Author Accepted Manuscript. Accepted for publication 30 September 2020

Please see published version in Journal of Cleaner Production.

Word count (including references) 9048

JCLEPRO-D-19-19694R2

How important is healthiness, carbon footprint and meat content when purchasing a ready meal? Evidence from a non-hypothetical discrete choice experiment.

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Abstract

Recent high-level reports state the population should decrease meat consumption to reduce greenhouse gas (GHG) emissions, as well as improve public health. This calls for new strategies to change dietary habits, especially as many consumers are reluctant to eat less meat. This study tests the effect of labelling a meat-based ready meal with different levels of carbon footprint and healthiness on consumers' willingness to pay (WTP) for these attributes. Participants took part in two sequential non-hypothetical discrete choice experiments (DCE). In the first experiment, they completed a DCE where the ready meals (i.e. beef lasagne) were labelled using a dual traffic light labelling system; one labelled for carbon footprint and one for healthiness. In the second experiment, participants repeated the DCE after they were told the carbon footprint and healthiness varied because of the meat and saturated fat content, respectively. The study found that participants were willing to pay a premium for the healthier lasagne and this did not change when they were given the information about saturated fat content. Participants were also willing to pay a premium for lasagne with a lower carbon footprint, but this decreased when they knew these meals contained less meat. Information about the meat content had the unintended consequence of discouraging people to buy lasagne with a low carbon footprint. The study provides an important insight for policy and industry into the effect of labelling information on consumers' purchasing decisions at a time when people are being encouraged to eat less meat.

Keywords: carbon footprint, meat, saturated fat, non-hypothetical discrete choice experiment, willingness to pay, sustainable diets.

Abbreviations: Discrete Choice Experiments (DCE), Becker-DeGroot-Marschak-based DCE (BDM-based DCE), greenhouse gas emission (GHGE), traffic light system (TLS), willingness to pay (WTP), marginal willingness to pay (mWTP), IPCC (International Panel on Climate Change), healthiness (HEA), carbon footprint (CF), environmental association (ENVIRO_ASSO), information about the meat and saturated fat content (INFO), expected taste of lasagne (TASTE).

Highlights:

- Consumers will pay a higher premium for healthier and lower carbon footprint meals.
- There is no clear preference for carbon footprint or healthiness in choosing a meal.
- Knowledge of the meat content reduces WTP for a meal with a lower carbon footprint.
- Reducing the saturated fat content of a meal is more acceptable than reducing meat.
- Expected tastiness influences the WTP for meals when the meat content is disclosed.

1. Introduction

Reducing consumption of animal-based food, especially meat, will be necessary to limit global warming. A recent International Panel on Climate Change (IPCC) report highlighted the importance of moving towards less meat intensive diets to reduce greenhouse gas (GHG) emissions and the pressures of agricultural production on natural resources, such as land, water and biodiversity (IPCC, 2019). Approximately 70% of agricultural land is used for livestock production and contributes approximately 14.5% of global GHG emissions (Gerber et al., 2013). While new technologies and improved livestock management systems will help reduce GHG emissions, this will not be enough to meet national and international emission reduction targets (Bajzelj et al., 2014). Consequently, consumers will have to make dietary changes, including eating less meat. Reducing high intakes of meat, especially red and processed, can also have health benefits, such as lowering the risk of cancers, such as colorectal cancer (WCRF, 2018). However, getting people to eat less meat presents a challenge for many reasons, not least because people enjoy eating meat and in high-income countries meat-based diets are considered the norm and therefore plays a strong cultural and social role (Sanchez-Sabate and Sabaté, 2019). Encouraging a reduction in meat consumption will require action across the food system and in many sectors, including policy and the food industry.

Increasing people’s knowledge about these issues allow them to make informed purchasing decisions (Aitken et al., 2020; Wong et al., 2020). Previous research shows a gap in consumer’s knowledge about the link between food consumption and climate change (Hartikainen et al., 2014; Camilleri et al., 2019), which is especially true in the case of eating meat (Wellesley and Froggatt, 2015; Macdiarmid et al., 2016). In contrast, consumers are generally aware of negative health consequence of eating a poor diet, but not necessarily that a high consumption of meat (particularly processed meat) increases the risk of some noncommunicable diseases, such as cancer (e.g. Mullee et al., 2017). Education alone is unlikely to change food habits but raising awareness of both the environmental impact and health risks associated with high intakes of meat is a necessary first step for dietary change.

Food labelling is a way to provide information at the point-of-purchase and is a policy strategy to change dietary habits endorsed by the World Health Organisation (WHO, 2004). The evidence for the effectiveness of food labelling on purchasing behaviour is mixed. Two recent meta-analyses, by Cecchini and Warin (2015) and Shangguan et al., (2019) suggest that food labelling could increase the purchase of healthier options and thereby improve dietary intakes (e.g. reducing total fat, saturated fat and salt consumption). A simple front-of-pack label is the traffic light system (TLS), which uses colour coding, red, amber and green, to signal the amount of key nutrients (i.e. fat, saturated fat, sugar and salt content) in a food item (FSA, 2013). The inclusion of multiple nutrients on the packaging can force consumers to make trade-offs between the nutrients when selecting a product. For example, Scarborough et al. (2015) asked consumers to choose from ready meals that differed in nutrient composition, finding they prioritised the options with a lower saturated fat and salt content over those with a lower total fat and sugar content. This research can be extended to understand trade-offs consumers make between health and the environment (e.g. carbon footprint) in making purchasing decisions, since healthier food does not necessarily have a lower carbon footprint (Macdiarmid, 2013). A research gap is understanding consumers' food purchasing decisions and trade-offs when presented with a dual labelling system. The findings provide important evidence for the development of policy interventions and for industry to change food purchasing behaviour. In this study non-hypothetical discrete choice experiments (DCE) were used to investigate the trade-offs people make when present with a dual labelling system, for health and climate change.

Discrete choice experiments are rooted in Lancaster's consumer theory (1966) which postulates that consumers do not derive utility from a good *per s*e, but from the attributes that characterise that good. It is this underpinning theoretical assumption that makes DCE an appropriate method to investigate trade-offs that consumers make between attributes of a given good. Therefore, DCE was selected in this study to investigate trade-offs consumers make between healthiness and carbon footprint of a ready meal.

These trade-offs were quantitatively explored eliciting preferences and estimating consumers' WTP for these attributes. Preferences are elicited by observing participants' choices among goods characterised by multiple attributes in several purchasing situations that are presented in the survey, assuming that participants always choose the good that maximize their utility. To assess preferences, DCEs are a more sophisticated evaluation of stated preference than other research methods, such as questionnaire surveys that use Likert scales to measure preferences for different attributes of a good. A limitation is that participants rate each attribute in isolation without having to make direct trade-offs between them (e.g. Aggarwal et al., 2016). In addition, participants' ratings cannot be easily included in standard economic models of consumer behaviour that are based on utility maximization (i.e. rational choice theory). Another alternative method to DCE is the contingent valuation method (CVM), a survey-based method that ask participants directly to state their WTP for a good or to make two or more choices in binary choice questions (e.g. YES/NO) to purchase the good at given prices. CVM elicits values for a good considered as a whole, without being able to elicit preferences and estimate WTPs for single attributes characterising the good. As our study aims to investigate trade-offs between attributes rather than simply between products, the use of DCE is more appropriate than CVM. In addition, CVM are less efficient than DCE from a statistical perspective because DCEs can increase the statistical efficiency of the parameters estimated so that smaller samples can be used (for a more detail, see Hensher et al., 2005). Two types of DCE exist; non-hypothetical and hypothetical DCE. A non-hypothetical DCE was used in this study. In non-hypothetical DCEs, participants have to purchase one of the goods they choose during the study, while in hypothetical DCE participants are only asked to express their intention to purchase a good and are not required to purchase one of the goods they selected during the experiment. It follows that participants in a hypothetical DCE have no financial incentive to reveal more truthful preferences. This phenomenon is called hypothetical bias, which often produces an overestimation of WTP compared to settings where real transactions occur (List and Gallet 2001; Murphy et al., 2005). Non-hypothetical DCE can minimize this bias, and, in theory, elicits truthful preferences and WTP (Gracia et al., 2011). Yet, non-hypothetical DCE have some of the limitations of hypothetical DCE and general state preference methods. For example, purchasing decisions made by respondents are made in isolation, while many other factors can affect food choices that are made in "real world" situations. These could include the composition of the food basket, the presence of substitutes, time constraints or choice environment (e.g. visibility of food options on the supermarket shelves). More reliable preferences and WTP can therefore be measured using revealed preference methods, using food purchasing data made by consumers in-store. However, it is not possible to study behaviour in-store for new products that are not yet available in the market. At the time of this study a dual traffic light system was not used to label food products in the United Kingdom (UK), and therefore non-hypothetical DCE becomes the most appropriate method to investigate consumers' response to this innovative labelling tool. While it was not possible to test the products in-store, we cooked the ready meals to match the labelling information for the participants to see during the study. Two versions of DCE were used to elicit WTP; a standard non-hypothetical DCE and a variation of the DCE method based on the Becker-De Groot-Marschak procedure (BDM-based DCE) (Richards et al., 2014; Palma et al. 2016).

