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Examining food preferences in the face of environmental pressures

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A B S T R A C T

This paper explores systematic differences in preferences for food products labelled with environmental footprints resulting from the production of food. Specifically, we use survey data from Irish consumers and explore the relative importance of the potential risk to water quality in addition to other environmental attributes associated with the production of meat (beef and chicken) and vegetable products based on a discrete choice experiment. A Latent Class Model (LCM) is employed to identify and distinguish distinct consumer segments as a function of preferences. We analyse if personal values and beliefs related to the environmental implications of producing food can differentiate preferences for different class segments. Results indicate that preferences are heterogeneous across a cohort of consumers. Specifically, consumers have a preference for environmental attributes such as carbon and water footprints, and potential risk to water quality in food products, with the majority of consumers willing to pay a price premium for more environmentally sustainable food products.

1. Introduction

Food preferences and dietary habits of consumers have been changing rapidly over the last decade due partly to growing consumer interest in attributes of food other than taste, quality, brand etc. For example, apart from the widely known health implications of food consumption, a growing body of literature suggests that consumers are also realising that their food choices have environmental impacts [1,2]. A recent survey of European Union (EU) citizens' attitudes and perceptions in relation to agriculture and climate change shows an increasing awareness among consumers of the connections between agriculture and the environment [3]. In particular, the report shows that a majority (69%) of EU citizens agree that farm practices need to change in the fight against climate change and that a majority (66%) are also willing to pay higher premiums for environmentally friendly food products. Evolving food preferences may reflect an interest in sustainable use of resources or a desire to support climate change mitigation efforts [4,5]. However, current evidence is insufficient to understand the value consumers place on the different environmental attributes associated with food products [6], in particular, the potential risk to water quality resulting from food production. In addition, while there is evidence to support the relative importance of carbon and water footprint attribute labels in consumers' food preferences, the risk to water quality associated with the production of the food product is still unknown. A better understanding of preferences for food, including the relative weighting that people place on various environmental attributes, not least the potential risk to water quality, is important evidence to support future agricultural and food production policies.

Over the last few decades, the quality of freshwater resources globally has been on the decline. This decline, predicated largely by human activities, in particular in the agricultural sector, poses a significant threat to access to safe and high-quality water plus has climate change mitigation impacts [7]. In the United States agricultural runoff is adjudged to be the primary source of challenges to water quality [8]. In Ireland, just over 47% of surface water bodies are assessed to be in moderate, poor, or bad ecological status as defined by the EU's Water Framework Directive [9]. Agriculture, particularly nutrient runoff, plays a significant role in this decline. While the negative impact of agricultural activities on water quality appears apparent, it is not clear what consumers' preferences are (or would be) when food producers consider the potential risk to water quality in the production of food products. Therefore, the main objective of this paper is to assess consumers' preferences for environmentally sustainable attributes (with particular emphasis on the potential risk to water quality resulting from the

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production of the food products) and to estimate consumers' willingness to pay for such attributes.

Many studies examine consumers' preferences and willingness to pay (WTP) for environmental attributes of food products (e.g., Refs. [10–14]. However, the majority of these studies examine consumers' preferences for environmental footprints measured either as carbon or water use footprints. We expand the notion of environmental footprints arising from food production by incorporating the potential risk to water quality arising from nutrient discharges to water bodies during food production. Our inclusion of the potential risk to water quality as a food attribute is borne out of the fact that the nature of agricultural production systems (e.g., livestock and crop production) raises the possibility that nutrients from animal manures and diffuse pollution from agrochemicals reach water bodies leading to a depletion in the quality of water [15]. The negative implications on the environment and humans when this happens have led to the introduction of certain production protocols such as nutrient management strategies at the farm level to mitigate this issue. Therefore, the potential risk to water quality arising from food production has become a necessary feature worthy of consideration in consumer food preference evaluation and this is one of the contributions of this paper.

To examine consumers' preferences for food products - beef, chicken and vegetables - labelled with different carbon footprints, water use, and potential risk to water quality we use data from a sample of Irish consumers. Potential pollution risk, as well as food safety consciousness, have been shown to be significant determinants of Irish consumers' food purchase decisions [16] implying that Irish consumers have some level of awareness of certain environmental attributes in food products. While we do not specifically address consumers' food safety concerns, however, food safety, nutrition and ecological concerns intricately contribute to consumers' judgement of sustainability, quality, safety and how "good" they perceive a food product to be which ultimately in combination with price informs their preferences and purchase decisions [16,17]. To understand consumer profiles, we also explore the role of personal values in leading consumers to choose products with positive environmental characteristics [18]. Consumers who believe that the food they eat can significantly influence the environment will want to choose food products that are likely to have a minimal negative impact on the environment. In contrast, pro-environmental attributes in food products are likely to be of less importance to consumers who have a contrary belief. For example [6], shows that consumers with positive attitudes toward the protection of the environment were more likely to choose food products that are more environmentally friendly. Thus, our hypothesis is that consumers with preferences for pro-environmental attributes in food (e.g., low carbon footprint, low water use intensity and low potential risk to water quality) associated with food production will adjust food purchases towards products with lower levels (or absence) of these attributes, all else equal.

2. Methodology

2.1. Survey instrument, data collection and sample

The data we used is from an online survey administered to a nationally representative sample of Irish adults based on gender, age, education, and county (region). The survey was administered in October 2021. Individuals who only occasionally or never purchase food for the household and those who do not regularly eat their main meal at home were excluded, as the target audience of the analysis were adults that purchase primary foodstuffs, i.e. household groceries. In this way, the survey reached only respondents who regularly make similar decisions with respect to purchasing meat and vegetables and excluded people who do not prepare meals at home regularly. A four-part survey was conducted using Limesurvey, an online survey platform. The questionnaire was pre-tested among a sample of $n = 50$ for each of the three food types. No changes were made to the final survey based on the pre-test. A total of 1249 respondents from the panel book of a professional survey company completed the survey. Respondents were invited to participate in the survey through email and were informed about the details of the survey including length and type. The average time necessary to complete the survey was almost 15 min. The first part of the survey asked initial screening questions to randomly filter respondents to one of three stated response choice experiment (CE) questions later in the survey but consistent with their dietary preferences. That is, vegetarians were only asked the vegetable CE question while other respondents were randomly presented with either the meat (beef or chicken) or vegetable CE question. Next, respondents answered five different attitudinal questions, all related to their attitudes and beliefs about climate change and environmental sustainability. Answers by respondents, shown in Fig. 1, were recorded using a 3-point Likert scale that ranged from "agree" to "disagree". The third part of the questionnaire comprised the CE questions, which simulated choices customers might face in purchasing beef, chicken, or vegetable products with product labelling distinguishing between the offered choices in terms of price, carbon footprint, water use, and associated risk to water quality. The final section captured the socio-demographic characteristics of individual consumers.

