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Combining stated and revealed preferences for valuing attributes associated with organic chicken meat

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Abstract

This paper examines consumer willingness to pay (WTP) for attributes of organic chicken meat in the UK, a product experiencing increasing popularity both domestically and internationally. We combine stated preference (SP) data from a discrete choice experiment with revealed preference (RP) data from supermarket scanner transactions in a joint estimation framework. This approach mitigates common limitations of analysing SP and RP data separately, such as hypothetical bias in SP and multicollinearity in RP. Using a heteroskedastic conditional logit model with interaction terms, we estimate WTP values that account for both preference heterogeneity and scale differences across datasets. Results indicate that consumers assign a substantial premium to the organic attribute, with joint estimates approximately 9 per cent higher than those based solely on SP data and more than double those from RP. These findings underscore the importance of integrating SP and RP data to inform evidence-based food policy.

Keywords: choice experiments; revealed preferences; stated preferences; joint estimation; organic food.

JEL classification: C25, Q18, Q51

1. Introduction

Over the past two decades, poultry consumption has nearly doubled worldwide, with most countries experiencing a linear growth in per capita consumption.[1] In the UK, chicken is the only type of meat that has seen increased

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1 https://www.poultryworld.net/poultry/

consumption over this period.[2] Within this category, organic chicken meat consumption has been rising exponentially in many countries, including the UK.[3]

Some of the reasons behind this growth include the fact that organic meat, characterized by a grass-rich diet, tends to be leaner, higher in antioxidants and richer in omega-3 fatty acids, contributing to its perceived health and taste benefits (Średnicka-Tober *et al.*, 2016; Vigar *et al.*, 2019). Thus, organic chicken is perceived to taste better while promoting higher animal welfare and environmental sustainability (e.g. Katt and Meixner, 2020; Ditlevsen *et al.*, 2020; Aweke, 2025). In the UK, organic certification (overseen by the Soil Association) ensures that animals are raised under free range conditions, fed organically and treated with antibiotics only when necessary (Jelliffe *et al.*, 2023). Hughes (2025) noted that in the UK, consumers are increasingly willing to invest in products that align with health, sustainability and quality. They are becoming more interested not only in their own health but also in the wellbeing of the community and the environment. Organic food and drink sales have risen in the past year, driven not only by inflation but also by a 4.6 per cent increase in unit sales.

The present paper makes two significant contributions to the literature. First, it provides insights into the valuation of various attributes associated with organic chicken (i.e. reducing the information gap about organic chicken). Second, it offers methodological advancements that improve the understanding and analysis of these attributes.

Regarding the reduction of the information gap about organic attributes, this study analyses consumer preferences for specific attributes usually associated with organic. Understanding how consumers value the various attributes of organic chicken meat is important for designing effective marketing strategies. Identifying the most valued attributes allows producers, supermarkets and other retailers to focus their efforts on enhancing and promoting these qualities. Despite the growing importance of organic chicken, valuation studies on consumers' willingness to pay (WTP) for its attributes remain limited and often use stated preference (SP) data, potentially suffering from hypothetical bias (e.g. Van Loo *et al.*, 2014; Thuannadee and Noosuwan, 2025). The present study estimates not only the WTP for the attribute 'organic' but also the WTP for other attributes typically associated with organic products, such as environmentally friendly production and animal welfare. Studies related to organic chicken often focus solely on the WTP for the attribute 'organic' and do not estimate the WTP for other related attributes (e.g. Van Loo *et al.*, 2011; Thuannadee and Noosuwan, 2025). However, estimating the WTP for these attributes is important because these other attributes might be relevant for consumers interested in purchasing organic chicken.

In addition, in a broader sense, this paper contributes to understanding the various motives behind purchasing organic meat. Although many studies have

2 https://www.fao.org/statistics/en/
3 https://www.organicdatanetwork.net/

analysed motives for purchasing organic food, the literature appears to lack a focus on organic meat.[4] This has been recognized as an important gap in the literature that we seek to address in the present paper (Aweke, 2025).