We used non-hypothetical DCEs in a within-subject experimental design to test; i) consumers' WTP and trade-offs between the carbon footprint and healthiness of a meat-based ready meal and ii) whether providing additional information about the meat and saturated fat content of the ready meal changes participants' purchasing decisions. The ready meal was a beef lasagne, which is a commonly purchased ready meal in the UK. Each participant was exposed to two different experimental conditions in which participants were provided with different information about the attributes. In the first condition participants were asked to choose between ready meals with different levels of carbon footprint and healthiness. A dual TLS was used to indicate each attribute; healthiness and carbon footprint. In the second condition, participants repeated the same DCE after being told that the carbon footprint was varied by changing the amount of meat in the lasagne and the healthiness was varied by changing the saturated fat content.

This study fills two gaps in the literature. First, it is the first non-hypothetical DCE to study consumers' WTP and trade-offs between carbon footprint and healthiness of a meat-based ready meal. The majority of previous DCE studies have tested the effect of food labelling for either nutrition and health (e.g. Scarborough et al., 2015; Akaichi et al., 2019) or environmental sustainability, such as carbon footprint, organic, food miles, biodiversity (e.g. de-Magistris and Gracia, 2016; Lombardi et al., 2017; Tait et al., 2019; Caputo et al., 2013; Akaichi et al., 2017) on purchasing behaviour. Few studies that have investigated trade-offs between nutrition and environmental sustainability using a dual labelling system for meat-based products, with the exception of Koistinen et al. (2013), Apostolidis and McLeay (2019) and Akaiki et al. (2020). Koistinen et al. (2013) found that Finnish participants were willing to pay higher prices for low fat meat than for meat with a low carbon footprint. Similar results were found among meat eaters in the UK (Apostolidis and McLeay, 2019; Akaiki et al., 2020). The main limitation of these studies is that they used hypothetical DCEs, which they acknowledge may have introduced hypothetical bias and undermine the reliability of the estimated WTP. Therefore, using a non-hypothetical DCE in this study improves on these previous studies.

Second, our study examined whether the provision of additional information about the meat and saturated fat content changes participants' WTP for the carbon footprint and healthiness of a ready meal. Previous DCE studies have not explored whether consumers would change their purchasing decisions when told the reduction in the carbon footprint is achieved by reducing the meat content. Other studies have presented carbon footprint labels to consumers, but without any specific reference to how reductions in carbon footprint of the food product were achieved (Thøgersen and Nielsen, 2015; Tait, 2019). Some studies have explicitly or implicitly linked carbon footprint to non-food related attributes, such as to transportation, which do not have a direct consequence for the consumer (Caputo et al., 2013; Akaichi et al., 2017). It is important to understand how different types of information on food labels will influences consumers' purchasing decisions for meat-based products.

2. Material and Methods

2.1. Experimental design

The experimental design of the study consisted of two treatments. In one treatment participants completed a non-hypothetical DCE and in the other a non-hypothetical BDM-based DCE. Participants in the DCE treatment were exposed to two sequential experimental conditions. In the first experimental condition (named DCE TLS), they were presented with nine choice tasks. The order in which the choice tasks were presented was randomised across participants to mitigate potential learning or fatigue effects. Each choice task consisted of three options, comprising two different lasagne and an opt-out (buy nothing) (Fig. 1). Participants were asked to select their most preferred option.

The lasagne had three attributes: carbon footprint, healthiness and price. Two TLS were used, one to indicate the level of carbon footprint (represent as a footprint) and the other the healthiness (represented as a heart). Participants were told that a green footprint means low carbon footprint, amber footprint moderate carbon footprint and red footprint high carbon footprint, and similarly, a green heart means very healthy, amber heart moderately healthy and red heart unhealthy (see Fig 1). The price attribute had nine levels and ranged from £1.00 to £5.00 in £0.50 increments. This was the market price range for beef lasagne ready meals across UK supermarkets at the time of the study. The nine choice tasks were generated using a D-efficient design using software Ngene (Choice Metrics, 2011), which is a statistical procedure to minimise the standard errors of estimated coefficients and hence obtain the most efficient estimates. The use of D-efficient designs can also potentially reduce the sample sizes needed in DCEs (Scarpa and Rose, 2008a). Estimated prior coefficients from the pilot study were used to generate the final design.

In the second experimental condition (named DCE INFO), the same participants were asked to make choices using the same set of nine choice tasks presented in the DCE TLS experimental condition. The order of choice tasks was again randomised. Before making their choices, participants were given additional information that revealed the reason for the different levels of carbon footprint and healthiness. Participants were told that the carbon footprint reflected the meat content of the lasagne:

i) Red footprint: 77g of beef per portion

ii) Amber footprint: 49g of beef per portion

iii) Green footprint: 28g of beef per portion

Participants were told that healthiness reflected the amount of saturated fat in the lasagne:

i) Red heart: 23g saturated fat per portion

ii) Amber heart: 10g saturated fat per portion

iii) Green heart: 5g saturated fat per portion

The DCE was non-hypothetical, therefore participants were told that one of the 18 choice tasks would be randomly selected, and this would be revealed at the end of the experiment. They would have to buy the lasagne they chose in that choice task at the price that was indicated (if they had not chosen the opt-out). The choice task selected was the same for all participants.

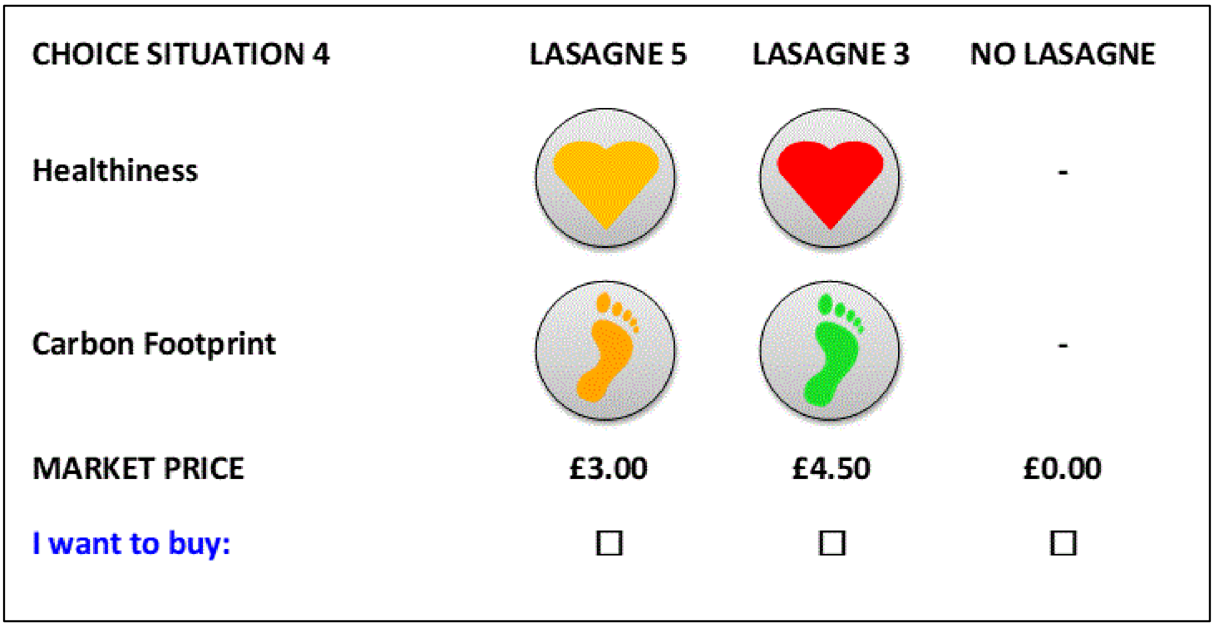

Fig 1. An example of one of the nine choice tasks.