To address any concern that respondents may not provide earnest responses or are not paying adequate attention to the survey questions, we embedded within the questionnaire a screening question. Respondents that failed this screening question were ultimately excluded from continuing with the survey. The question asked respondents to select "option B" from a list of answer choices before continuing with the survey. In addition to the choice experiment, the survey also included questions to elicit the socio-demographic characteristics of the respondents. A copy of the survey instrument is available in the online supplementary material accompanying this paper.

2.2. Choice experiment

A stated choice experiment (CE) is a preference elicitation method used in consumer surveys (as well as in other contexts). In particular, respondents are asked to express their preferred choices across a set of alternatives iteratively, across a certain number of choice sets. Each alternative is described by a set of attributes and each attribute is characterised by levels that vary across alternatives. Each choice card included two alternatives and an opt-out, which could be selected by respondents who did not like any of the alternatives. This opt-out (no choice) alternative increases the realism of the task. Each alternative was described by three non-monetary, environmental attributes and the price of the food product. The non-monetary attributes were carbon footprint (amount of CO_2 emissions equivalent), water use intensity, the risk to water quality and price as outlined in Table 1, all characterised by three levels (high, medium, and low). To improve the clarity of the

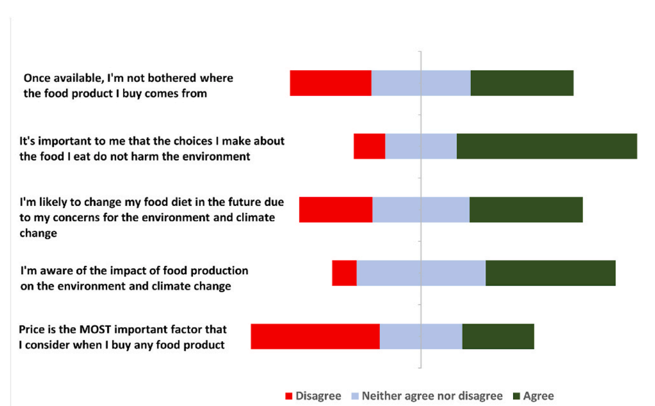

Fig. 1. Personal values and preferences regarding the impact of food production on the environment.

Table 1
Attributes and attribute levels for food products used in the choice experiment.

Attributes		Levels: Beef	Chicken	Vegetable	Reference
Carbon footprint	Low	<20 kg CO2 equiv./kg	<5 kg CO2 equiv./kg	<220g CO2 equiv./kg	Gerber et al. [64]
	Moderate	20–30 kg CO2 equiv./kg	5–7.5 kg CO2 equiv./kg	220–400g CO2 equiv./kg	Ponsioen and Blonk [67]
	High	>30 kg CO2 equiv./kg	>7.5 kg CO2 equiv./kg	>400g CO2 equiv./kg	
Water use	Low	<150L/kg	<5L/kg	<100L/kg	Mekonnen and Hoekstra [66]
	Moderate	150–180L/kg	5–10L/kg	100–150L/kg	Hess et al. [65]
	High	>180L/kg	>10L/kg	>150L/kg	Murphy et al. [19]; Mekonnen and Hoekstra [20]
Risk to water quality	Low	low	Low	Low	
	Moderate	Moderate	Moderate	Moderate	O'Boyle et al. [9]
	High	High	High	High	
Price		2.20–8.18/400g	1.29–7.29/400g	1.99–6.19/kg	

attributes and their levels and assist participants in choosing their preferred options, the carbon and water footprints were also presented in quantitative terms. Quantifying risk to water quality is more complex and to reduce the cognitive burden and make it easier to understand, we provided detailed explanations to respondents and presented the attribute in terms of the associated potential risk to water quality resulting from producing the food. Carbon footprint is presented as the amount of carbon dioxide emissions equivalent per kilogram of food (CO_2e/kg). The water use attribute represents the litres of water used per kilogram of food produced (L/kg). These quantitative levels are based on estimates from the literature (e.g., Refs. [19,20]. Table 1 shows an overview of the attributes and levels used in the CE. In the case of price, the amount levels range between 2.20 and 8.18/400g, 1.29–7.29/400g and 1.99–6.19/kg for beef, chicken and vegetable products, respectively. The price attribute levels are based on the average (plus or minus one standard deviation) of the prevailing prices from three major supermarket chains in Ireland [14].

In real life, personal choices for food products are influenced by other attributes such as taste, freshness, nutrient content, colour, brand, packaging, etc. To avoid biases caused by missing attributes, the survey explained to respondents that meat and vegetables in the choice cards have equivalent characteristics to the products they usually purchase and only differ with respect to the environmental attributes described.

The allocation of the attribute levels across the choice cards was designed using a sequential experimental design with a Bayesian information structure geared towards minimizing the expected D_b-error and optimised for a Bayesian WTP-efficiency [68,70]. Accordingly, the design was performed in three stages. In the first stage, we generated a D-efficient orthogonal design based on an MNL model to obtain Bayesian parameter priors.[1] D-efficient MNL-based designs perform well even for models with a different asymptotic variance-covariance estimator such as those with continuous or discrete preference mixing [62,69]. For the second stage, this design was used in the pilot survey of 50 respondents (from the main target population) for each of the food types. In the final stage, the parameter estimates from the pilot were used as the priors for the experimental design for the main survey. The final CE survey consisted of a set of 8 choice questions, each comprising two experimentally designed food-type alternatives and a "None" or opt-out option. The software Ngene was used to generate each of the designs [63]. Before commencing the choice task respondents are shown an example choice alternative with a text description of how the product should be interpreted to reinforce the earlier description provided to participants. An example of a choice task used in the survey is presented in Fig. 2.

[1] One drawback to D-efficient modelling is the dependence on priors about the population values of the parameters to be estimated. With no available reliable priors, we establish parameter priors for the first stage by setting the initial values close to zero and using the Ngene software to generate the design needed to obtain new priors from the pilot survey which we subsequently use for the main experimental design.

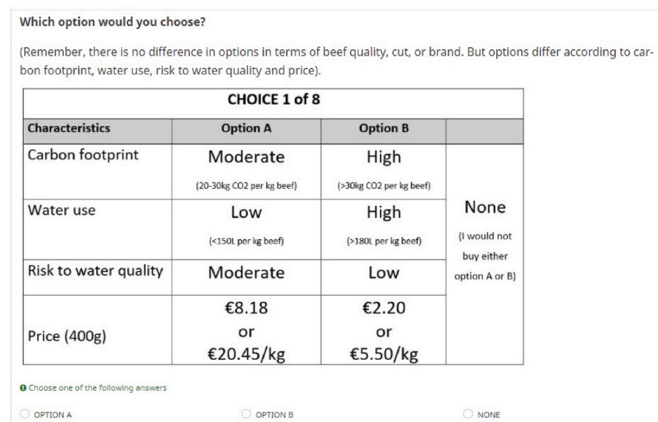

Fig. 2. Example of a choice set used in the consumer survey.