In terms of methodological contribution, the paper applies a joint estimation framework that integrates SP and RP data while accounting for preference heterogeneity, thereby improving the robustness and external validity of the results. The revealed preference (RP) data is scanner data from a UK panel sourced from Kantar Worldpanel, and the SP data stems from a choice experiment (CE). The joint dataset includes up to 66,994 observations. This combined approach addresses the limitations inherent in both methods, such as the hypothetical bias of SP techniques and the attribute correlation issues in RP methods.[5]

The literature indicates that estimates of consumers' WTP using either dataset type have limitations. SP methods have been criticized for hypothetical bias, where consumers may overstate or understate their preferences (Cummings, 1986; Cummings and Taylor, 1999; Hausman, 2012; Whitehead *et al.*, 2012; Mitchell *et al.*, 2013; Penn *et al.*, 2018; Gschwandtner and Burton, 2020). Conversely, RP methods face challenges such as heteroskedasticity and multicollinearity among attributes, complicating the estimation of WTP for individual attributes. Additionally, endogeneity can be a problem (Wooldridge, 1996; Combris *et al.*, 1997; Bishop *et al.*, 2011; Ribeiro *et al.*, 2024). Combining the two methods makes it possible to take advantage of the strengths and reduce the weaknesses of both.

While some studies combine revealed scanner data with stated data from CEs, there are still only a limited number of studies using this approach in the food literature (e.g. Brooks and Lusk, 2010). The use of the joint dataset also allows for the comparison of different WTP estimates, using each dataset independently and in combination. Together, our results show that consumers are willing to pay more for the organic attribute when datasets are combined, 9 per cent more than in the SP case and 139 per cent more than in the RP case.

A second methodological contribution is the use of a heteroskedastic conditional logit (CLHet) model with interaction terms between individual and alternative-specific variables, a state-of-the-art discrete choice model. This approach allows for simultaneous relaxation of assumptions related to inter-alternative error structures, the accommodation of scale heterogeneity across data sources, and explicit modelling of systematic taste heterogeneity. These are features not jointly addressed in much of the prior SP-RP literature.

4 There are few exceptions but often these studies do not estimate WTPs (e.g. Revoredo-Giha and Gschwandtner, 2021).

5 To estimate the WTP, this paper took advantage of the availability of a SP survey from 2016, which was matched with a representative RP data for the same period. Although the data were collected eight years ago, it is believed that the exercise provides useful results for two reasons: first, the WTP estimates provide a figure for a relatively normal year (for example, 2016 compared to 2020–21, which were affected by the Covid-19 pandemic, and 2021–23, when the inflationary period generated by the Ukraine-Russia conflict affected consumer decisions). Second, and probably more importantly, the data allows a comparison of WTP estimates using each data set and one that combines both types of data, using a state-of-the-art discrete choice model (CLHet with interactions).

A third methodological contribution of this paper is the clear and replicable procedure for constructing RP choice sets that align with the structure of SP tasks—an area often overlooked or treated ambiguously in the literature. By filtering scanner panel data to reflect discrete household choices, defining product availability based on store week observations across households, and incorporating a behaviourally grounded status quo (SQ) option (no purchase), the paper offers a practical guide for harmonizing SP and RP data. This approach improves the internal consistency of joint models and addresses a gap in empirical guidance for combining these data sources. Therefore, the present paper contributes to the literature in terms of product (organic chicken meat), data (combined SP and RP) and method (joint estimation using CLHet).

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature, focusing on studies most closely related to this research. Section 3 describes the econometric models and datasets used, including SP and RP data. Section 4 presents joint estimation results, compares them with individual SP and RP results, and discusses WTP estimates for policy evaluations. Finally, Section 5 concludes with a short discussion of the implications of the study.

