had little effect on the CV question. It is possible that other covariates, such as the bid level, income parameter and latent attitudes, mask the effect of response certainty. We also do not find any effect of perceived policy consequentiality ($\beta_{Consequential}$) on respondents' choices. Consequentiality was included following Czajkowski et al. (2017) work which used the hybrid choice approach to show that the perceived consequentiality of respondents' involvement in the question significantly influenced choices. This corresponds with Vossler and Watson (2013) work on consequentiality beliefs. There was no statistically significant effect on respondents' choices in both models. This result suggests that respondents who did not believe the survey to be consequential did not choose any differently than others. To summarise, we find mixed results on the effects of socioeconomic variables on choices.

By contrast, the parameters represent the effect of socioeconomic variables on the latent variable. Three parameters were chosen for the structural equations as they may directly influence latent precautionary concern. Both models report statistically significant effects of charity involvement ($\gamma_{Charity}$), belief in experts ($\gamma_{Experts}$), and blue-planet II viewership (γ_{BP}). Both models report a relatively large, positive, and statistically significant effect of involvement (defined as donating or being a member) with an environmental charity, confidence in experts, and viewing the Blue-Planet II documentary series. Combined with the highly significant positive, this finding suggests that variables corresponding to pro-environmental behaviour indirectly influence respondents' choices through their latent attitudes.

The measurement model includes the (ζ) and (τ) parameters. The (ζ) represents the effect of the latent variable on the indicator questions and were consistent in positive sign, statistical significance, and relative magnitudes between models. Q14, which asked respondents about their concern for the future effects of microplastics on humans, was the most important determinant in both models possibly as it was the most precautionary indicator of the three. The (τ) parameters were almost all highly significant and represent the effect of each level of the indicator questions on latent attitudes. The consistent result is that higher scores on the Likert scales suggest stronger precautionary attitudes, which indirectly influence the choice probabilities. To summarise, the HCMs extend the probit models by showing that latent precautionary attitudes strongly influence the likelihood of voting for a precautionary policy. This suggests that WTP is also positively related to latent attitudes.

5.3. Precautionary WTP

Following Abate et al. (2020), Figure 2 compares the fitted WTP with the estimated latent precautionary variable. The individual and question-specific estimates for the latent variable are calculated from the HCMs. For ease of inference, the levels of the latent variable are binned into quantiles. The fitted WTP is derived from the question-specific probit models with covariates included. The reported values are the mean values per quantile and are calculated using the Krinsky-Robb bootstrap method.[9] There is always a positive difference in WTP between questions, and the difference marginally increases for more concerned respondents. This implies a sample-wide preference for resolving the irreversible release of microplastics compared to reducing uncertainty. WTP was positively related to the levels of the latent variable. That is, more precautionary respondents reported higher WTP.[10]

6. Discussion

This paper has demonstrated that latent precautionary attitudes positively influenced respondents' willingness to pay for precautionary restrictions on microplastics. The finding that higher levels of the latent attitude correlate with higher WTP suggests that precautionary attitudes influence WTP and is consistent with the hybrid choice literature (Abate et al. 2020; Buckell, Hensher, and Hess 2021; Faccioli et al. 2020). Determinants of precautionary attitudes were charity involvement, consumption of pro-environmental media, and belief in experts. The strong effect of viewership on latent precautionary attitudes is consistent with Hynes et al. (2020) examination of the Blue-Planet effect. We suggest that viewership influences choices indirectly by increasing specific knowledge about microplastics, which then influence attitudes (Fransson and Garling 1999). However, Kollmuss and Agyeman (2002) caution that the link between awareness, intentions, and behaviour is weak. Instead, revealed preferences for environmental quality, such as charity membership, appear to be stronger determinants of behaviour. This suggestion is corroborated by the larger magnitude of the charity parameter in both models. Furthermore, there is empirical support for charity/organisational membership being a statistically significant predictor of choices in Abate et al. (2020); Faccioli et al. (2020). However, both viewership and charity membership reported smaller effects than confidence in experts. The large positive sign suggests that respondents who were more confident in experts providing information about microplastics were more willing to pay for precautionary measures. This variable is of special importance to the microplastic scenario where there is currently a deal of scientific uncertainty.[11] Catarino et al. (2021) argued that the evident widespread concern about microplastics could be due to the conflation of microplastics with larger plastics, while Kramm et al. (2022) argued for the role of the media on negative perceptions of microplastics. The policy implication is that the benefits of pollution abatement may be warped by public awareness of the pollutant; whether scientifically accurate or not. More generally, this work implies that immediate policy action to abate the irreversible flow of microplastics may have a strong base of public support. Indeed, respondents were willing to pay more for a precautionary approach rather than waiting.