In the BDM-based DCE treatment, participants were exposed to only the first experimental condition (BDM-based DCE TLS) and completed one set of nine choice tasks. This was the same set used in the DCE TLS experimental condition. Participants were not told about the meat and saturated fat content of the lasagne because the BDM-based DCE is more cognitively demanding than the DCE TLS and the cognitive burden of 18 choices was considered too high for participants.

The BDM-based DCE implies a different preference elicitation procedure compared to the DCE TLS. Like the DCE TLS, participants were told that a binding choice task would be randomly selected at the end of the experiment. However, participants in this treatment were informed that they would not have to buy the selected lasagne at the price indicated in the binding choice task but at a market price that would be randomly selected from a uniform distribution of prices (from £1.00 to £5.00 in £0.50 increments) at the end of the experiment. If the price of their chosen lasagne was higher than or equal to the randomly selected market price, participants had to buy the chosen lasagne at the randomly selected market price. Otherwise, they did not buy the chosen lasagne.

In all treatments and conditions, the nine lasagne (frozen) were shown to the participants during the experiment, but they did not taste them. This was to replicate a shopping environment where consumers are faced with a new product that they cannot taste before purchasing it. At the beginning of the experiment participants were asked about how hungry they felt, to test if hunger influenced their decision about the lasagne they chose. They rated their current level of hunger and how full they felt using a seven-point Likert scale. At the end of the experiment, they filled in a short questionnaire about their socio-demographic characteristics, consumption habits and other attitudinal variables (e.g. whether they were a member of an environment association (e.g. WWF, Greenpeace), frequency with which they ate lasagne). They also rated their expectation of the taste of each lasagne using a seven-point Likert scale, from tasting 'extremely bad' to tasting 'extremely good'. See the online supplementary Appendix A for variables included in the analyses.

2.2. Product development

The nine lasagne were designed by nutritionists and prepared by cooks at the Human Nutrition Unit at The Rowett Institute, University of Aberdeen. All the lasagne comprised the same ingredients; minced beef, tomatoes, tomato puree, onion, carrot, courgette, celery, peppers, beef stock, oil, milk or cream, butter or margarine, flour, lasagne sheets and cheese.

The carbon footprint and healthiness were varied by changing the quantity of these ingredients in each lasagne, mainly the amount of meat and by using high and low saturated fat versions of the same food item, respectively. A portion of lasagne weighed 400g. The lasagne were prepared and cooked by staff at The Rowett Institute then tested for tastiness, palatability and appearance. Where necessary the lasagne were remade using the same ingredients but varying the quantity, while maintaining the GHG emissions and nutrient criteria.

The levels of saturated fat content in the lasagne were based on the UK Food Standard Agency guidance; green ≤1.5g/100g, amber >1.5 to ≤5.0g/100g, red >5.0g/100g (FSA 2013). The carbon footprint was the sum of the GHG emissions (kgCO_2e) associated with each ingredient in the lasagne (GHG data published by Audsley et al. (2009)). The system boundaries for these data are from primary production to the point of the regional distribution centre. This does not include food processing, retail, household use and waste but these would be similar for all the lasagne because it was only the ingredients that varied. There are no standardised guidelines for labelling GHG emissions of food therefore the three levels were set by the researchers; green ≤0.26 kgCO_2e/100g, amber >0.26 to <0.4 kgCO_2e/100g, red ≥0.4 kgCO_2e/100g. The variation in beef content between the lasagne was within the range of commercially prepared lasagne (7% to 20% beef). The term 'carbon footprint' was a common term used by the public and used on some food packaging at the time of the study. In the pilot study, participants did not associate the meat content of the lasagne with the healthiness attribute and therefore we could assume participants' decisions related to the healthiness of the lasagne this was not influenced by the knowledge of the meat content.

2.3. Sample and data collection

Participants aged 18 years or older were recruited from the local area to allow face-to-face experiments. Every effort was made to recruit a representative sample based on socio-demographic characteristics by using a number of recruitment methods; posters placed in workplaces, including the University, community centres across the city and retail outlets, giving out flyers distributed at local community events (e.g. football match) and through snowball sampling. An information sheet was sent to people who contacted us and expressed an interest in the study, which stated that the purpose was to understand consumers' food choices (specifically a beef lasagne) and that they would have to buy one of the lasagne based on the choices they make in the experiment. All participants were given an unconditional £10 show up fee.

The study received ethical approval from The Rowett Institute Ethics Committee at the University of Aberdeen and all participants gave written informed consent to take part prior to the study. The experiment was conducted at the Scottish Experimental Economics Lab (University of Aberdeen) between January 2015 and April 2016, with between nine and 19 people per session.

One hundred and five participants completed the study, with 65 assigned randomly to the DCE treatment and 40 to the BDM-based DCE treatment. This sample size is typical for a non-hypothetical DCE for experiments and using a within-subject experimental design doubles the number of observations in the DCE treatment group (Akaichi et al., 2019). The minimum sample size to detect a significant result for the estimated coefficients ($p<0.05$) was 68, according to our D-efficient experimental design (calculated using the software Ngene) and therefore our sample size exceeded the minimum sample size (see the online supplementary Appendix B). The mean age of the participants was 36.5 years (range 19 to 70 years) and 57% were female. Forty four percent had a college diploma or an undergraduate degree and 34% had a postgraduate degree as their highest qualification. The mean household's total annual income was approximately £34,000. A comparison of the study population with the national and regional population is shown in Table 1. The mean age and proportion of females was similar, but the study sample comprised a higher proportion of participants with a higher educational level and total annual income.

Table 1 Characteristics of national, regional and study populations.

Variable	Description	National (Scotland)	Regional (Aberdeen City)	Study sample
FEMALE[a]	% Female	51.5%	50.5%	57.1%
AGE[a]	Age in years	40.3	40.4	36.5
EDU_1[a]	% with no education or primary or secondary education	49.9%	49.1%	22.1%
EDU_2[a]	% university degree	24.0%	23.9%	44.2%
EDU_3[a]	% postgraduate degree	26.1%	27.0%	33.7%
INCOME[b]	Annual total household income	£18,315	£22,000	£34,375

a Source: Scotland's Census, 2011 https://www.scotlandscensus.gov.uk/what-census
b Source: SG, 2017 https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome

2.4. Discrete choice modelling data analysis

Data from the experiment was modelled using Random Utility Models (McFadden, 1973). The utility (U) that participant i attaches to each alternative j in each choice task k ($U_{i,j,k}$) is split into two parts; $V_{i,j,k}$, the part of the utility observed by the researcher, and $\varepsilon_{i,j,k}$, which cannot be observed by the researcher, so that, $U_{i,j,k} = V_{i,j,k} + \varepsilon_{i,j,\mathrm{k}}$. Participants i chooses the alternative j that maximizes is utility $U_{i,j,k}$ in choice task k. More specifically, random parameter multinomial logit models were estimated in WTP space (with correlated coefficients) (Train and Weeks, 2005). Estimation in WTP space has several advantages with respect to standard estimation in preference space. First, it allows direct estimation of marginal WTP (mWTP) for different levels of carbon footprint and healthiness, which is the amount of money that participants are willing to pay for a unit improvement of a product (e.g. lasagne labelled amber rather than labelled red). Second, it reduces possible biases due to the confounding of variation in scale (i.e. the standard deviation of the unobserved part of the utility) and WTP (Train and Weeks, 2005). Many studies have shown that models in WTP space fit data are better than those in preference space (e.g. Scarpa et al., 2008b; Hole and Kolstad, 2012) and an estimation approach was recently adopted in studies investigating consumers' preferences for food products (e.g. Cerroni et al., 2019; Lin et al., 2019). A more extensive explanation of WTP space models and advantages with respect to preference space models are provided in the online supplementary Appendix C

2.4.1. Marginal willingness to pay for carbon footprint and healthiness

Participants' mWTP for different levels of carbon footprint and healthiness were estimated by pooling observations collected from the DCE TLS and BDM-based DCE TLS treatment groups. Pooling was possible because analyses indicated that mWTP elicited via DCE TLS and BDM-based DCE TLS were not statistically significantly different, suggesting that the two elicitation mechanisms are comparable. Results from these analyses are provided in the online supplementary material Appendix D.