In Ireland, as well as in Europe more generally, food products are not compulsorily differentiated based on environmental footprint labelling so the exact products as described in the CE are hypothetical. Following [21] we presented a 'cheap talk' script before commencing the CE task. The objective of the cheap talk is to lead respondents to reveal their real preferences making them aware of the existence of hypothetical bias and to be aware of their budget. Previous studies have shown that including cheap talk in a CE can be effective in reducing this bias [22,23].

2.3. Empirical analyses

In a CE exercise, an underlying assumption is that choice data are consistent with a random utility maximisation (RUM) framework [24,25]. The RUM model assumes that the utility of individual i choosing alternative j in choice occasion t can be described as:

$$U_{ijt} = \beta' X_{ijt} + \epsilon'_{ijt} \quad (1)$$

where X_{ijt} is a vector of observed characteristics relating to alternative j, which we refer to as option A, B, or C (where A and B represent the three product alternatives and C refers to the "None" alternative) chosen by individual i; β is a vector of structural taste parameters, which characterises choices; and ϵ_{ijt} is the random and unobserved part of the utility. We assume that consumers have heterogeneous preferences for environmentally sustainable attributes in beef, chicken, and vegetable food products. Specifically, we assume a discrete form of preference heterogeneity that allows food consumers to be sorted into a particular class, c, with marginal utility parameters that vary by class membership, termed a Latent Class Model (LCM) [23,26,27]. The LCM, within the random utility maximisation (RUM) framework, draws on the assumption of finite mixture modelling where it is assumed that a mixture of unobserved class segments exists in a population with each class segment characterised by class-specific sets of utilities [2,27]. We provide more details of the LCM class segmentation in the next section.

2.4. Specification of the latent class model and class membership

The LCM model sorts respondents into several classes differentiated by their estimated utility functions (of stated preferences over the attributes) and individual-specific characteristics. For our study, the identification of the optimal number of classes was accomplished as follows. In the absence of any known statistical test, we use a combination of the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC) and the log-likelihood (LL) statistics to inform the choice of the number of classes [28]. We estimate models with the same specification of two to five classes (i.e., c) for each of the three food types and the result is presented in Table 2. Across the beef, chicken and vegetable models the best model fit was achieved for a 3-class model considering the rate of change of the BIC, AIC and LL as well as the number of parameters to be estimated as one moves from one class to the next. The BIC and AIC values of models above the 3-class models did not significantly improve the model fit. Furthermore, Akaike weights, following [29] model selection criteria, suggest a 3-class model represents the best model fit for each of the three food products.

In the latent class model, the respondents' utility within a class is homogeneous but heterogeneous across the classes. If we assume that U_{icjt} is the indirect utility individual i receives by choosing to purchase a food type of alternative j in choice set $(1, \ldots, J)$ at choice occasion t, conditional on being in class c we can specify the indirect utility as:

$$U_{icjt} = V_{icjt}(X_{jt}; \beta_c) + \epsilon_{icjt}, \quad (2)$$

where $V_{icjt}(\cdot)$ is the observable component of indirect utility a respondent i in class-c receives from consuming food j; X_{jt} is a 1 x N vector of attributes associated with food type, j, including associated price attribute following [30] framework; β_c is a vector of marginal utility parameters; and ϵ_{icjt} is an unobservable independent and identically distributed Gumbel Type-1 extreme value error term assumed to be independent of individuals, alternatives and choice situations. Individual i will choose alternative j, if and only if $U_{icjt} \geq V_{ickt} \, \forall j \neq k$. Since indirect utility is random, we can estimate only the probability that individual i chooses a food type of alternative j with different carbon footprint, water use and risk to water quality attributes in a choice situation t conditional on being in class c. Class membership, π_c, is modelled using a logit specification $\left(\pi_c = exp(\zeta) / \left(\sum_{c=1}^{C} exp(\zeta)\right)\right)$, with ζ representing respondent-specific characteristics. In the past, many choice experiment studies based on latent class models have included variables related to personal beliefs and attitudes within ζ in the class allocation function (e.g., Ref. [31]. However, recent evidence suggests that this approach is not appropriate [32]. Measuring beliefs and attitudes is difficult because there is no particular objective way of measuring beliefs and attitudes. Typically surveys use Likert scales, which are used as a proxy for the overall belief or attitude [33]. While the proxy gives an indication of the underlying belief, it is collected with measurement error. Including this proxy in the deterministic part of the class allocation function makes it correlated with the error term and subject to endogeneity bias. To address endogeneity caused by indicator variables, integrated choice and latent variable (ICLV) models (or hybrid models) have been proposed but are computationally challenging (e.g., Refs. [34–36]. We investigate how class membership is associated with respondents' beliefs and values regarding environmental implications of food production subsequent to LCM model estimation by regressing estimated class membership probabilities on the five attitudinal questions described earlier, thus circumventing the endogeneity issue.

Table 2
LCM model selection criteria.

Latent classes	Log-likelihood	AIC	BIC	Parameters
Beef				
2	−2551.19	5255.85	5233.85	22
3	−2401.07	5053.3	5017.3	36
4	−2360.03	5068.87	5018.87	50
5	−2329.1	5104.69	5040.69	64
Chicken				
2	−2725.06	5605.31	5583.31	22
3	−2557.52	5368.99	5332.99	36
4	−2507.46	5367.65	5317.65	50
5	−2473.59	5398.67	5334.67	64
Vegetable				
2	−2714.61	5584.56	5562.56	22
3	−2593.85	5441.92	5405.92	36
4	−2565.85	5484.78	5434.78	50
5	−2499.73	5451.39	5387.39	64

AIC: Akaike information criteria.
BIC: Bayesian information criteria.

The LCM's log-likelihood function is

$$logL = \sum_{i=1}^{I} log\left\{ \sum_{c=1}^{C} \pi_c \frac{exp(\beta_c X_{ij})}{\sum_{j=1}^{J} exp(\beta_c X_{ij})} \right\} \quad (3)$$

The probability of choosing j can therefore be stated as:

$$Prob(U_{icjt} \geq U_{ickt}) = Prob(V_{icjt} + \epsilon_{icjt} \geq V_{ickt} + \epsilon_{ickt}) \forall k \quad (4)$$

Assuming that the observable portion of utility is linear in parameters, we specify V_{icjt} as:

$$V_{icjt} = \beta_0 * ASC_{cjt} + \beta_1 * PRICE_{cjt} + \beta_2 * CF_{cjt} + \beta_3 * WU_{cjt} + \beta_4 * RISK_{cjt} + \beta_5 * SOCIO_{cjt} \quad (5)$$

where $PRICE_{cjt}$ is the price of alternative j in choice situation t (measured in Euros); CF_{cjt} and WU_{cjt} are continuous variables of carbon emission equivalents in kg and water usage in L, respectively. $RISK_{cjt}$ is a categorical variable measuring the potential risk to water quality. $SOCIO_{cjt}$ represents variables explaining the individual-specific characteristics. ASC is alternative specific constant, equivalent to the "None" or opt-out option in the survey and is parameterised as equal to one if the participant chose "None", and 0 if alternative A or B was chosen. As illustrated in Fig. 1, the CE was an unlabeled experiment with the "None" option representing a choice for neither of the other options available rather than an active selection of an (unknown) status quo option. This means that the coefficient on the ASC variable, β_0, does not have a practical policy interpretation [37]. Thus, for our discussions in what follows in the results and discussion sections, we focus largely on the environmental attributes and price.