One challenge to the method is the use of HCMs. Usage of the HCM for causal inference or benefits transfer, would encounter Chorus and Kroesen (2014) critiques[12] as any policy targeting the latent precautionary attitudes reported in this work may be erroneous. Instead, this work uses the HCM to demonstrate that the more precautionary respondents are, the stronger their support (expressed in higher WTP) may be for abatement. Although the central result of WTP for abatement being consistently larger than that for resolving uncertainty is robust to using econometric method, future research is advised to be cautious in overstating the benefits of the HCM.

One limitation is collecting the data in April 2020 as part of a time sensitive project. A quick response was to ask respondents whether their income had been affected by the pandemic. 319/670 respondents (47%) reported yes, and the effect on the results was a negative income effect on WTP. As this finding suggests that the benefits of precautionary restrictions may have been higher before the pandemic, future work is invited to investigate how attitudes towards marine pollution have shifted.

Future work on microplastics could evaluate the benefits of restrictions on intentionally added microplastics in other sectors; examples include tyres, detergents, paints and agriculture (ECHA, 2019). Methodologically, the CV literature may benefit from a HCM using Bivariate or Multivariate Probit for more complex CV formats. Finally, future research to estimate the option value (OV) or Quasi-Option Value (QOV) for precautionary restrictions would be valuable in informing the uncertainty-irreversibility trade-off.

6.1. Summary

To summarise, respondents were willing to pay to abate the irreversible release of microplastics into the marine environment. Although there are challenges to the timing of the data collection, the conclusions were highly robust to specification. When confronted with uncertain effects and irreversible releases, respondents preferred precautionary policies. Acting immediately to reduce the irreversible release of microplastics into the environment, even while the scientific effects are highly uncertain, has strong support at the respondent level. This work suggests to policymakers that there is support for the precautionary principle at the respondent level.

Notes

1. Microplastics are defined as polymer containing particles up to a maximum of five milometers in diameter (ECHA, 2019).
2. It is currently fair to assume that microplastics are irreversibly released given that there is no practical or cost-effective method of recovering microplastics from the marine environment presently available.
3. There is a wider literature on uncertainty and mitigation in climate change and the interested reader is directed to Alfred (2012) among others.
4. The pre-testing of the survey took around three months and used a relatively small pool of potential respondents. Experts were consulted on the scientific effects of microplastics. These included toxicologists, chemists, environmental scientists, industry experts, policymakers and economists. Ten short interviews using the talk-aloud method were undertaken with potential respondents to understand how they evaluated the survey. Finally, a small pilot of 53 respondents using convenience sampling was undertaken. Multiple changes were made to the valuation questions to increase incentive compatibility and plausibility, primarily through scenario text and payment vehicle.
5. Question Two actually used the double-bound dichotomous choice format but we omit that discussion here to focus on attitudes towards WTP.
6. While Vij and Walker (2016) argued that linearly including attitudinal indicators raises the possibility of endogeneity, Budziński and Czajkowski (2018) were cautious on whether the HCM truly corrected for endogeneity.
7. Replication code and data are freely available. See Data Availability Statement.
8. We simulated individual WTP using the Krinsky-Robb bootstrap function in the R DCChoice package (Nakatani et al, 2021).
9. WTP for welfare calculations should still be based on the simpler bid-only probit model.
10. A plot of the distribution of the estimated latent variable from both models is available in the Appendix.
11. One anonymous reviewer suggested that the perceived effectiveness of each policy option may influence WTP. Although we do not observe this directly, respondent certainty about each question is measured. For example, the greater certainty for Question Two may indicate that respondents were more confident in this scenario being effective. This may then begin to explain the increased WTP. However, certainty may also measure scenario understanding or preference for immediate abatement, and so there is some measurement error associated with this line of reasoning.
12. I am thankful to an anonymous reviewer for discussing Chorus and Kroesen (2014) excellent work discussing the HCM in transport models.