The observed part of the utility ($V_{i,j,k}$) in the random parameter multinomial logit in WTP space (Model 1) is specified as in Equation 1:

$$V_{i,j,k} = -\lambda_{PRICE,i} PRICE_{i,j,k} + (\lambda_i \beta_{HEA\_AMBER,i}) HEA\_AMBER_{i,j,k} + (\lambda_i \beta_{HEA\_GREEN,i}) HEA\_GREEN_{i,j,k} + (\lambda_i \beta_{CF\_AMBER,i}) CF\_AMBER_{i,j,k} + (\lambda_i \beta_{CF\_G,i}) CF\_GREEN_{i,j,k} \quad (1)$$

where $\lambda_i = \alpha_i / \mu_i$, α_i indicates participants' preferences for the price of the lasagne ($PRICE_{i,j,k}$) and μ_i is the scale parameter (the standard deviation of the unobserved part of the utility, $\varepsilon_{i,j,k}$). The other coefficients indicate:

i) $\beta_{HEA\_AMBER,i}$ = mWTP for lasagne labelled amber for healthiness (HEA) (instead of red)

ii) $\beta_{HEA\_GREEN,i}$ = mWTP for lasagne labelled green for healthiness (HEA) (instead of red)

iii) $\beta_{CF\_AMBER,i}$ = mWTP for lasagne labelled amber for carbon footprint (CF) (instead of red)

iv) $\beta_{CF\_GREEN,i}$ = mWTP for lasagne labelled green for carbon footprint (CF) (instead of red)

To account for heterogeneity of preferences (i.e. participants may not have the same preference for an attribute level), it was assumed that the coefficients followed given distributions and estimated means and standard deviations of these distributions (Train, 2009). In other words, participants could have different preferences for the same attribute. It was assumed that the mWTP coefficients were normally distributed, while the α_i is log-normally distributed.

Model 2 explored the interaction effects of socio-demographic and attitudinal variables on mWTPs. The variables $HEA\_AMBER_{i,j,k}$, $HEA\_GREEN_{i,j,k}$, $CF\_AMBER_{i,j,k}$, and $CF\_GREEN_{i,j,k}$ were interacted with a rating of how *HUNGRY* participants felt before the experiment on a scale from 1 (not at all hungry) to 7 (extremely hungry), *FREQUENCY* (number of time per week they ate lasagne), *ENVIRO_ASSO* (1=member of an environmental association, 0=not a member), *FEMALE* (1=female, 0=male) and *INCOME* (household annual net income).[1] Models 1 and 2 were estimated by using methods of maximum simulated likelihood estimation (MSLE) relying on 1,000 Halton draws in STATA 13.1 (Train, 2009).

2.4.2. Marginal willingness to pay and additional information

Model 3 explored whether additional information about the meat and saturated fat content of the lasagne affected mWTP for lasagne varying in carbon footprint and healthiness, respectively. This was estimated using data collected from the DCE TLS and DCE INFO using a within-subject analysis. Model 3 (Equation 2) is the equivalent of Model 1 but includes a vector of interaction $X_{i,j,i}$ variables that shows the impact of the information

[1] Other variables were not included because of multicollinearity issues (see Appendix A Table A.2).

about meat and saturated fat on mWTPs for carbon footprint and healthiness, respectively. These interaction variables are: $HEA\_AMBER_{i,j,k} * INFO_i$, $HEA\_GREEN_{i,j,k} * INFO_i$, $CF\_AMBER_{i,j,k} * INFO_i$, and $CF\_GREEN_{i,j,k} * INFO_i$. The variable $INFO_i$ is equal to 1 when participant *i* was exposed to the additional information (and 0 otherwise). The coefficients of these interaction variables (B_i) indicate whether mWTPs differ before (e.g. $HEA\_AMBER_{i,j,k}$) and after participants received the additional information (e.g. $HEA\_AMBER_{i,,j,k} * INFO_i$).

$$V_{i,j,k} = -\lambda_{PRICE,i} PRICE_{i,j,k} + (\lambda_i \beta_{HEA\_AMBER,i}) HEA_{AMBER\,i,k,j} + (\lambda_i \beta_{HEA\_GREEN,i}) HEA_{GREEN\,i,k,j} + (\lambda_i \beta_{CF\_AMBER,i}) CF_{AMBER\,i,k,j} + (\lambda_i \beta_{CF\_GREEN,i}) CF_{GREEN\,i,k,j} + (\lambda_i B_i) X_{i,k,j} \quad (2)$$

Model 4 is an extension of Model 3 and examines if the participants' expected taste of the lasagne influenced the mWTPs. The variables $HEA\_AMBER_{i,j,k} * INFO_i$, $HEA\_GREEN_{i,j,k} * INFO_i$, $CF\_AMBER_{i,j,k} * INFO_i$, and $CF_GREEN_{i,j,k} * INFO_i$were interacted with the variable *TASTE. TASTE* is equal to 1, if participant *i* rated lasagne labelled red to be tastier than those labelled green or amber (otherwise is 0). Other socio-demographic and attitudinal variables (*ENVIRO_ASSO*, *FEMALE* and *INCOME)* were included in Model 4 using interaction terms. Models 3 and 4 were estimated by using methods of maximum simulated likelihood estimation (MSLE) relying on 1,000 Halton draws in STATA 13.1 (Train, 2009).

3. Results and discussion

3.1. Marginal willingness to pay for healthiness and carbon footprint

The results from Model 1 show that participants were willing to pay a higher premium for healthier lasagne; £1.47 and £0.84 more for those labelled green and amber than those labelled red, respectively (Table 2). A Wald test shows that the difference between green and amber was statistically significant ($\chi 2 = 14.700$, $p<0.01$), meaning that participants preferred lasagne labelled green over those labelled amber for healthiness. For the carbon footprint, participants were willing to pay a premium of £1.87 for lasagne labelled green over those labelled red, but they were not willing to pay a premium for lasagne labelled amber. Comparing healthiness to carbon footprint, participants were willing to pay significantly more for lasagne labelled amber for healthiness than for those labelled amber for carbon footprint (Wald test: $\chi 2 = 8.860$, $p<0.01$). Inversely, the mWTP was significantly higher for lasagne with the lowest carbon footprint (labelled green) than the healthiest lasagne (labelled green) (Wald test: $\chi 2 = 14.110$, $p<0.01$). This suggests that participants do not have a consistent preference for one attribute over the other. Distributions of estimated mWTPs are presented in Fig. 2. As a measure of reliability of the models, the results of the standard deviations of estimated coefficients' distributions in both models indicate that the assumption of normally distributed mWTPs is reasonable and plausible (Table 2).

Interestingly, participants do not have a consistent preference for one attribute over the other. This differs from previous studies that found consumers in Finland, Spain and the UK were willing to pay higher premiums for meat with low fat than a low carbon footprint (Koistinen et al., 2013; Apostolidis and McLeay, 2019; Akaiki et al., 2020). However, there is a five-year temporal gap between data collected by Koistinen et al. (2013) and our study, during which time public awareness about climate change has increased (Phillips et al., 2018), which may explain the WPT for products labelled with a lower carbon footprint. Another major difference is that these studies are hypothetical DCE, which can generate hypothetical bias.

Adjustments for the socio-demographic variables, gender and income were made in Model 2. A likelihood ratio test (Train, 2009) ($\chi 2 = 9.084$) indicates that Model 2 does not explain consumers' behaviour better than Model 1, but the estimation of Model 2 provides important results regarding the effects of these socio-demographic variables on participants' choice behaviour. The results showed that women were more concerned about health than men and were willing to pay higher premiums for lasagne labelled amber (£1.05) and green (£0.66) for the health attribute, with is in-line with results reported by Akaiki et al. (2020). It is also consistent with previous observations showing that women tend to be more willing to change their eating habits towards healthy diets and to follow dietary recommendations (e.g., Fagerli and Wandel, 1999).

There was no consistent difference in the mWTP for carbon footprint between men and women. Women had a higher mWTP for lasagne labelled amber in carbon footprint (£0.41) than men, but mWTP for lasagne labelled green in carbon footprint (-£0.27) was lower for women than men. A greater women's propensity towards sustainable food option than men is consistent with previous literature (e.g., Apostolidis & McLeay, 2019), but a recent study reported that the impact of gender on WTP for sustainable food is not as important as the impact of gender on WTP for healthier food options (Akaiki et al., 2020). Participants with a higher household annual income had a significantly higher mWTP for both healthier and lower carbon footprint lasagne than households with a lower income, but the premiums were small (<£0.05). Differences in responses between gender and income groups have implications for maximising effectiveness of a new labelling system since it could elicit a variety of responds in different sectors of the population. Future research needs to focus on the responses of different sectors of the populations to develop effective strategies and policies to reduce meat consumption through labelling.