Our analytical model assumes that the utility of consuming a given food type depends on the attributes shown in Table 1. We hypothesise that consumers' utility increases with better environmentally friendly attributes in food. For instance, food types with low or medium carbon footprints increase utility relative to a high carbon footprint product. In addition, utility decreases as price increases, consistent with neoclassical economic theory. The premium that consumers place on the food alternatives will be a function of their preferences for the identified environmental attributes in the food. We compute mean consumers' marginal WTP for each attribute of the food types. The β parameters in equation (4) are not readily amenable for policy discussion, as they are measured in utility space. The ratio of two β estimates is easily interpreted as the marginal rate of substitution between the two associated attributes. If the price attribute is used as the denominator, the ratio is evaluated in metric and is equivalent to the willingness to pay and more amenable to discussion. Willingness to pay for the non-monetary attribute j is computed as the negative ratio of the partial derivative of the utility function with respect to the non-monetary attribute j, divided by the derivative of the utility function with respect to the price attribute given below [38,39]:

$$WTP_{cj} = \frac{\frac{\partial U_{cj}}{\partial Attribute}}{\frac{\partial U_{cj}}{\partial Price}} = -\left(\frac{\beta_{ck}}{\beta_p}\right) \quad (6)$$

3. Results

3.1. Sample characteristics

We first describe the characteristics of our sample across the different food types. The complete data set comprises 3152 (beef), 3408 (chicken), and 3432 (vegetables) observations (394, 426 and 429 respondents, (*total* = *1249*) each performing 8 choice tasks) with three alternatives per choice task, for a total of 9,456, 10,224, and 10,296 alternatives evaluated in the CE. Table 3 reports some socio-demographic characteristics of the survey sample. The sample represents a broad range of household members, and consequently food purchasers, in terms of gender split, marital status, educational attainment, and employment status. As noted in section 2, a nationally representative sample was initially contacted but respondents that only occasionally or never purchase food for the household and those who do not regularly eat their main meal at home were subsequently excluded. Table 3 reports sample descriptive statistics for socio-demographic variables and the most recent census data for comparison. The variables are broadly similar but as anticipated the survey sample is not closely representative of the Irish population across the socio-demographic variables presented.

3.2. Results of analyses of the choice experiment

All models and analyses described below were estimated using Stata software version 17.0 (StataCorp). The results of the LCM model for each food type are presented in Table 4. For reference, estimation results for an MNL model specification, which assumes homogeneous preferences across households, are reported in Table A1 in the Appendix.

3.2.1. Results from the LCM analyses

The LCM model estimates for the 3 food types are reported in Table 4. The estimates of class shares are listed towards the bottom of the table. For beef, class 1 represents 33.5% of respondents, class 2 represents 26.9% of respondents, and class 3 makes up 39.6% of respondents. Similarly, for chicken and vegetable models each of the classes are relatively large with all 20% or above in size. As anticipated, across food types and classes, the estimated price coefficient is negative, indicating dis-utility as prices increase, though, in the case of vegetable, class 2, the coefficient estimate is not statistically different from zero. Among this class price is not an important attribute.

For each of the environmental footprint attributes, all dummy coded, the reference category is the 'high' option on the choice card, i.e., higher levels of carbon emissions, higher water use, or higher risk of water pollution. The coefficient estimates on the environmental footprint parameters, where they are statistically significant, are all positive. This indicates higher utility associated with products with better environmental footprints.

3.2.2. Results of the willingness to pay (WTP) estimation

The estimates of consumers' marginal WTP (MWTP), calculated from the estimates of the marginal utility parameters for each attribute and food type are presented in Table 5, and graphically in Appendix B. Overall, the results show that consumers in our sample responded rationally to increases in the prices for the food products presented to them as the price attribute is negative and statistically significant across the food types (with the exception of class 2 vegetable consumers). Consumers place a price premium on the identified sustainability attributes across the 3 food types, with two general exceptions. First, beef consumers in class 1 are not willing to pay more for products with a lower carbon footprint or reduced risk of water pollution. In the case of water use, the estimates suggest an inconsistency, indicating that they are willing to pay 0.63/400g beef extra for products with moderate versus high water use, though willingness to pay for low versus high water use is not significantly different from zero. The second exception is among class 2 vegetable consumers. The price coefficient for this class is small in magnitude, and statistically insignificant (see Table 4). The consequence is that the MWTP estimates are large in magnitude, but also statistically insignificant. Thus, we constrain the price attribute for this class to zero following [40].

Beginning with the estimates for beef, households in classes 2 and 3 are willing to pay substantial premiums for beef with low environmental footprints. For example, class 3 members are willing to pay 6.9 extra for 400 g of product with a low compared to a high carbon footprint. In the case of class 2 members, the premium is approximately 8.0. In the case of water use, the premiums are 6.0 for low relative to high water use. With respect to risk to water quality, the premiums are highest at 11.5 and 10.2 for low relative to high risk to water quality. These estimated premiums are conditional on other attributes and therefore cannot be summed to calculate a total willingness to pay for all environmental attributes. The magnitude of the willingness to pay premiums is relatively high compared to nominal supermarket prices, with the price attribute levels in the CE varying between 2.20 and 8.18 per 400 g. For reference, the median price attribute presented to respondents in the choice experiment is 5.19 per 400 g of beef product.

All three consumer classes for the chicken product are willing to pay a premium for a more environmentally sustainable product. Class 2 have the highest WTP, followed by class 3 and then class 1. Among class 1 consumers the MWTP is 0.9 for moderate versus high water use, 1.1 for moderate versus the high risk of water pollution, and 1.4 for moderate versus high carbon footprint, in all cases for 400 g of chicken. For class 2 consumers MWTP is substantially higher. For example, MWTP is 8.5 for low versus high water use and 6.4 for low versus high risk to water quality. The median price attribute presented to respondents in the choice experiment is 4.29 per 400 g of the chicken product.