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Data availability statement

The anonymised survey data and replication R code is freely available from the authors GitHub repository: https://github.com/pmpk20/PhDHybridChoiceModelPaper

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Appendix

Sample truncation

As an extension, we can examine the robustness of the results to altering our sample. To ensure the results hold when excluding less valid responses, the sample can be truncated using five possible rules. The rules included respondents failing a dominated test, believing the survey to be inconsequential, or reporting a low understanding of the survey were excluded from the truncated sample (Rakotonarivo, Schaafsma, and Hockley 2016; Schaafsma et al. 2014; Vossler and Watson 2013). Respondents were asked to indicate their certainty about their valuations, and those reporting the lowest-level of uncertainty were also excluded from the truncated sample as this may indicate hypothetical bias in the responses (Scasny and Zverinova 2014).

Table A1. 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
Q1 Gender	Female = 0, Male = 1	Gender differences but direction uncertain	0.000	0.000	0.473	2.000
Q2 Age	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
Q3 Distance	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
Q4 Trips	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
Q5 Knowledge	No knowledge = 1, Little = 2, Average = 3 Good = 4, Strong = 5	Positive relationship to WTP	1.000	3.000	2.818	5.000
Q6 Research Response	0 = No, 1 = Yes	N/A	0.000	1.000	0.5104	1.000
Q6 Research Certainty	Unsure = 0, Quite sure = 1, Very sure = 2	Decreased WTP with certainty	0.000	1.000	1.378	2.000
Q7 Treatment Response	0 = No, 1 = Yes	N/A	0.000	1.000	0.645	1.000
Q7 Treatment Certainty	Unsure = 0, Quite sure = 1, Very sure = 2	Decreased WTP with certainty	0.000	2.000	1.437	2.000
Q7 Treatment Upper Response	0 = No, 1 = Yes	N/A	0.000	1.000	0.618	1.000
Q7 Treatment Lower Response	0 = No, 1 = Yes	N/A	0.000	0.000	0.399	1.000
Q8 Dominated Test	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
Q12 CE Certainty	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
Q17 Responsibility Firms	0 = No, 1 = Responsible	Theory mixed	0.000	1.000	0.761	1.000
Q17 Responsibility Consumers	0 = No, 1 = Responsible		0.000	1.000	0.573	1.000
Q17 Responsibility Government	0 = No, 1 = Responsible		0.000	1.000	0.703	1.000

(*Continued*)

Table A1. Continued.

Variable	Coding	Expectation	Min.	Median	Mean	Max.
Q17 Responsibility Local Authority	0 = No, 1 = Responsible		0.000	0.000	0.402	1.000
Q18 Charity	No = 0, Yes = 1	Positive relationship with WTP	0.000	0.000	0.404	2.000
Q19 Knowledge	No knowledge = 1, Little = 2, Average = 3 Good = 4, Strong = 5	Positive relationship with WTP	1.000	3.000	3.001	5.000
Q20 Consequentiality	No = 0, Don't Know = 1, Yes = 2	Used for truncation	0.000	1.000	1.137	2.000
Q21 Experts	Likert Scale 1–5	Theory mixed	1.000	4.000	3.596	5.000
Q22 Education	Secondary = 1, Further = 2, Bachelor = 3, Postgrad = 4	Positive relationship with WTP	0.000	2.000	2.404	4.000
Q23 Employment	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
Q24 A Coronavirus	No = 0, Yes = 1	Theory mixed	0.000	1.000	0.533	2.000
Q24 Income	£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
Q25 Survey	1–10 scale	Used for truncation	1.000	9.000	8.597	10.000

Notes: Protest voters were identified from the text responses as those stating that they are against paying anything for the scenario and excluded from the truncated sample. Harshly applying truncation rules leads to a sample size of 304. This sample can be assumed to be the most valid responses. Results indicate that the conclusions of this work are robust to alternatively estimating with this truncated sample.

Table A2. Question one probit model with covariates ($N = 670$).

Variable	Estimate	Std. Err.	*P*. Value
Intercept	−1.305***	0.316	<0.001
Gender	0.048	0.106	0.648
Age	−0.003	0.004	0.45
Distance	−0.001	0.003	0.922
BP	0.272***	0.081	0.001
Charity	0.309***	0.096	0.001
Certainty	0.142*	0.079	0.073
Experts	0.273***	0.062	<0.001
Income	0.189*	0.107	0.077
Consequentiality	0.278***	0.075	<0.001
BID	−0.011***	0.002	<0.001
Estimation statistics:			
AIC	794.839	LogLik	−386.420
BIC	844.420	Adj. R^2	0.144

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A3. Question two probit model with covariates ($N = 670$).