Lastly, we found that the rating of participant's hunger before the experiment, the number of times they ate lasagne per week and being a member of an environmental association did not affect mWTP for the healthiness or carbon footprint of lasagne.

Table 2
Marginal WTP estimates from random parameter multinomial logit in WTP space

Variable	**Model 1** Coefficient Mean (robust standard error)	**Model 2** Coefficient Mean (robust standard error)
OPT-OUT	2.048*** (0.321)	3.339*** (0.424)
Health		
HEA_AMBER	0.844*** (0.125)	-0.368** (0.162)
HEA_GREEN	1.466*** (0.134)	0.360* (0.190)
Carbon footprint		
CF_AMBER	0.129 (0.110)	-0.199 (0.201)
CF_GREEN	1.873*** (0.168)	2.023*** (0.181)
Gender		
HEA_AMBER_FEMALE	-	1.046*** (0.171)
HEA_GREEN_FEMALE	-	0.655*** (0.190)
CF_AMBER_FEMALE	-	0.412** (0.162)
CF_GREEN_FEMALE	-	-0.266** (0.112)
Income		
HEA_AMBER_INCOME	-	0.006** (0.003)
HEA_GREEN_INCOME	-	0.045*** (0.003)
CF_AMBER_INCOME	-	0.008** (0.003)
CF_GREEN_INCOME	-	0.025*** (0.003)
PRICE	-0.649** (0.320)	-1.110*** (0.386)
	Standard deviation (robust standard error)	**Standard deviation** (robust standard error)
Health		
HEA_AMBER	1.109*** (0.133)	0.852*** (0.063)
HEA_GREEN	1.925*** (0.107)	2.138*** (0.112)
Carbon footprint		
CF_AMBER	1.072*** (0.216)	0.427*** (0.083)
CF_GREEN	1.886*** (0.181)	2.217*** (0.122)
PRICE	2.206*** (0.346)	2.258*** (0.371)
Observations	2,835	2,808
Log-Lhood	-692.084	-687.542

*p<0.1; **p<0.05; ***p<0.01;

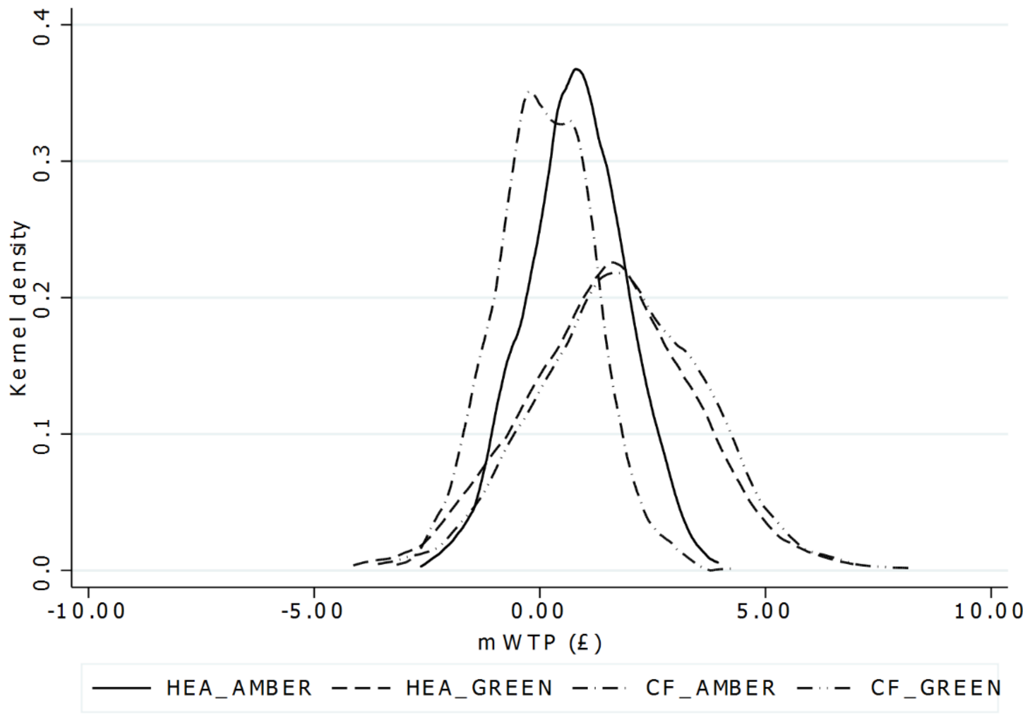

Fig. 2. Kernel densities of mWTPs for each attribute of the lasagne, when participants only have information about healthiness and carbon footprint (DCE TLS).

3.2. Marginal willingness to pay and additional information

Models 3 and 4 investigate the influence of providing additional information about the meat and saturated fat content of the lasagne on mWTP (Table 3). Results from Model 3 suggest that participants were more willing to accept a reduction in the saturated fat content than a reduction in the meat content of the lasagne. Given the information about the meat content of the lasagne, participants' mWTP for the lasagne with the lowest carbon footprint (labelled green) decreased by £0.84. In contrast, when they received the information about the saturated fat content, their mWTP for lasagne labelled amber for healthiness increased by £0.64. There was no significant effect of the additional information on the preference for lasagne labelled green for healthiness or amber for carbon footprint (Table 3). Distributions of estimated mWTPs are presented in Fig. 3. As a measure of reliability of the models, the results of the standard deviations of estimated coefficients' distributions in both models indicate that the assumption of normally distributed mWTPs is reasonable and plausible (Table 3).

The reduction observed in mWTP for the lower carbon footprint lasagne when participants were given the additional information about the meat content suggests they did not associate the carbon footprint in the first experimental condition with the meat content of the lasagne. The lack of awareness of the link between climate change and meat consumption was found in previous studies published around the time of the experiment (Hartikainen et al., 2014; Wellesley and Froggatt, 2015; Macdiarmid et al., 2016). The decrease in mWTP for lasagne with a lower meat content may have been expected because of a general reluctance among the UK general population to eat less meat. A recent survey reported that 55% of the British public had no intention of reducing their meat consumption (Lee and Simpson 2016). These findings are indicative of the value many people place on meat in their diet (Sanchez-Sabate and Sabaté, 2019). This study adds to the literature showing that consumers are willing to pay a premium for a meat-based meal labelled with a low the carbon footprint but not when the meal has less meat.

Model 4 does not explain consumers' behaviour better than Model 3 (likelihood ratio test $\chi 2 = 1.058$), but it shows important differences in the respond to labelling information by different groups. This is important for understanding the policy-relevant implications of a labelling system to inform purchasing decisions and changing dietary intakes to reduce meat consumption. Differences were found between women and men once they knew about the saturated fat content of the lasagne; women were willing to pay a higher premium for lasagne labelled amber for health (£0.56) (Model 4 in Table 3). This finding is consistent with results obtained from the estimation of Model 2. In contract, the effect of information about the meat content on mWTP for lasagne was equivalent for women and men, suggests that eating meat is equally important to them, consistent with observations reported in a previous study (Macdiarmid et al. 2016). However, more recent literature review found that women are generally more willing to decrease meat consumption than men (Sanchez-Sabate and Sabaté, 2019). The majority of data in the literature review came from self-reported from surveys, with no consequential food purchasing decisions, which may explain some of the difference in findings. Participants with higher household annual net incomes were willing to pay an extra premium for healthier lasagne, even when they knew the lasagne contain less saturated fat. This finding is consistent with results obtained from the estimation of Model 2. Being a member of an environmental consumer association had no effect on the mWTP.

Table 3
Impact of information on marginal WTP estimates from random parameter multinomial logit in WTP space.