2. Background literature

While there have been a number of RP and SP joint estimation applications in other literatures, notably in marketing and transportation where joint estimation is rooted (e.g. Ben-Akiva *et al.*, 1994; Swait *et al.*, 1994; Hensher *et al.*, 1998; Ellickson *et al.*, 2019), in the economic food literature only a few studies have estimated RP and SP data separately to assess validity (e.g. Brookshire *et al.*, 1982; Griffith *et al.*, 2008; Gschwandtner, 2018), and to our knowledge, there is only one study that conducts a full joint estimation (Brooks and Lusk, 2010). Most existing research relies exclusively on SP data, particularly discrete CEs (see Caputo and Scarpa, 2022; Lizin *et al.*, 2022 for recent reviews), while some studies use RP data such as scanner data (e.g. Schulz *et al.*, 2012; Staudigel *et al.*, 2022; Ribeiro *et al.*, 2024). This study uses a joint estimation approach to assess consumer WTP for organic chicken and other related labels.

Studies have consistently found that consumers are willing to pay premiums for organic labels and have also found evidence of premiums for labels usually associated with organic. Some studies have highlighted consumer concerns related to the use of antibiotics and hormones, focusing on human health and food safety (e.g. McEachern *et al.*, 2004; Yiridoe *et al.*, 2005; Loureiro and Umberger, 2007; Wier *et al.*, 2008; Naspetti *et al.*, 2009; Gschwandtner, 2018; Awake, 2025).

However, consumers are also increasingly concerned about the environmental impact of food and show interest in attributes and labels related to environmentally friendly production, local sourcing, country of origin, traceability, carbon footprint and prescribed grazing (e.g. Caputo *et al.*, 2013a, b;

Zanoli *et al.*, 2013; Li *et al.*, 2016; Jensen *et al.*, 2019; Ditlevsen *et al.*, 2020; Katt and Meixner, 2020; Kilders *et al.*, 2024; Aweke, 2025).

Another important category of sustainability claims relates to farming systems, such as free range and animal welfare labels, animal friendliness and gene editing with a focus on animal welfare (McEachern *et al.*, 2004; Carlsson *et al.*, 2007; Zander *et al.*, 2010; Lagerkvist *et al.*, 2011; Vanhonacker *et al.*, 2014; Jensen *et al.*, 2019; Kilders *et al.*, 2021). However, only few studies have specifically evaluated consumer preferences for animal welfare in chicken production (Carlsson *et al.*, 2005; Pouta *et al.*, 2010; Campbell *et al.*, 2013; Van Loo *et al.*, 2014).

'Quality' is an attribute often associated with organic products, although it is not always clear what exactly this encompasses. Consumers tend to believe that organic products possess several attributes that contribute to higher quality. In some cases, they even prefer the 'Quality' attribute over the organic label itself (Gschwandtner and Burton, 2020). Other studies have also identified 'Quality' as an important attribute related to organic food, but these do not specifically refer to meat or chicken meat (Griffith *et al.*, 2008; Guenther *et al.*, 2015).

When it comes to organic meat, most studies analyse preferences for beef, which is not surprising given that beef is one of the most consumed meat types, especially in the form of hamburgers in the US, Canada and the UK. For example, of the 28 studies analysed in Cicia *et al.* (2010), 18 focus on beef, 8 on pork and only 3 on poultry. More recent studies specifically about preferences for chicken or poultry meat appear to be relatively rare (Van Loo *et al.*, 2011, 2014; Gschwandtner and Burton, 2020; Thunnadee and Noosuwan, 2025; Aweke, 2025).

These studies usually find that consumers are willing to pay significant premiums for environmental or ethical attributes associated with organic meat, such as animal welfare and environmentally friendly production, or for the organic label itself. However, there is often a gap between the premium consumers state they are willing to pay and what they actually pay in supermarkets, due to the hypothetical nature of the studies. For instance, Gschwandtner and Burton (2020) show that implementing mechanisms to correct for hypothetical bias has a significant impact, reducing WTP values to as low as 46 per cent of what they would have been without such treatment. The fact that recent studies analysing consumer preferences for organic meat might suffer from hypothetical bias has been acknowledged as a potential limitation of the literature that the present study seeks to address (Thuannadee and Noosuwan, 2025).