Mean MWTP for environmental attributes associated with vegetable products are substantially lower than those associated with beef or chicken. Across all environmental attributes and attribute levels (relative to high) WTP is 1.6/kg or lower. Moreover, the median price attribute presented to respondents in the choice experiment was 4.09 per kg of vegetables. As noted earlier, members of Class 2 are not willing to pay for improved environmental attributes associated with the

Table 3
Socio-demographic and economic characteristics of the sample.

	Description	Sample (n = 1249) (%)	Irish population[a] (%)
Food groups	Beef	31.7	
	Chicken	34.1	
	Vegetable	34.2	
Age (years)	<25	7	33.2
	25–44	38.6	29.5
	>45	54.5	37.2
Gender	Male	48.9	49.3
	Female	50.8	50.7
Marrital status	Single	33.4	41.1
	Married	55.4	47.7
	Others	11.3	11.2
Education level	None	0.9	13.3
	Junior cert or equiv.	8.2	15.5
	Leaving cert or equiv.	31.5	29.2
	Third level	59.4	42
Employment status	Employed (FT/PT/Self-employed)	62.5	53.4
	Unemployed	9.6	7.9
	In education	2.6	11.4
	Retired	18.6	14.5
	Others	6.7	12.8

[a] Computed from the Central Statistics Office (CSO) Census 2016.

Table 4
Latent class model results of preferences for different food types with three classes.

	Beef			Chicken			Vegetables		
	Class1	Class2	Class 3	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Carbon footprint									
Moderate	0.368	1.090***	0.669***	4.775**	1.310***	0.952***	0.986***	0.870***	0.590***
	(0.386)	(0.182)	(0.111)	(2.369)	(0.188)	(0.086)	(0.324)	(0.211)	(0.098)
Low	0.456	2.124***	0.710***	−0.360	1.621***	0.787***	2.310***	1.013***	0.466***
	(0.386)	(0.249)	(0.180)	(0.836)	(0.249)	(0.140)	(0.574)	(0.280)	(0.125)
Water use									
Moderate	0.835***	1.163***	0.663***	3.202*	0.589***	0.800***	0.288	1.068***	0.496***
	(0.218)	(0.168)	(0.097)	(1.693)	(0.177)	(0.095)	(0.242)	(0.180)	(0.078)
Low	−0.211	1.611***	0.614***	−2.510	1.748***	1.105***	1.509***	0.796***	0.454***
	(0.348)	(0.253)	(0.163)	(1.945)	(0.248)	(0.155)	(0.412)	(0.246)	(0.107)
Risk to water quality									
Moderate	0.305	1.819***	0.739***	3.762*	1.096***	0.604***	0.661**	1.338***	0.662***
	(0.257)	(0.194)	(0.103)	(2.095)	(0.172)	(0.073)	(0.303)	(0.203)	(0.077)
Low	0.517	2.725***	1.173***	−0.557	1.317***	0.948***	0.068	1.317***	0.639***
	(0.318)	(0.260)	(0.170)	(0.843)	(0.257)	(0.139)	(0.549)	(0.304)	(0.129)
Price	−1.326***	−0.266***	−0.102***	−3.462**	−0.205***	−0.234***	−3.710***	−0.000	−0.422***
	(0.168)	(0.039)	(0.029)	(1.446)	(0.038)	(0.022)	(0.509)	(0.043)	(0.047)
ASC ("No Buy")	−10.193***	2.806***	−1.310***	−21.968***	2.508***	−1.675***	−24.603***	3.181***	−2.589***
	(1.173)	(0.289)	(0.227)	(8.328)	(0.251)	(0.170)	(3.298)	(0.364)	(0.247)
Socio-demographics	Yes			Yes			Yes		
Class share	33.5	26.9	39.6	22.3	24.3	53.4	29.8	20.4	49.9
Observations	3152	3152	3152	3408	3408	3408	3432	3432	3432
Log-likelihood	−2416.22			−2578.34			−2619.33		
AIC/BIC	4920.44/5235.23			5244.68/5562.91			5326.67/5645.2		

Robust standard errors in parenthesis; ***p<0.01, **p<0.05, *p<0.1.

Table 5
Marginal willingness to pay estimates for the three food types.

VARIABLES	(1)			(2)			(3)		
	Beef			Chicken			Vegetable		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Carbon footprint									
Moderate	0.278	4.091***	6.535***	1.379***	6.402***	4.078***	0.266***	–	1.399***
	(-0.318–0.874)	(2.775–5.408)	(3.217–9.853)	(0.924–1.835)	(3.569–9.236)	(3.326–4.829)	(0.087–0.444)		(0.925–1.874)
Low	0.344	7.972***	6.943***	−0.104	7.921***	3.368***	0.623***	–	1.106***
	(-0.241–0.929)	(5.127–10.817)	(2.556–11.330)	(-0.586–0.378)	(4.687–11.156)	(2.189–4.547)	(0.368–0.877)		(0.597–1.615)
Water use									
Moderate	0.630***	4.367***	6.485***	0.925***	2.877***	3.427***	0.078	–	1.177***
	(0.305–0.954)	(2.822–5.912)	(2.803–10.167)	(0.403–1.447)	(1.252–4.502)	(2.703–4.150)	(-0.056–0.212)		(0.741–1.612)
Low	−0.159	6.045***	6.005***	−0.725**	8.539***	4.730***	0.407***	–	1.076***
	(-0.659–0.342)	(3.569–8.520)	(1.883–10.126)	(-1.427 to −0.023)	(5.198–11.879)	(3.410–6.051)	(0.201–0.612)		(0.620–1.533)
Risk to water quality									
Moderate	0.230	6.828***	7.220***	1.087***	5.354***	2.584***	0.178**	–	1.569***
	(-0.181–0.642)	(4.725–8.931)	(3.529–10.910)	(0.608–1.565)	(3.035–7.672)	(1.811–3.358)	(0.016–0.340)		(1.099–2.039)
Low	0.390	10.227***	11.466***	−0.161	6.436***	4.058***	0.018	–	1.515***
	(-0.098–0.879)	(6.845–13.610)	(4.946–17.986)	(-0.593–0.271)	(3.566–9.305)	(2.818–5.299)	(-0.273–0.310)		(0.975–2.055)
Class share (%)	33.5	26.9	39.6	22.3	24.3	53.4	29.8	20.4	49.9
Observations	3152			3408			3432		

95% confidence intervals in parenthesis; ***p<0.01, **p<0.05, *p<0.1.

vegetable product presented in the survey, given the statistically insignificant price coefficient. At first sight, this result is surprising, as the respondents to the vegetable CE question include vegetarians and vegans, which anecdotally might be considered to be more environmentally conscious compared to meat eaters and therefore derive utility from more sustainably produced vegetables. However, only 14% of respondents to the vegetable CE question (61 of 429 respondents) neither eat beef nor chicken and therefore are potentially vegetarian/vegan. When the model is estimated excluding observations for the 61 potential vegetarian or vegan respondents, the estimated coefficients are broadly similar to those reported in Table 4.