	Model 3	Model 4
Variable	**Coefficient**	**Coefficient**
	Mean (Robust standard error)	**Mean** Robust standard error)
OPT-OUT	0.791** (0.384)	1.452*** (0.362)
Health		
HEA_AMBER	0.621*** (0.139)	0.602*** (0.108)
HEA_GREEN	0.977*** (0.175)	1.308*** (0.127)
Carbon footprint		
CF_AMBER	-0.006 (0.159)	0.432*** (0.111)
CF_GREEN	1.190*** (0.140)	0.942*** (0.125)
Additional information		
HEA_AMBER_INFO	0.642*** (0.168)	-0.509 (0.354)
HEA_GREEN_INFO	0.005 (0.147)	-0.225 (0.341)
CF_AMBER_INFO	0.005 (0.158)	0.116 (0.395)
CF_GREEN_INFO	-0.841*** (0.205)	-0.687 (0.458)
Expected taste of lasagne		
HEA_AMBER_INFO_TASTEHEA	-	0.185 (0.185)
HEA_GREEN_INFO_TASTEHEA	-	-0.252 (0.188)
CF_AMBER_INFO_TASTECF	-	0.489 (0.668)
CF_GREEN_INFO_TASTECF	-	-1.342* (0.706)
Member of environmental association		
HEA_AMBER_INFO_ENVIRO_ASSO	-	0.038 (0.524)
HEA_GREEN_INFO_ENVIRO_ASSO	-	1.122 (0.726)
CF_AMBER_INFO_ENVIRO_ASSO	-	0.881 (0.821)
CF_GREEN_INFO_ENVIRO_ASSO	-	-0.950 (0.976)
Gender		
HEA_AMBER_INFO_FEMALE	-	0.561* (0.318)
HEA_GREEN_INFO_FEMALE	-	0.216 (0.314)
CF_AMBER_INFO_FEMALE	-	-0.478 (0.320)
CF_GREEN_INFO_FEMALE	-	0.470 (0.389)
Income		
HEA_AMBER_INFO_INCOME	-	0.020*** (0.004)
HEA_GREEN_INFO_INCOME	-	0.004 (0.003)
CF_AMBER_INFO_INCOME	-	0.002 (0.005)
CF_GREEN_INFO_INCOME	-	- 0.008 (0.006)
PRICE	-0.344* (0.184)	-0.498** (0.212)
	Standard deviation (Robust standard error)	**Standard deviation** (Robust standard error)
Health		
HEA_AMBER	1.588*** (0.206)	0.617*** (0.051)

HEA_GREEN	0.942*** (0.081)	0.941*** (0.058)
Carbon footprint		
CF_AMBER	0.239** (0.107)	0.740*** (0.109)
CF_GREEN	0.970*** (0.140)	1.139*** (0.080)
Additional information		
HEA_AMBER_INFO	0.273*** (0.096)	0.337*** (0.095)
HEA_GREEN_INFO	0.073 (0.127)	0.388*** (0.084)
CF_AMBER_INFO	0.054 (0.094)	0.086*** (0.075)
CF_GREEN_INFO	0.344*** (0.096)	0.791 (0.085)
PRICE	1.358*** (0.199)	1.358*** (0.199)
Observations	3,510	3,510
Log-Lhood	-791.720	-791.191

**p*<0.1; ***p*<0.05; ****p*<0.01;

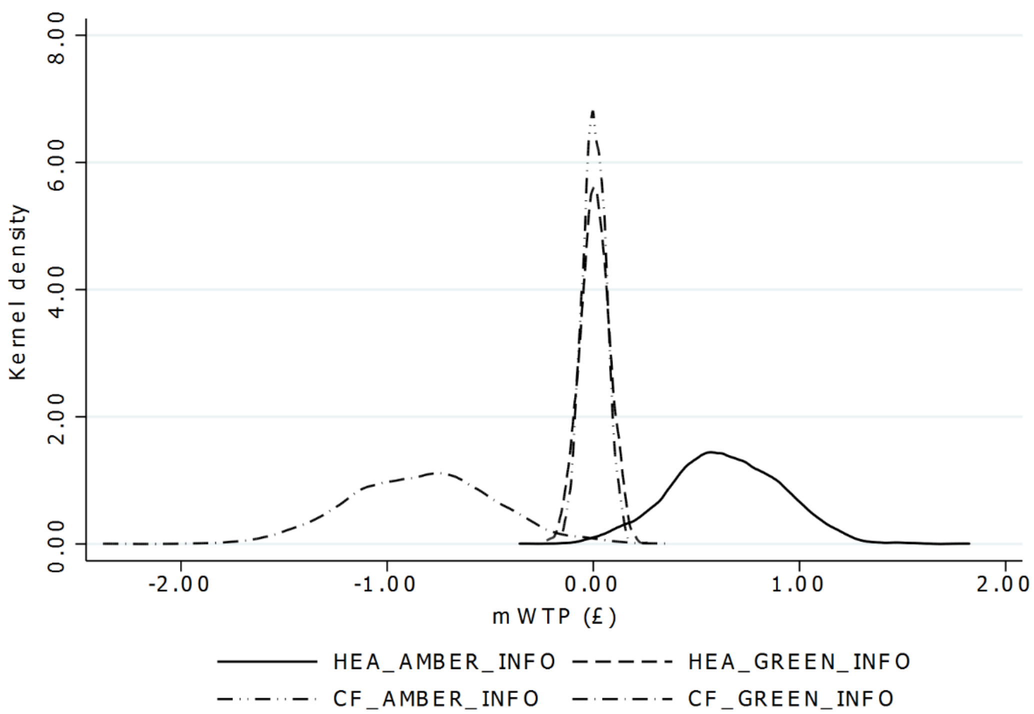

Fig. 3. Kernel densities of mWTPs for each attribute of the lasagne, when participants have the with additional information about the meat and saturated content (DCE INFO).

Results from Model 4 show that the expected taste of the lasagne significantly decreased participants' mWTP for lasagne with the least meat (-£1.34) (Table 3). This is in-line with previous studies reporting taste as one of the reasons people do not want to eat less meat (Whitmarsh, 2009, Macdiarmid et al., 2016, Graça et al. 2019). Fig. 4 shows participants expected the tastiness of the lasagne to increase with greater amounts of meat and saturated fat; rating the lasagne with the highest meat and highest saturated fat content (labelled red/red) as the tastiest of all the lasagne. However, the expected taste did not significantly influence the mWTP for healthiness despite the lasagne with higher saturated fat content being rated tastier (Fig 4).

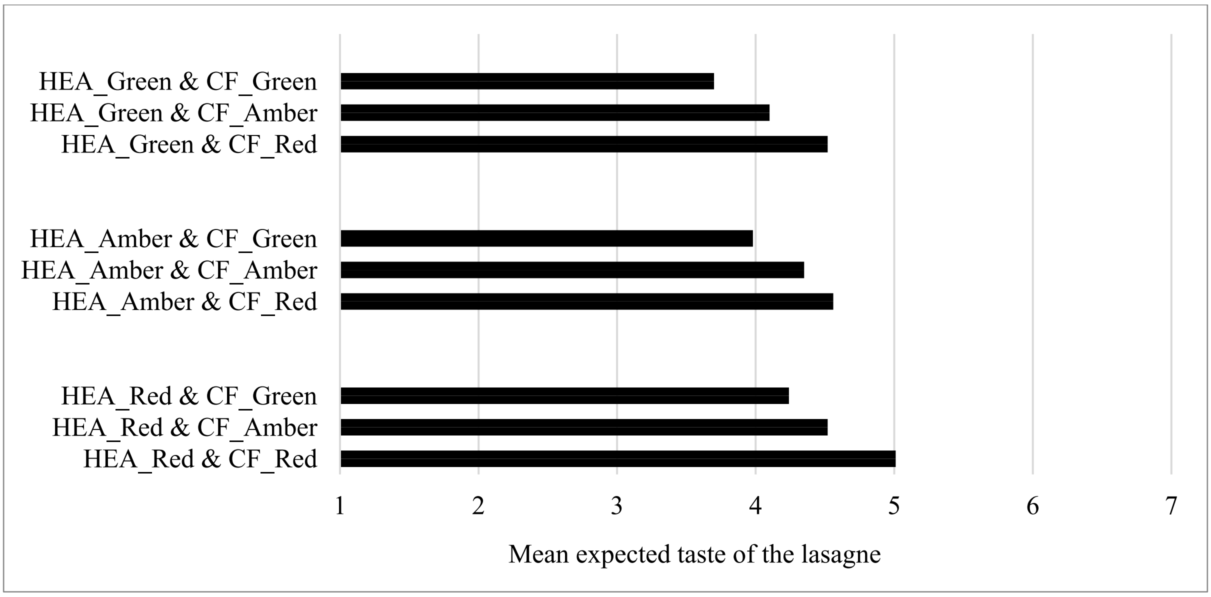

Fig. 4. The mean expected taste of each lasagne on a scale from extremely bad (1) to extremely good (7), CF = carbon footprint.