Given the significant increase in poultry consumption, particularly chicken meat, over the last decades, the relative scarcity of studies analysing preferences for this type of meat constitutes a gap in the food literature. As already mentioned, the focus on organic meat and on organic chicken specifically appears to be missing. The present paper aims to address this limitation and fill this gap.

The present study uses part of the same SP dataset as Gschwandtner and Burton (2020) but has a completely different focus. While Gschwandtner and Burton (2020) concentrate on hypothetical bias treatments and estimation, the present study combines the SP chicken data from that study with RP data from Kantar from the same year to estimate a joint SP/RP model for attributes related to organic chicken meat.

In terms of methodology, Brooks and Lusk (2010) is the closest to the present study. The authors combined scanner purchase data with responses from a CE to estimate the WTP for cloned milk, a product unavailable at grocery stores. They demonstrated that combining revealed scanner data with stated data from the CE leads to better out of sample prediction performance than using either dataset alone. The results using pooled data indicated that US consumers were willing to pay more than three times the amount for organic milk to avoid milk from cloned cows.

Our research is similar in spirit to their study but aims to validate their results regarding the method in a different context, namely, that of organic chicken meat. To the best of our knowledge, there have been no combined SP-RP evaluations of chicken meat. As the study by Brooks *et al.* (2010) points out, one of the advantages of joint estimation is that it helps determine whether survey-based choices are consistent with people's revealed preferences, as indicated by scanner data. This is especially important given the identified hypothetical bias concerning credence attributes in organic products (e.g. Wier *et al.*, 2008; Whitehead *et al.*, 2010; Gschwandtner and Burton, 2020; Haghani *et al.*, 2021). Combining people's stated preferences from survey answers with RP data from actual market transactions helps achieve a fuller and more accurate picture of consumer preferences.

Another advantage of joint estimation, as highlighted in the Brooks and Lusk (2010) study, is that in revealed data, attributes are often correlated with each other, making it difficult to isolate the effect of a specific attribute. Joining revealed data with stated data is useful because the process of collecting stated data is fully under the control of the researcher. This ensures that price changes are uncorrelated with other variables of interest, making it easier to determine the effect and calculate the WTP for a specific attribute. As Von Haefen *et al.* (2008) argued, SP data provides a means of econometrically identifying parameters that would be confounded using RP data alone. The authors have shown how combining SP and RP data can address the multicollinearity and endogeneity problems present in RP data.

As described by Hensher (2010), one of the biggest disadvantages of RP data is that it usually does not include the 'no buy' alternative, as only prices for purchased items are observed. Combining revealed data with SP data makes it possible to incorporate such a 'no buy' alternative and understand why people do not purchase a specific product. By using a joint SP and RP estimation with the advantages mentioned above, the present paper addresses another important limitation in the food literature.[6]

A final trend that can be identified by examining food literature related to preferences for meat is that the number of studies from the US appears to be much larger than the number of studies from other countries, including Europe. There is a comparatively larger number of studies from smaller Nordic countries such as Denmark, Norway, the Netherlands and Sweden in Europe. This is probably due to the long-standing tradition these countries have in human and corporate social responsibility (Anselmsson and Johansson, 2007; Anselmsson *et al.*, 2014; Ditlevsen *et al.*, 2020; Aweke, 2025). However, the number of studies from Europe still lags behind those from the US. Given the strong emphasis now placed in Europe on sustainability and on organic production specifically, this is another shortcoming that the present study seeks to address.

Our study advances the literature by being the first to estimate the WTP for attributes related to organic chicken meat using a joint stated and revealed preference estimation approach. This method is expected to provide more accurate estimates of consumer preferences for chicken meat attributes, such as organic and related attributes, compared to existing studies. Furthermore, our use of the heteroskedastic conditional logit model offers advantages over previously employed methods for joint estimation, further enhancing the reliability of our results. Recent literature on organic food has recognized that integrating market data with survey-based approaches can offer deeper insights into the main drivers of organic product consumption (Aweke, 2025). This is the key focus of our present study.