3.2.3. Class membership

The relationship between class membership and standard socio-demographic variables (e.g., age, gender, income) is considered within the LCM models itself. For all three food products, estimated coefficients related to socio-demographic characteristics are not statistically significant. For brevity of the tables, these results are not reported.

Statistically insignificant parameter estimates on the socio-demographic variables suggest that the classes cannot be distinguished based on either age, gender or income. This is not unique to this study, as there is widespread evidence that many socio-demographic and economic characteristics are not associated with consumer decisions with respect to sustainable consumption and management [2,13,41].

To avoid endogeneity concerns in the LCM estimation we investigate the relationship between personal values and attitudes on class membership by regressing predicted class membership probabilities, $\widehat{\pi_c}$, on the five attitudinal questions described earlier in Fig. 1. Estimates based on the seemingly unrelated regression estimator [42] are reported in Table 6, where the coefficients show how the probability of membership of the classes differs with respondents' beliefs. Class 3 results are simply a linear combination of the first two classes and are not reported. Starting with price, respondents in agreement with the statement "Price is the MOST important factor that I consider when I buy any food product" (*P_priceA*), are 17% points more likely to be members of class 1 in the case of beef consumers, and the likelihood of being in the two other classes equivalently lower. In the case of both chicken and vegetable consumers, those that agree with the price statement are also more likely to be members of their respective class 1. Respondents that agree with the statement "It's important to me that the choice I make about the food I eat does not harm the environment" *P_noharmentA*) are less likely to be class 1 members in the case of beef, chicken, and vegetables by 12, 14, and 18% points, respectively. Another of the 5 statements is "I'm likely to change my food diet in the future due to my concerns for the environment and climate change" *P_dietchangeA*). In the case of beef and vegetables, those in agreement with the statement are less likely to be members of the respective class 1, whereas in the case of chicken there is no association between agreement with this statement and membership of any of the classes.

Generally, class 1 is more likely to be comprised of respondents for which price is a key factor influencing purchasing decisions and/or those without personal concerns for either food sustainability or the environment. Membership share for class 1 ranges between 20.4% in the case of vegetable consumers and 33.5% for beef consumers. The converse is the share of consumers that have expressed preferences in favour of food products produced in an environmentally sustainable manner. Based on the estimates of the models, the results suggest that people with personal beliefs supporting the importance of environmental protection and sustainability of food production are more likely to adjust food purchase and consumption patterns consistent with their values.

4. Discussion

4.1. Consumers' preferences for environmental attributes, beliefs and willingness to pay

Environmental attributes are potentially an important aspect of consumers' preferences for beef, chicken and vegetable food products, at least for a substantial share of consumers in our study. Relative to products with high environmental footprints, in general, consumers prefer beef, chicken and vegetables labelled with lower environmental footprints. These preferences are more pronounced with beef and chicken products in comparison to vegetable products. For example, we see a clear-cut distinction between the different class segments of consumers for the beef and chicken respondents in terms of utilities from each attribute as well as motivations for this based on self-reported personal values. However, this distinction is not quite as pronounced in the case of vegetable purchasing decisions. One of the reasons may be that majority of the respondents who answered the vegetable survey may feel that they are already engaging in sustainable consumption behaviour when buying vegetables rather than meat products. Alternatively, respondents may feel that meat production is more polluting and carbon intense than vegetable crops, so their perception of environmental damage from vegetables is relatively low. Consequently, their willingness to pay for more sustainable vegetable versus meat production is also lower. Nonetheless, a majority of consumers in our sample have preferences for more sustainably produced food products. These results are similar to the findings of [13] for environmental footprint labels in potato products among German consumers [43]; for yoghurt products among US consumers [14]; among Canadian consumers and [40] for ground beef and potatoes among Canadian and German consumers. Thus, our research provides further evidence that apart from the usual credence attributes in food products such as taste, quality, brand, freshness etc., consumers are aware of and are interested in environmentally sustainable attributes in food [43,44].

The evidence buttressing consumers' preferences for food products with lower carbon and water footprints relative to those with higher

Table 6
Seemingly unrelated regression estimates of class membership probabilities.

VARIABLES	(1) Beef		(2) Chicken		(3) Vegetables	
	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2
P_availableA	0.130***	−0.096***	0.076***	−0.084***	0.033*	−0.032*
	(0.094–0.167)	(-0.132 to −0.059)	(0.044–0.108)	(-0.117 to −0.050)	(-0.002–0.068)	(-0.065–0.000)
P_noharmentA	−0.122***	0.068***	−0.141***	0.086***	−0.184***	0.110***
	(-0.155 to −0.090)	(0.035–0.100)	(-0.170 to −0.111)	(0.055–0.117)	(-0.214 to −0.153)	(0.081–0.138)
P_dietchangeA	−0.090***	0.065***	−0.019	−0.022	−0.119***	0.111***
	(-0.123 to −0.056)	(0.032–0.098)	(-0.050–0.012)	(-0.055–0.011)	(-0.149 to −0.089)	(0.083–0.138)
P_awareA	0.130***	−0.063***	−0.071***	0.019	0.042***	−0.015
	(0.097–0.162)	(-0.096 to −0.030)	(-0.101 to −0.041)	(-0.013–0.050)	(0.010–0.074)	(-0.044–0.015)
P_priceA	0.171***	−0.021	0.131***	−0.062***	0.126***	−0.123***
	(0.139–0.203)	(-0.053–0.011)	(0.104–0.157)	(-0.090 to −0.034)	(0.097–0.155)	(-0.150 to −0.096)
Constant	0.249***	0.284***	0.269***	0.245***	0.369***	0.157***
	(0.216–0.281)	(0.252–0.317)	(0.241–0.297)	(0.216–0.275)	(0.338–0.400)	(0.129–0.186)
Observations	3152	3152	3408	3408	3432	3432
R-squared	0.119	0.032	0.115	0.034	0.127	0.100

95% confidence intervals in parenthesis; ***p<0.01, **p<0.05, *p<0.1; Class 3 is reference class.
P_availableA = [Agree]Once available, I'm not bothered where the food product I buy comes from.
P_noharmentA = [Agree]It's important to me that the choice I make about the food I eat do not harm the environment.
P_dietchangeA = [Agree]I'm likely to change my food diet in the future due to my concerns for the environment and climate change.
P_awareA = [Agree]I'm aware of the impact of food production on the environment and climate change.
P_priceA = [Agree]Price is the MOST important factor that I consider when I buy any food product.