Variable	Estimate	Std. Err.	*P*. Value
Intercept	−0.28	0.311	0.368
BID	−0.01***	0.002	<0.001
Gender	0.038	0.107	0.721
Age	−0.008*	0.004	0.070
Distance	−0.001	0.003	0.988
BP	0.181**	0.084	0.031
Charity	0.288***	0.1	0.004
Certainty	0.062	0.083	0.459
Experts	0.215***	0.062	0.001
Income	0.026	0.108	0.807
Consequentiality	0.264***	0.075	<0.001
Estimation statistics:			
AIC	772.8001	LogLik	−375.400
BIC	822.3802	Adj. R^2	0.114

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A4. Question one hybrid choice model with sociodemographic in structural equation only ($N = 670$).

Coefficient	Estimate	Std. Err.	*P*. Value
$\beta_{Intercept}$	−39.696***	4.466	<0.001
β_{BID}	−23.275***	2.611	<0.001
λ	20.847***	0.862	<0.001
γ_{Age}	−0.001	0.003	0.453
γ_{Gender}	−0.057	0.093	0.270
$\gamma_{Distance}$	−0.001	0.002	0.437
γ_{Income}	0.186**	0.092	0.022
$\gamma_{Experts}$	0.486***	0.054	<0.001
$\gamma_{Consequential}$	0.332***	0.068	<0.001
γ_{BP}	0.325***	0.068	<0.001
$\gamma_{Charity}$	0.291**	0.085	<0.001
$\gamma_{Certainty}$	−0.075	0.189	0.186
ζ_{Q13}	0.618***	0.049	<0.001
ζ_{Q14}	0.638***	0.051	<0.001
ζ_{Q15}	0.531***	0.048	<0.001
$\tau_{Q13,1}$	−0.567***	0.181	0.151
$\tau_{Q13,2}$	0.152	0.174	0.271
$\tau_{Q13,3}$	1.752***	0.186	<0.001
$\tau_{Q13,4}$	2.781***	0.203	<0.001
$\tau_{Q14,1}$	−0.831***	0.195	0.056
$\tau_{Q14,\ 2}$	−0.128	0.178	0.494
$\tau_{Q14,3}$	1.245***	0.183	0.001
$\tau_{Q14,4}$	2.454***	0.198	<0.001
$\tau_{Q15,1}$	−1.195***	0.192	0.003
$\tau_{Q15,2}$	−0.480***	0.164	0.160
$\tau_{Q15,3}$	0.676***	0.164	0.019
$\tau_{Q15,4}$	1.676***	0.174	<0.001
Estimation statistics			
Iterations	97	LL (start)	−4414.918
AIC	5798.77	LL (final, whole model)	−2872.383
BIC	5957.89	LL (Choice)	−416.1021

Table A5. Question two hybrid choice model with sociodemographic in structural equation only ($N = 670$).

Coefficient	Estimate	Std. Err.	*P*. Value
$\beta_{Intercept}$	−36.973***	6.116	<0.001
β_{BID}	−29.169***	3.454	<0.001
λ	29.075***	1.582	<0.001
γ_{Age}	−0.003***	0.004	0.442
γ_{Gender}	−0.087	0.087	0.321
$\gamma_{Distance}$	0.001	0.002	0.573
γ_{Income}	0.058	0.097	0.552
$\gamma_{Experts}$	0.434***	0.030	<0.001
$\gamma_{Consequential}$	0.330***	0.068	<0.001
γ_{BP}	0.214***	0.079	<0.001
$\gamma_{Charity}$	0.292***	0.074	<0.001
$\gamma_{Certainty}$	−0.018	0.063	*0.399*
ζ_{Q13}	0.594***	0.051	<0.001
ζ_{Q14}	0.675***	0.055	<0.001
ζ_{Q15}	0.636***	0.055	<0.001
$\tau_{Q13,1}$	−0.736***	0.174	<0.001
$\tau_{Q13,2}$	−0.052	0.167	0.756
$\tau_{Q13,3}$	1.497***	0.179	<0.001
$\tau_{Q13,4}$	2.497***	0.194	<0.001
$\tau_{Q14,1}$	−0.949***	0.196	<0.001
$\tau_{Q14,\ 2}$	−0.244	0.182	0.179
$\tau_{Q14,3}$	1.125***	0.186	<0.001
$\tau_{Q14,4}$	2.336***	0.201	<0.001
$\tau_{Q15,1}$	−1.258***	0.206	<0.001
$\tau_{Q15,2}$	−0.495***	0.180	0.006
$\tau_{Q15,3}$	0.716***	0.181	<0.001
$\tau_{Q15,4}$	1.751***	0.192	<0.001
Estimation statistics			
Iterations	106	LL (start)	−4146.733
AIC	5783.12	LL (final, whole model)	−2864.559
BIC	5942.24	LL (Choice Model)	−400.6043

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A6. Hybrid choice model question one truncated sample ($N = 304$).