3. Empirical analysis

This section describes the empirical models used in the estimation, including the strategy followed to integrate SP and RP data into a joint framework. Discrete choice models are widely used to analyse how individuals make choices among alternatives that differ across multiple attributes, allowing researchers to estimate the marginal utility of specific attributes and their influence on choice probabilities under the assumption of utility-maximizing behaviour (McFadden, 1973; Train, 2009). Two discrete choice models are used in the present paper: the conditional logit (CLogit) and the heteroskedastic conditional logit (CLHet) with the joint estimation of the scale parameter. Section 3.1 presents the CLogit, which provides a baseline estimation of attribute-level preferences, followed by the CLHet model that accounts for preference heterogeneity and scale differences between the SP and RP datasets. This modelling strategy improves comparability across data sources

6 There is a significant body of literature on RP and SP joint estimations, particularly in the fields of marketing and transportation (e.g. Ben-Akiva and Morikawa, 1990; Ben-Akiva *et al.*, 1994; Swait *et al.*, 1994; Hensher *et al.*, 1998; Feit *et al.*, 2010; Ellickson *et al.*, 2019) as well as environmental economics (e.g. Adamowicz *et al.*, 1994; Whitehead *et al.*, 2008; Chen *et al.*, 2019; Whitehead and Lew, 2020). In contrast, the number of similar studies in the food literature is very limited.

and enables more accurate estimation of WTP by addressing scale heterogeneity.

Discrete choice models analyse consumer choices and the WTP for key attributes, testing hypotheses about factors influencing consumer preferences and the monetary valuation of these attributes. A particular focus is placed on the role of sociodemographic variables in affecting choice and WTP. By incorporating interactions between socioeconomic variables and product attributes, the analysis moves beyond the homogeneity assumption of the conditional logit model and allows for heterogeneity. The hypothesis tested is that joint RP and SP estimation yields more accurate parameter estimates and WTP values. Previous research, such as Carson *et al.* (1996), has shown that RP and SP methods, despite differing estimation approaches, are grounded in common preferences, making joint estimation feasible and potentially valid. Phaneuf *et al.* (2013) also demonstrated that the baseline marginal WTP derived from SP aligns with the marginal implicit price of attributes in RP, which is underpinned by random utility theory. In the following subsections, we briefly discuss the two models CLogit and CLHet used in our application.

3.1 Conditional logit model

The conditional logit (CLogit) model, introduced by McFadden (1973), is a widely used discrete choice model for analysing how individuals make selections among a set of alternatives that differ in observed characteristics. Unlike the multinomial logit (MNL), which models choices based on characteristics of individuals X_i, the CLogit allows for variation in choices driven by alternative-specific attributes (Z_{ij}), and how they influence choice probabilities. This is particularly suitable for the present study, where product attributes such as ‘Organic’, ‘Animal Welfare’ or ‘Price’ vary across options.

Under the random utility maximization, the utility U_{ij} that individual i derives from alternative j is composed of an observable component V_{ij} and an unobserved stochastic term ε_{ij}:

$$U_{ij} \; = \; V_{ij} \; + \varepsilon_{ij}. \tag{1}$$

The deterministic component is typically specified as a linear function of the observed attributes: $V_{ij} = Z_{ij}\alpha$, where α is a vector of parameters to be estimated. The model assumes consumers choose the alternative that yields the highest utility U, in line with the random utility maximization framework (McFadden, 1973).

Assuming that the error terms ε_{ij} are independent and identically distributed, the probability P that individual i chooses alternative j from set J_i is:

$$P_{ij} = \frac{\exp\left(Z_{ij}\alpha\right)}{\sum_{m=1}^{j} \exp\left(Z_{im}\alpha\right)}, \; m \in J_i. \tag{2}$$

While the CLogit model captures preferences for observed attributes, it imposes independence of irrelevant alternatives (IIA) property, which assumes proportional substitution across alternatives and assumes independent error terms. This may be restrictive, particularly when alternatives are similar and may share unobserved attributes (see Hoffman *et al.*, 1988; Phanikumar *et al.*, 2007).