To test the internal validity of the results we compared participants' choice behaviour in two similar choice tasks. It would be expected the proportion of participants choosing the same options to be the same in the two choice tasks. This hypothesis was tested using the Cochran's Q test and failed to reject the null hypothesis of equality of proportions, suggesting high internal validity and supports the reliability of our findings (see on-line supplementary material in Appendix E). In addition, the correlations between variables elicited in the final questionnaire completed by participants was investigated. These results show that the direction of the expected associations was observed in the data (see Appendix A, Table A.2).

The findings of this study have important implications for the information used on front-of-pack food labelling. While the non-hypothetical nature of the DCE is a significant strength of this study, there are some limitations that should to be considered. First, the participants were not recruited from a random sample within the population, rather we used a wide range of strategies in an attempt to recruit a representative sample of the population. The proportion of women to men and the mean age of the sample were similar to population averages, but there was a greater representation of participants with a high level of educational attainment and household income. Studies have suggested that attitudes towards reducing meat consumption is similar across income groups and the national survey the UK shows there is very little difference in the amount of meat purchased and saturated fat consumed between income groups (Reynolds et al. 2019). However, we have to consider that cost is one of the most important factors shaping food purchasing decisions and it is often perceived as a main barrier to the buying healthier and more environmentally sustainable products. Given that the average annual household total income of the participants is slightly higher than the general population, the WTP estimated in this study may be slightly inflated. Second, the sample size was relatively small compared to hypothetical DCE, but the size is not unusual for a non-hypothetical economic experiment using a within-subject design. The sample size is higher than the estimate of the sample size needed to detect a significant result. Overall, some caution would be needed in extrapolating the finding to a wider population.

There are several areas where the research could be taken forward. The aim of the study was to mimic a real purchasing situation where consumers had to make a decision based only on the appearance and information about a new ready meal. Future studies could explore other reasons for participants' purchasing decisions. In addition, while meat and saturated fat are good proxies for carbon footprint and healthiness, respectively, varying other ingredients or nutrients could elicit different preferences.

4. Conclusions

Recent reports, including the IPCC (2019), highlight the need to eat less meat. This study provides an important and timely insight into the potential effectiveness of front-of-pack labelling to tackle both climate change and health. In this case, making information about the meat content more explicit than carbon footprint had the unintended consequence of inhibiting purchasing of a more environmentally sustainable meal. This is important for both the food industry and governments in finding ways to motivate consumers to change their diet.

The study makes two important contributions to the literature. First, it the first non-hypothetical DCE study to examine consumers' trade-offs between healthiness and carbon footprint of a meat-based ready meal, where participants had to make purchasing decisions involving real payments. This tends to elicit truthful preferences and reduces the tendency of participants to overstate the value of a good seen in hypothetical choice scenarios (e.g. Murphy et al., 2005). Second, the observation of the effect of information about the meat and saturated fat content on purchasing decisions. Using a within-subject design we were able to test how people might change their mind about purchasing a good when given information about the meat content. Previous DCE studies have not explicitly link carbon footprint labels to specific strategy to reduce GHG emissions through dietary change that have direct personal consequences or investigated how consumers may change their decisions (Thøgersen and Nielsen, 2016; Tait, 2019; Caputo et al., 2013; Akaichi et al., 2017). This study provides important evidence for the potential use of front-of-pack labels to encourage people to purchase healthier food products with a low carbon footprint.

Acknowledgments

The authors would like to thank Sylvia Stephen for help in creating recipes for lasagnes and the cooks at the Human Nutrition Unit at The Rowett Institute for preparing them. Thanks go to Professor Mandy Ryan for her comments on an early version of the manuscript.

The authors have no conflict of interest to disclose.

Funding: This study was funded by the Scottish Government's Rural and Environment Science and Analytical Services Division (RESAS).

References

Aggarwal, A., Rehm, C.D., Monsivais, P., Drewnowski, A., 2016. Importance of taste, nutrition, cost and convenience in relation to diet quality: Evidence of nutrition resilience among US adults using National Health and Nutrition Examination Survey (NHANES) 2007–2010. Prev. Med. 90, 184–192. https://doi.org/10.1016/j.ypmed.2016.06.030

Aitken, R., Watkins, L., Williams, J., Kean, A., 2020. The positive role of labelling on consumers' perceived behavioural control and intention to purchase organic food. J. Clean. Prod. 225(10), 120334. https://doi.org/10.1016/j.jclepro.2020.120334

Akaichi, F., Glenk, K., Revoredo-Giha, C., 2019. Could animal welfare claims and nutritional information boost the demand for organic meat? Evidence from non-hypothetical experimental auctions. J. Clean. Prod. 207, 961-970. https://doi.org/10.1016/j.jclepro.2018.10.064

Akaichi, F., Nayga Jr., R.M., Nalley, L.L., 2017. Are there trade-offs in valuation with respect to greenhouse gas emissions, origin and food miles attributes? Eur. Rev. Agric. Econ. 44(1), 3–31. https://doi.org/10.1093/erae/jbw008

Apostolidis, C., McLeay, F., 2019. To meat or not to meat? Comparing empowered meat consumers' and anti-consumers' preferences for sustainability labels. Food Qual. Prefer. 77, 109-122. https://doi.org/10.1016/j.foodqual.2019.04.008

Audsley, E., Brander, M., Chatterton, J.C., Murphy-Bokern, D., Webster, C., Williams, A.G., 2009. How Low Can We Go? An assessment of greenhouse gas emissions from the UK food system and the scope for reduction by 2050. WWF-UK. http://dspace.lib.cranfield.ac.uk/handle/1826/6503

Bajzelj B., Richards, K.S., Allwood, J.M., Smith, P., Dennis, J.S., Curmi, E. et al., 2014. Importance of food-demand management for climate mitigation. Nat. Clim. Change 4(10), 924-929. https://doi.org/10.1038/nclimate2353

Camilleri, A.R., Larrick, R.P., Hossain, S., Patino-Echeverri, D., 2019. Consumers underestimate the emissions associated with food but are aided by labels. Nat. Clim. Change 9, 53–58. https://doi.org/10.1038/s41558-018-0354-z

Caputo, V., Nayga Jr, R.M., Scarpa, R., 2013. Food miles or carbon emissions? Exploring labelling preference for food transport footprint with a stated choice study. Aust. J. Agric. Res. Econ. 57(4), 465-482. https://doi.org/10.1111/1467-8489.12014

Cecchini, M., Warin, L., 2015. Impact of food labelling systems on food choices and eating behaviours: a systematic review and meta-analysis of randomized studies. Obes. Rev. 17(3), 201-210. https://doi.org/10.1111/obr.12364

Cerroni, S., Watson, V., Kalentakis, D., Macdiarmid, J.I., 2019. Value-elicitation and value-formation properties of discrete choice experiment and experimental auctions. Eur. Rev. Agric. Econ. 46(1), 3–27. https://doi.org/10.1093/erae/jby014

ChoiceMetrics, 2011. Ngene 1.1 User manual and reference guide. http://www.choice-metrics.com/download.html (accessed 23 November 2015) de-Magistris, T., Gracia, A., 2016. Consumers' willingness-to-pay for sustainable food products: the case of organically and locally grown almonds in Spain. J. Clean. Prod. 118, 97-104. https://doi.org/10.1016/j.jclepro.2016.01.050

Fagerli, R. A., Wandel, M, 1999. Gender differences in opinions and practices with regard to a 'healthy diet'. Appetite, 32 (2) 171-190 https://doi.org/10.1006/appe.1998.0188

Food Standards Agency, 2013. Guide to creating a front of pack (FoP) nutrition label for pre-packed products sold through retail outlets. https://www.food.gov.uk/sites/default/files/media/document/fop-guidance_0.pdf (accessed 30 October 2019).

Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J. et al., 2013. Tackling climate change through livestock – A global assessment of emissions and mitigation opportunities. Food and Agriculture Organization of the United Nations (FAO), Rome. http://www.fao.org/3/a-i3437e.pdf (accessed 30 October 2019).