Coefficient	Estimate	Std. Err.	*P*. Value
βintercept	−67.439***	6.692	<0.001
βBID	−32.326***	8.302	<0.001
λ	23.704***	1.982	<0.001
γAge	−0.001	0.005	0.409
γGender	−0.122	0.174	0.242
γDistance	−0.002	0.004	0.328
γIncome	0.220	0.189	0.122
γExperts	0.670***	0.140	<0.001
γConsequentiality	0.279***	0.098	0.002
γBP	0.443**	0.189	0.010
γCharity	−0.005	0.192	0.489
γCertainty	0.470*	0.343	0.086
ζQ13	0.591***	0.083	<0.001
ζQ14	0.620***	0.090	<0.001
ζQ15	0.624***	0.084	<0.001
τQ13 1	−0.361	0.368	0.164
τQ13 2	0.673**	0.355	0.029
τQ13 3	2.262***	0.398	<0.001
τQ13 4	3.349***	0.431	<0.001
τQ14 1	−0.740**	0.421	0.040
τQ14 2	0.316	0.372	0.198
τQ14 3	1.803***	0.408	<0.001
τQ14 4	3.058***	0.455	<0.001
τQ15 1	−1.290***	0.498	0.005
τQ15 2	0.062	0.355	0.431

(*Continued*)

Table A6. Continued.

Coefficient	Estimate	Std. Err.	*P*. Value
$\tau Q15$ 3	1.441***	0.362	<0.001
$\tau Q15$ 4	2.585***	0.384	<0.001
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

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A7. Hybrid model: question two truncated sample ($N = 304$).

Coefficient	Estimate	Std. Err.	*P*. Value
$\beta intercept$	−33.033***	28.222	0.003
βBID	−42.867***	12.709	<0.001
λ	28.685***	2.863	<0.001
γAge	−0.005	0.017	0.260
$\gamma Gender$	−0.070	0.337	0.335
$\gamma Distance$	−0.004	0.007	0.135
$\gamma Income$	0.149	0.148	0.121
$\gamma Experts$	0.517***	0.202	<0.001
$\gamma Consequentiality$	0.058	0.157	0.297
γBP	0.438**	0.404	0.014
$\gamma Charity$	−0.036	0.602	0.440
$\gamma Certainty$	0.425***	0.236	0.001
$\zeta Q13$	0.677***	0.124	<0.001
$\zeta Q14$	0.767***	0.129	<0.001
$\zeta Q15$	0.739***	0.110	<0.001
$\tau Q13$ 1	−0.859**	0.799	0.012
$\tau Q13$ 2	0.214	0.810	0.280
$\tau Q13$ 3	1.812***	0.838	<0.001
$\tau Q13$ 4	2.912***	0.874	<0.001
$\tau Q14$ 1	−1.285***	0.881	0.002
$\tau Q14$ 2	−0.102	0.877	0.400
$\tau Q14$ 3	1.455***	0.907	<0.001
$\tau Q14$ 4	2.761***	0.932	<0.001
$\tau Q15$ 1	−1.838***	0.813	0.001
$\tau Q15$ 2	−0.408	0.807	0.147
$\tau Q15$ 3	1.002***	0.823	0.005
$\tau Q15$ 4	2.177***	0.844	<0.001
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

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A8. Hybrid choice model question one no structural equation ($N = 670$).

Coefficient	Estimate	Std. Err.	*P*. Value
βintercept	15.424	2.711	<0.001
βBID	−27.997	4.032	<0.001
λ	31.295	0.414	<0.001
ζQ13	0.729	0.08	<0.001
ζQ14	0.763	0.086	<0.001
ζQ15	0.638	0.073	<0.001
τQ13 1	−2.072	0.113	<0.001
τQ13 2	−1.377	0.082	<0.001
τQ13 3	0.195	0.059	0.001
τQ13 4	1.203	0.079	<0.001
τQ14 1	−2.372	0.147	<0.001
τQ14 2	−1.703	0.1	<0.001
τQ14 3	−0.354	0.061	<0.001
τQ14 4	0.838	0.069	<0.001
τQ15 1	−2.481	0.139	<0.001
τQ15 2	−1.793	0.1	<0.001
τQ15 3	−0.652	0.061	<0.001
τQ15 4	0.337	0.058	<0.001
Estimation statistics			
Estimation method	bfgs	Iterations	79
Convergence	Successful	LL(start)	−4414.918
Number of individuals	670	LL(final, whole model)	−2982.136
Number of observations	2680	LL(final,indic Q13)	−913.4787
Number of inter-person draws	1000 (Halton)	LL(final,indic Q14)	−898.1458
AIC	6000.27	LL(final,indic Q15)	−858.6931
BIC	6106.36	LL(final,choice)	−461.5334

Table A9. Hybrid choice model question two no structural equation ($N = 670$).