To account for preference heterogeneity, the model is extended by including interaction terms between product attributes (Z_{ij}) and individual-specific characteristics (X_i). This approach allows the marginal utility of an attribute to vary across individuals.[7] Similarly to Cushing (2008), the modified choice probability is given by:

$$P_{ij} = \frac{\exp\left(Z_{ij}\alpha \ + Z_{ij}.\ X_i\beta\right)}{\sum_{m\in J_i} \exp\ (Z_{im}\alpha \ + \ Z_{im}.\ X_i\beta)}. \tag{3}$$

Here, β captures the differential impact of individual characteristics on the valuation of attributes. For example, the interactions *Price x Income* would allow price sensitivity to differ by income group. If $\beta = 0$, the model simplifies to Equation (2), reverting to a homogeneous preference structure.

In addition, the model includes an opt-out option, termed ‘status quo’ (SQ) in our CE, following Whitehead *et al.* (2008). This third alternative represents the choice of ‘none of the above’ in both SP and RP data and improves behavioural validity in the choice tasks, allowing respondents to express a preference for no purchase and thereby better reflecting actual decision-making. In the CLogit framework, the SQ alternative is included by assigning zero values to all product attribute dummies and retaining only individual-specific variables. Incorporating the SQ option avoids forced choices and ensures more accurate estimation of WTP.

3.2 Heteroskedastic conditional logit and scale parameter (joint estimation)

Combining the stated and revealed data into a joint model introduces challenges such as scale heterogeneity and, in some cases, state dependence.[8] However, unlike traditional joint estimations that survey the same individuals for both RP and SP data, the samples in this study are independent, so the main focus lies on correcting for scale differences between datasets.

Scale differences arise because the variance of the unobserved component of utility typically differs between SP and RP data. In SP surveys, the struc-

7 To ensure the robustness of the findings, the original analysis in the study also tested a mixed logit model. This was primarily done to address critiques of the IIA assumptions and to verify whether the CLogit model with interaction terms effectively addressed these concerns. However, a limitation arises from the random allocation of attributes to the choices, resulting in no specific attributes being linked to particular choices or groups of attributes. Alternative 1 in the mixed logit model lacks fixed attributes, preventing an analysis of how consumer attributes influence choice probability.

8 State dependence in survey data refers to the phenomenon where a respondent’s answer to a current question is influenced by their previous answer to a related question. A scale difference between two datasets means that the ranges of values between the two sets are vastly different, even if they are measuring the same concept.

tured experimental setting often encourages respondents to evaluate trade-offs more systematically, which reduces error variance. These differences can be explicitly modelled by introducing a scale parameter μ, which is inversely related to the variance of the error term (see Vass *et al.*, 2018):

$$\sigma^2_{\epsilon_{i,j}} = \frac{\prod^2}{6\mu}. \tag{4}$$

The heteroskedastic conditional logit (CLHet) model extends the basic conditional logit by allowing the scale parameter to vary across individuals. Normalizing the utility scale and incorporating μ into the choice probability yields:

$$P_{ij} = \frac{\exp\left(\mu V_{i,j}\right)}{\sum_{m\in J_i} \exp\left(\mu V_{i,m}\right)}. \tag{5}$$

To capture individual-level heterogeneity in scale, μ_i is modelled as a function of observable characteristics $X_{i\gamma}$, where γ is a vector of parameters that incorporates the effect of individuals on the scale parameter (following Hole *et al.*, 2006):

$$\mu_i = \exp\left(X_{i\gamma}\right). \tag{6}$$

Substituting this into the utility function gives

$$P_{ij} = \frac{\exp\left(\mu_i \beta Z_{ij}\right)}{\sum_{j=1}^{J} \exp\left(\mu_i \beta Z_{ij}\right)}. \tag{7}$$

In this formulation, the numerator $\exp(\mu_i \beta Z_{ij})$ represents the utility associated with alternative j for individual i, where μ_i captures individual-level scale heterogeneity. As previously specified, μ_i is a function of individual characteristics $X_{i\gamma}$, allowing the error variance to differ across respondents. This structure reflects how personal traits influence the relative weight given to each attribute in the choice process, β is a vector of coefficients associated with the product attributes Z_{ij}, which vary across alternatives. The denominator sums the exponentiated utilities of all alternatives available to individual i, ensuring that the probabilities across all alternatives sum to one. In the CLHet model, the $\exp(X_{i\gamma})$ treats μ_i as positive for all individuals and collapses to the conditional logit model when $\gamma = 0$.