Graça, J., Godinho, C.A., Truningera, M., 2019. Reducing meat consumption and following plant-based diets: Current evidence and future directions to inform integrated transitions. Trends Food Sci. Technol. 91, 380-390. https://doi.org/10.1016/j.tifs.2019.07.046

Gracia, A., Loureiro, M.L., Nayga Jr., R.M.., 2011. Are Valuations from Nonhypothetical Choice Experiments Different from Those of Experimental Auctions? Am. J. Agric. Econ. 93(5), 1358-1373. https://doi.org/10.1093/ajae/aar054

Hartikainen, H., Roininen, T., Katajajuuri, J.-M., Pulkkinen, H., 2014. Finnish consumer perceptions of carbon footprints and carbon labelling of food products. J. Clean. Prod. 73(15), 285-293. https://doi.org/10.1016/j.jclepro.2013.09.018

Hensher, D.A., Rose, J.M., Greene, W.H., 2005. Applied choice analysis: a primer. Cambridge University Press: New York.

Hole, A.R., Kolstad, J.R., 2012. Mixed logit estimation of willingness to pay distributions: a comparison of models in preference and WTP space using data from a health-related choice experiment. Empir. Econ. 42, 445–469. https://doi.org/10.1007/s00181-011-0500-1

Intergovernmental Panel on Climate Change, 2019. Climate Change and Land, an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. https://www.ipcc.ch/2019/08/08/land-is-a-critical-resource_srccl/ (accessed 20 October 2019).

Koistinen, L., Pouta, E, Heikkilä, J., Forsman-Hugg, S., Kotro, J., Mäkelä, J. et al., 2013. The impact of fat content, production methods and carbon footprint information on consumer preferences for minced meat. Food Qual. Prefer. 29, 126–136. https://doi.org/10.1016/j.foodqual.2013.03.007

Lancaster, K.J., 1966. A New Approach to Consumer Theory. J. Political Econ. 74(2), 132–157.

Lee, L., Simpson, P., 2014 Are we eating less meat? A British Social Attitudes report. NatCen Social Research. http://natcen.ac.uk/media/1116002/vegetarian-society-bsa-2014.pdf (accessed 22 October 2019).

Lin, W., Ortega, D.L., Caputo, V., 2019. Are Ex-Ante Hypothetical Bias Calibration Methods Context Dependent? Evidence from Online Food Shoppers in China. J. Cons. Aff. Affairs, 520–544. https://doi.org/10.1111/joca.12202

List, J.A., Gallet, C.A., 2001. What Experimental Protocol Influence Disparities between Actual and Hypothetical Stated Values? Environ. Res. Econ. 20(3), 241-54. https://doi.org/10.1023/A:1012791822804

Lombardi, G.V., Berni, R., Rocchi, B., 2017. Environmental friendly food. Choice experiment to assess consumer's attitude toward “climate neutral” milk: the role of communication. J. Clean. Prod. 142(1), 257-262. https://doi.org/10.1016/j.jclepro.2016.05.125

Macdiarmid, J.I., Douglas, F., Campbell, J., 2016. Eating like there's no tomorrow: Public awareness of the environmental impact of food and reluctance to eat less meat as part of a sustainable diet. Appetite 96, 487-93. https://doi.org/10.1016/j.appet.2015.10.011

Macdiarmid J.I. 2013. Is a healthy diet an environmentally sustainable diet? Proceeding Nutrition Society 72, 1, 13–20. https://doi.org/10.1017/S0029665112002893

McFadden, D., 1973. Conditional logit analysis of qualitative choice behaviour, in: Zarembka P., (Eds.). Frontiers in Econometrics. Academic Press, New York, pp. 105-142.

Mullee, A., Vermeire, L., Vanaelst, B., Mullie, P., Deriemaeker, P., Leenaert, T. et al., 2017. Vegetarianism and meat consumption: A comparison of attitudes and beliefs between vegetarian, semi-vegetarian, and omnivorous subjects in Belgium. Appetite 114(1), 299-305. https://doi.org/10.1016/j.appet.2017.03.052

Murphy, J.J., Allen, P.G., Stevens, T.H., Weatherhead, D., 2005. A Meta-analysis of Hypothetical Bias in Stated Preference Valuation. Environ. Res. Econ. 30(3), 313-25. https://doi.org/10.1007/s10640-004-3332-z

Palma, M.A., Behe, B.K., Hall, C.R., Huddleston, P. T., Fernandez, T., 2016. Tracking position premiums in discrete choice experiments. Appl. Econ. Lett., 1269-1273. https://doi.org/10.1080/13504851.2016.1150941

Phillips, D., Curtice, J., Phillips, M., Perry, J., 2018. British Social Attitudes: The 35th Report, The National Centre for Social Research, London. https://www.bsa.natcen.ac.uk/media/39284/bsa35_full-report.pdf (accessed 20 December 2019)

Reynolds, C.J., Horgan, G.W., Whybrow, S., Macdiarmid, J.I., 2019 Healthy and sustainable diets that meet greenhouse gas emissions reduction targets and are affordable for different income groups in the UK. Public Health Nutrition 22(8):1503-1517. https://doi.org/10.10017/S136898003774

Richards, T.J., Hamilton, S.F., Allender, W.J., 2014. Social Networks and New Product Choice. Am. J. Agric. Econ. 96 (2), 489–516. https://doi.org/10.1093/ajae/aat116

Sanchez-Sabate, R., Sabaté, J., 2019. Consumer Attitudes Towards Environmental Concerns of Meat Consumption: A Systematic Review. Int. J. Environ. Res. Public Health. 16(7), 1220, https://doi.org/10.3390/ijerph16071220

Scarborough, P., Matthews, A., Eyles, H., Kaur, A., Hodgkins, C., Raats. M. et al., 2015. Reds are more important than greens: how UK supermarket shoppers use the different information on a traffic light nutrition label in a choice experiment. Int. J. Behav. Nutr. Phys. Act. 12, 151, https://doi.org/10.1186/s12966-015-0319-9

Scarpa, R., Rose J.M., 2008a. Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why. Aust. J. Agric. Res. Econ. 52, 253–282. https://doi.org/10.1111/j.1467-8489.2007.00436.x

Scarpa, R., Thiene, M., Train, K., 2008b. Utility in WTP space: a tool to address confounding random scale effects in destination choice to the Alps. Am. J. Agric. Econ. 90(4), 994-1010. https://doi.org/10.1111/j.1467-8276.2008.01155.x

Shangguan, S., Afshin, A., Shulkin, M., Ma, W., Marsden, D., Smith, J. et al., 2019. A Meta-Analysis of Food Labeling Effects on Consumer Diet Behaviors and Industry Practices. Am. J. Prev. Med. 56(2), 300-314. https://doi.org/10.1016/j.amepre.2018.09.024

Tait, P., Saunders, C., Dalziel, P., Rutherford, P., Driver, T., Guenther, M., 2019. Estimating wine consumer preferences for sustainability attributes: A discrete choice experiment of Californian Sauvignon blanc purchasers. J. Clean. Prod. 233(1), 412-420. https://doi.org/10.1016/j.jclepro.2019.06.076

Thøgersen, J., Nielsen, K.S., 2015. A better carbon footprint label. J. Clean. Prod. 125, 86-94. https://doi.org/10.1016/j.jclepro.2016.03.098

Train, K., 2009. Discrete Choice Methods with Simulation, second ed. University Press, Cambridge.

Train, K., Weeks, M., 2005. Discrete Choice Models in Preference Space and Willingness-to-Pay Space, in: Scarpa, R., Alberini, A. (Eds.), Applications of Simulation Methods in Environmental and Resource Economics, Springer, Dordrecht, pp. 1-16.

Wellesley, L., Froggatt, A., 2015. Changing Climate, Changing Diets: Pathways to Lower Meat Consumption. https://www.chathamhouse.org/publication/changing-climate-changing-diets (accessed 15 October 2019).

Whitmarsh, L., 2009. What's in a name? Commonalities and differences in public understanding of “climate change” and “global warming”. Pub. Underst. Sc. 18(4), 401-20. https://doi.org/10.1177/0963662506073088

World Cancer Research Fund, 2018. Diet, nutrition, physical activity and cancer: a global perspective. The third Expert Report. https://www.wcrf.org/dietandcancer (accessed 12 October 2019).

World Health Organisation. 2004. Global Strategy on Diet, Physical Activity and Health. https://www.who.int/nmh/wha/59/dpas/en/ (accessed 22 October 2019).

Wong, E.Y.C., Chan, F.F.Y., So, S., 2020. Consumer perceptions on product carbon footprints and carbon labels of beverage merchandise in Hong Kong. J. Clean. Prod. 242(1), 118404, https://doi.org/10.1016/j.jclepro.2019.118404