Coefficient	Estimate	Std. Err.	*P*. Value
βintercept	29.147***	4.078	<0.001
βBID	−32.37***	5.368	<0.001
λ	36.714***	1.142	<0.001
ζQ13	0.674***	0.083	<0.001
ζQ14	0.765***	0.089	<0.001
ζQ15	0.731***	0.080	<0.001
τQ13 1	−2.001***	0.106	<0.001
τQ13 2	−1.332***	0.081	<0.001
τQ13 3	0.195***	0.060	0.001
τQ13 4	1.176***	0.081	<0.001
τQ14 1	−2.368***	0.135	<0.001
τQ14 2	−1.691***	0.098	<0.001
τQ14 3	−0.346***	0.063	<0.001
τQ14 4	0.841***	0.072	<0.001
τQ15 1	−2.600***	0.145	<0.001
τQ15 2	−1.862***	0.104	<0.001
τQ15 3	−0.667***	0.066	<0.001
τQ15 4	0.352***	0.063	<0.001
Estimation statistics			
Estimation method	bfgs	Iterations	60
Convergence	Successful	LL(start)	−4146.73
Number of individuals	670	LL(final, whole model)	−2957.36
Number of observations	2680	LL(final,indic Q13)	−913.50
Number of inter-person draws	1000 (Halton)	LL(final,indic Q14)	−898.22
AIC	5950.72	LL(final,indic Q15)	−858.76
BIC	6056.81	LL(final,choice)	−429.42

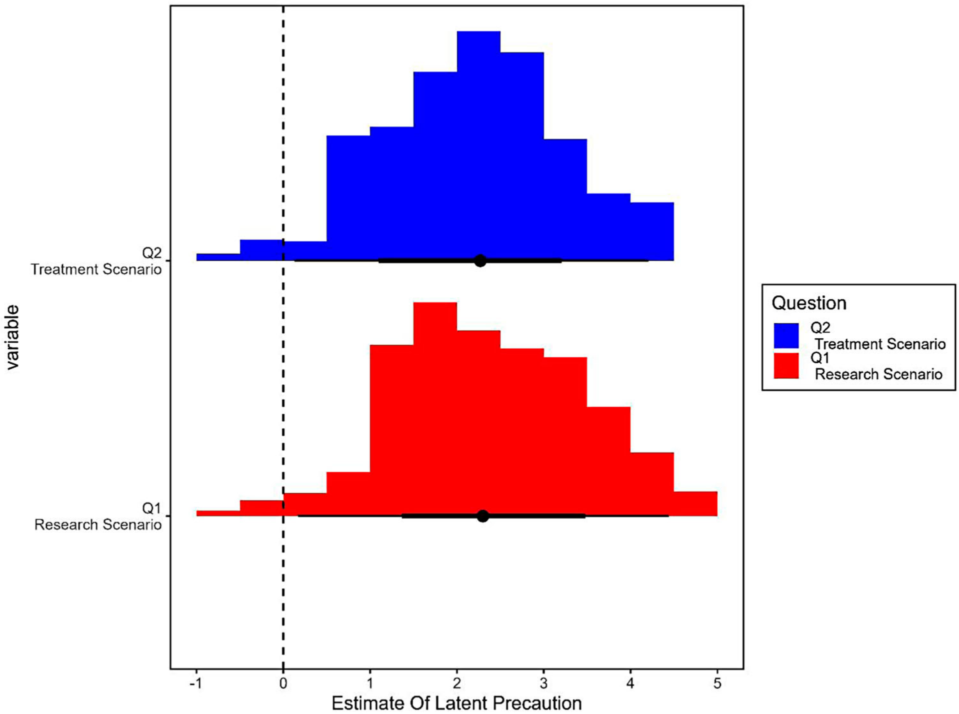

Figure A1. Distribution of the latent variable by model.