footprints is not new in the literature [2,12,13,40,43,45,46]. However, a novel finding from this research is that consumers understand and have a preference for food products with less potential risk to water quality, and are willing to pay a price premium on food products with this attribute. This is in addition to having a preference for and willingness to pay higher price premiums for low carbon and water use footprints. The relative attribute importance (RAI) for the expressed choices, calculated as the ratio of the difference in the maximum and minimum utility associated with an attribute over the sum of the utility of all attributes is shown in Table 7 [2,47]. The RAI calculations indicate that potential risk to water quality is as important in consumers' decisions related to food purchases as carbon and water footprints. This is particularly pronounced among beef consumers. Weighting across the three classes of beef consumers, the RAI is highest for potential risk to water quality at 41%, followed by the price attribute at 28%, then carbon footprint and finally water use. While price is a relatively important product attribute, the risk to water quality is the most important environmental attribute driving consumers' choices. Combined, the price and risk to water quality attributes explain 69% of beef consumers' purchasing decisions. In the case of chicken, the RAI is highest for water use, with practically similar importance for all other attributes. In relation to consumers of vegetables, the RAI is highest for price at 44%, followed by water use footprint then carbon. The RAI statistics just mentioned are weighted across classes but there is considerable variation between classes. For example, in terms of price, RAI is 59% among class 1 beef consumers versus 12% among class 2. More generally, the RAI statistics illustrate the wide heterogeneity in preferences for environmentally sustainable attributes in food. While not universal, there are substantial consumer cohorts that are willing to pay a premium for sustainably produced food products, which includes the risk of water pollution, as well as carbon and water footprints. Consumers are not just concerned about the carbon footprint of their food but the wider sustainability of food production, which includes potential risks to water quality. The challenge for public policy is to develop a transparent, and verifiable labelling system so that consumers can be adequately informed in their food choice decisions at the point of purchase.

A hypothesis in our study is that personal values and beliefs associated with climate change are expected to amplify consumers' interpretation of footprint-labelled products, influencing their motivation to choose such products. This hypothesis is supported by our findings, in that consumers with strong personal values strongly align towards concern for environmental sustainability and climate change are more likely to choose food types labelled with lower footprints. They are likely to adjust their food consumption in line with the presence (or absence) of such environmental attributes. Prices of food products, although very important, do not appear to be a strong driver of preference for environmental attributes among a large share of the consumers in our sample. These findings complement a significant recent literature stream that has pointed out the significant positive relationship between individuals' ecological concern and environmentally conscious behaviour including those related to sustainable consumption (e.g., Refs. [2,6,10,13,40,48–51].

4.2. Policy implications of our findings on agri-food production systems

One of the important policy issues that arise from the analysis of this type is in relation to consumers' willingness to pay for environmentally sustainable food products in the entire agri-food sector. Specifically, would this understanding change farmers' production practices in the future and what role should the agri-food industry play in moving to more sustainably produced food products? It is important to note that consumer preference for sustainably produced food is not novel. In recent years organic food products have moved from niche to a minor though noticeable market share in response to popular media information regarding the health and environmental effects of food products produced using conventional practices [52,53]. The experience of the organic sector is relevant for developing policy support to improve the sustainability of food production in a financially viable manner. However, this research shows that preferences for sustainably produced food are not just a niche product and is distinct from organically produced food products. Over 60% of respondents in this study across the food types have preferences across environmental attributes and express potential willingness to pay a premium for such products. The challenge for food policy is to effectively translate this interest into actual purchasing behaviours. The extent to which this can be done may significantly impact farming and the agri-food industry, moving environmentally sustainable food products from niche to mainstream. Achieving such an outcome is not without significant challenges, including, challenges for consumers. The competing demands in relation to deciphering labelling information from nutrition, quality, and sustainability attributes may lead to information overload, an outcome of which may have a negative impact on actual purchase decisions [54,55].

The analysis presents a snapshot of preferences from autumn 2021, which was towards the end of an extended period (10+ years) of low price inflation in Ireland. The recent high inflationary period will impact consumers' purchasing decisions, especially where income growth doesn't match price growth. The extent to which these societal issues may impact purchasing decisions in relation to environmental sustainability attributes is not known from the current research. However, notwithstanding the change in the economic climate, it still remains that a substantial share of consumers is willing to pay a price premium for more environmentally sustainable products. It is also the case that the price remains a key decision attribute across a cohort of other consumers and a potential barrier for them.

There is evidence that the agri-food industry is already responding to consumer preferences on environmental sustainability. For example, in Ireland, the State agency responsible for supporting and enabling Ireland's food, drink and horticulture producers to sell their outputs worldwide, Bord Bia, has been at the forefront of policy efforts to develop a sustainable agri-food sector in Ireland. This is partly in recognition of the need to support climate change mitigation efforts within agriculture, as well as, increased awareness that consumers' preferences have been shifting towards more environmentally sustainable food choices. Bord Bia's Origin Green programme, for example, is striving to make the sector more environmentally sustainable and

Table 7
Relative (re-scaled) attribute importance (RAI).

	Beef				Chicken				Vegetable			
	RAI (%)				RAI (%)				RAI (%)			
	Class 1	Class 2	Class 3	Weighted avg.	Class 1	Class 2	Class 3	Weighted avg.	Class 1	Class 2	Class 3	Weighted avg.
Carbon footprint	5%	38%	0%	12%	37%	17%	20%	23%	19%	25%	17%	20%
Water use	27%	15%	14%	19%	6%	61%	30%	32%	18%	75%	0%	26%
Risk to water quality	9%	35%	71%	41%	27%	11%	30%	25%	9%	0%	17%	10%
Price	59%	12%	14%	28%	30%	11%	20%	20%	54%	0%	67%	44%
Class size	33%	27%	40%		22%	24%	54%		20%	30%	50%	

Note: RAI computed (re-scaled) for only environmental attributes and price (Vermunt and Magidson, 2005).

efficient, including developing a measurable food and drink sustainability programme across the supply chain (origingreen.ie). The Origin Green programme has developed meticulous initiatives on the supply side to improve sustainability metrics. In addition, Bord Bia is collaborating with the Irish agriculture and food development authority, Teagasc, to showcase and promote the uptake of environmentally friendly farm practices on farms via its Signpost Programme. However, the approach on the consumer or demand side has been broad-based via media campaigns to market the sustainability credentials of Irish food products. The evidence here suggests that there is broad market support for sustainably produced food, with a majority of consumers expressing preferences over environmental attributes. However, consumer preferences are quite heterogeneous so generic broad-based marketing campaigns may not be sufficient to enable consumers to make fully informed decisions consistent with their preferences on environmental attributes. Consumers potentially need product-specific sustainability information at the point of sale. Furthermore, whereas high price has traditionally been cited as a significant barrier for consumers purchasing environmentally sustainable products [56–58], the research findings here suggest that the barrier of high prices may be less severe than in the past. Nonetheless, consumers are unlikely to pay associated price premiums without verifiable product-specific sustainability information at the point of sale. There is already extensive work developing environmental labelling for food products [59,60] but this too should begin to encompass risks of water pollution from agricultural systems in addition to carbon and water footprints.