The CLHet framework also relaxes the independence of IIA assumption by allowing for heterogeneous scales. This is particularly relevant in SP-RP combinations, where contextual and informational differences across datasets may otherwise lead to biased estimates. In addition, the model includes interaction terms between product attributes and individual characteristics to account for systematic preference heterogeneity.

While joint estimation studies often rely on MNL or nested logit models, the CLHet specification is more appropriate here due to its ability to model continuous heterogeneity in scale and taste parameters, both of which are central to this study's objectives. Finally, while more general models such as those correcting for attribute non-attendance (ANA) have recently gained popularity (e.g. Hindsley *et al.*, 2021), they were not implemented in the current study. Given the randomization of attribute ordering in the SP design, applying ANA would require discarding a large number of observations, which could substantially reduce statistical power. Nonetheless, such models offer promising avenues for future research.

4. Data description

This section provides an overview of the SP and RP datasets utilized in this paper. Detailed summaries of the data are provided in the tables referenced within this section, which can be found below.

4.1 SP data and consumer behaviour

The SP data was collected in April 2016 via an online survey conducted by a professional market research firm. All procedures performed in the research were by the ethical standards of the 1964 Helsinki Declaration and its later amendments, ensuring respect for individuals, informed consent, careful risk benefit analysis and protection of privacy and confidentiality. The background information of the survey provided the participants with all the necessary information on the nature, purpose and process of the project, as well as contact details of the research team. The questionnaire did not record any personal data, and all data was anonymous. Information about this, taken directly from the survey, can be found in Fig. A1 in the Appendix. The survey, lasting approximately 30 minutes, included responses from 505 households across the UK and consisted of four sections:

1. **Recalled purchases:** Questions about the respondent's purchasing behaviour over the previous week, including details on quantity, price, attribute labels, quality and purchase locations.
2. **Warm-up questions:** These were combined with hypothetical bias treatments, such as:
   - **Cheap talk:** A script emphasizing the need for realistic responses, including a budget constraint reminder.
   - **Honesty priming:** Exercises prompting truthful responses by priming honesty through true/false statements. Four treatment combinations were randomly assigned to participants: 'Cheap Talk' + 'Honesty Priming', 'Cheap Talk' only, 'Honesty Priming' only and 'No Treatment' (control).

These two measures aimed to reduce potential hypothetical bias (Cummings and Taylor, 1999; Carlsson *et al.*, 2005; Jacquemet *et al.*, 2011; Tonsor *et al.*, 2011; De-Magistris *et al.*, 2013). A more detailed description of the CE and hypothetical bias treatments used in the CE and their impact can be found in Gschwandtner and Burton (2020).

3. **Choice experiment (CE):** Respondents completed a series of choice tasks using unlabeled designs with three alternatives per card (Options A, B or a SQ Option C). Attributes included various levels for price, organic certification, chemical usage, environmental friendliness, quality and animal welfare. A description of the attributes and their levels can be found in Fig. A2 and Table A1 in the Appendix. The choice questions were generated using a fractional factorial D-optimal design, following the procedure illustrated by Street *et al.* (2005).
4. **Sociodemographics and attitudes:** Information on socioeconomic characteristics, lifestyle choices and perceptions related to organic food, the environment, health and happiness.