5. Conclusion and limitations

The objective of this study is to examine preferences for environmental attributes embedded in three food types — beef, chicken and vegetables; identify preference heterogeneity among consumer groups based on consumer characteristics including personal values/beliefs relating to sustainable consumption and climate change; and finally, estimate how much consumers are willing to pay for environmental attributes in the different food types.

Overall, we conclude that a majority of consumers express a preference for environmental sustainability attributes of food, though preferences vary across consumer cohorts and food types. Furthermore, we find that accounting for the personal values or beliefs of consumers, as opposed to socio-demographic factors, could contribute to a better understanding of consumer choice of sustainable food products. It is apparent that different segments of consumers exist and understanding what differentiates consumer segments, as well as drivers of sustainable consumption beyond traditional socio-demographic characteristics, would serve to support targeted climate change mitigation efforts, at least from a sustainable food consumption perspective. It may be more useful for public policy and marketing purposes to focus on behavioural and psychological biases when targeting sustainable consumption programmes and products. In line with prior empirical work, our results suggest that environmental labels can provide valuable information to enable consumers to choose food products consistent with their underlying preferences [2,14,40,61]. The policy implications of our results arise from the finding that consumer heterogeneity matters to a large extent in the context of food products labelled with environmental footprints in Ireland. Indeed, while many consumers would avoid environmentally unsustainable food choices, this is not true for approximately one-quarter of the respondents in our sample. Strategically targeting consumer segments with adequate messaging in relation to eco-labelling using a consumer-friendly, footprint labelling system will be useful in this regard. In addition, public policy-makers and industry leaders involved in sustainable food products and labelling may also be interested in our finding that consumers expressed concerns not just for carbon and water footprints but also about the potential risk of water pollution in the assessed food products. Nonetheless, as our results show, there is heterogeneity in consumer preferences for this attribute with regard to consumers' personal value systems. This also suggests a need for targeted communication and information dissemination to convey to consumers the environmental impacts of food production, particularly to those who may be less concerned with the sustainability status of the food they consume.

While the research is specific to Ireland, it is likely that broadly similar findings are applicable in other countries, particularly high-income, western countries such as those in Europe or North America. Cultural or food traditions may mean that the precise quantitative estimates presented here do not translate exactly to other countries but the broad result that a substantial share of consumers has preferences over the environmental sustainability attributes of food production will still be relevant. And also that there is likely to be considerable heterogeneity of preferences across consumer cohorts and food types.

As with all research, this study is not without certain limitations. First, the water quality attribute that we included in the labels was qualitative, though detailed explanations on how the attribute should be assessed were provided. Nonetheless, a quantitative measure in addition to the qualitative description might be better suited for this purpose. Therefore, further research can expand on this by including a quantitative measure of food production's impact on water quality as an attribute in food choice modelling. Secondly, as common with other discrete choice experiments, we could not include all possible factors that might influence consumers' food choices e.g., the origin of the food, nutritive qualities etc. This was purposeful as we wanted to reduce the cognitive burden on respondents when assessing each attribute and alternative as our focus was mainly on the water quality attribute. However, further research might expand the range of factors included to feature attributes not addressed in this present study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jafr.2022.100476.

Appendix A

Table A1
The MNL choice model estimates for the three food types

	Beef		Chicken		Vegetable	
	β	RAI	*β*	RAI	*β*	RAI
Carbon footprintrowhead						
Moderate	0.532***	4%	0.735***	52%	0.155**	3%
Low	0.512***		0.360***		−0.129	
Water userowhead						
Moderate	0.410***	22%	0.487***	9%	0.337***	26%
Low	0.290***		0.554***		−0.116	
Risk to water qualityrowhead						
Moderate	0.645***	30%	0.482***	1%	0.402***	42%
Low	0.814***		0.478***		−0.035	
Price	−0.249***	45%	−0.274***	38%	−0.251***	29%
ASC (“None”)	−1.275***		−1.190***		−1.687***	
LL	−3025.85		−3241.13		−3318.41	
BIC	6124.94		6556.12		6710.75	
Observation	9456		10,224		10,296	

Note: RAI = Relative attribute importance; ASC = Alternative specific constant.
RAI re-scaled for the environmental attributes and price only.
LL = Log likelihood; BIC = Bayesian information criterion.
***p<0.01, **p<0.05, *p<0.1.

Appendix B

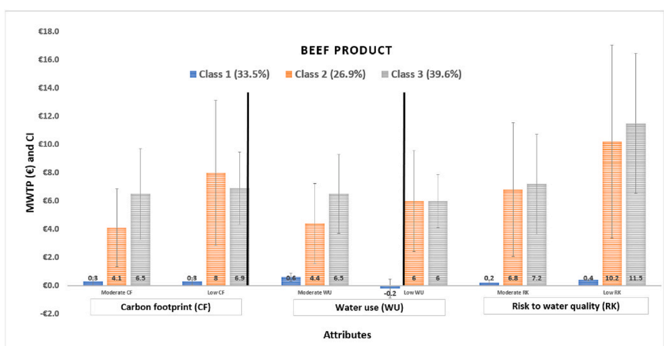

Fig. B1. Marginal WTP for different segments of beef consumers

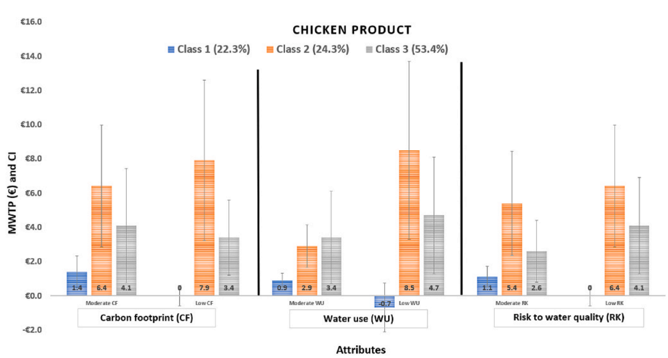

Fig. B2. Marginal WTP for different segments of chicken consumers

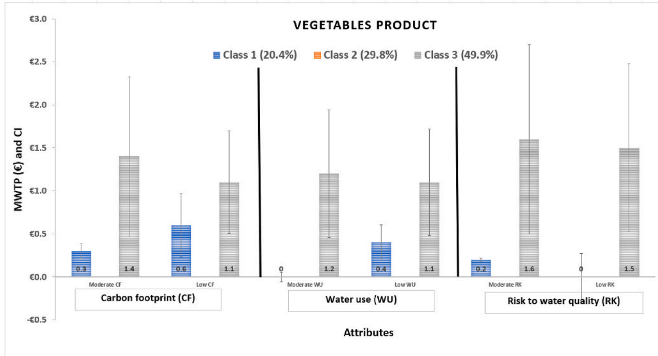

Fig. B3. Marginal WTP for different segments of vegetable consumers

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