The attributes selected for this CE were deliberately chosen to reflect key factors influencing consumer preferences for organic products. These attributes were identified based on literature and market analysis, ensuring their relevance to the decision-making process for the average UK shopper. For instance, the inclusion of 'Organic', which inherently covers low chemical usage and environmentally friendly practices, aligns with consumer concerns about sustainability and food safety. Similarly, the 'Environmental Friendliness' and 'Animal Welfare' attributes address the growing consumer demand for ethical and sustainable farming practices. The inclusion of the 'Eco Friendly' and 'Freedom Food' logos aims to enhance clarity and relevance, as these symbols are familiar within the UK market.

The 'Quality' attribute was incorporated to capture perceptions of premium branding and superior product quality, as supported by prior research (e.g. Griffith *et al.*, 2008; Guenther *et al.*, 2015). Price levels, ranging from realistic market values to a "choke price" of £10/400 g, were selected to balance feasibility with the need to identify consumer thresholds. This design allows for the assessment of price sensitivity and WTP for organic and associated attributes. By limiting most attributes to two levels and using a D-optimal fractional factorial design, the complexity of the choice tasks was minimized, ensuring that respondents could make informed decisions within the survey's 30-minute duration. An example of a choice card can be found in Fig. A3 in the Appendix.

The CE provided the study with an average of eight rounds of choice cards, resulting in 12,120 observations ($505 \times 8 \times 3 = 12{,}120$). Key sociodemographic statistics are presented in Table 1 below. These include 60 per cent female respondents and 67 per cent married; on average, respondents were 50 years old, had just below one child per household, had 13.5 years of education, and a net income of £2,454 per month.

Compared with UK demographics, these figures differ in several characteristics. This is not surprising because these variables refer exclusively to the household member responsible for grocery shopping. Many studies show that the main shoppers are mostly adult women, thus shifting age and years in education upwards (Lea *et al.*, 2005; Arbindra *et al.*, 2005; Stobbelaar *et al.*, 2007).

Table 1. Summary statistics SP data: individuals ($N = 505$).

Variable	Description	Mean	Std. Dev.	Min.	Max.
Female	=1 if gender is female	0.602	0.49	0	1
Age	Age of respondent	50.447	15.636	18	80
Married	=1 if respondent is married	0.667	0.472	0	1
Children	Number of children in household	0.614	0.98	0	6
Vegetarian	=1 if respondent is vegetarian	0.044	0.204	0	1
Education	< High school to professional degree	3.782	1.589	1	8
High education	=1 if respondent has higher education	0.392	0.489	0	1
Income	Net Income	2,454	1,918	250	10,500
High income	Income > UK average (£2,336[a])	0.251	0.434	0	1
Professional	Occupation as professional	0.206	0.405	0	1
Services	Occupation in service industry	0.051	0.221	0	1
Sales	Occupation in sales	0.087	0.282	0	1
Farmer	Occupation as farmer	0.002	0.044	0	1
Construction	Occupation in construction	0.016	0.125	0	1
Transports	Occupation in transport	0.028	0.164	0	1
Government	Occupation in government	0.024	0.152	0	1
Retired	Respondent is retired	0.269	0.444	0	1
Other	Occupation other than above	0.190	0.393	0	1
Unemployed	Respondent is unemployed	0.127	0.333	0	1
ProEnvir	Score on 'Green' behaviour scale	54.473	8.609	16	70
ProOrganic	Score on 'Pro organic' scale	44.368	12.581	10	70
ConOrganic	Score on 'Con organic' scale	40.372	10.384	10	70
Happy 1	Feeling happy lately	3.547	0.885	1	5
Happy 2	Satisfied with life	3.606	0.951	1	5
Diet	=1 if respondent is on diet	0.156	0.363	0	1
Healthy	Score on 'Healthy lifestyle' scale > 50 (10–70)	0.921	0.270	0	1

[a]Average monthly net income in 2016, source: ONS.

4.2 RP data and the impact of socioeconomic characteristics

The RP dataset contains 336,970 chicken purchases from 26,658 UK households in 2016, drawn from the Kantar UK Panel. Purchases were limited to chicken breast products up to 1 kg to ensure consistency with the products evaluated in the SP survey. After filtering, the final RP dataset included 9,948 households and 58,170 observations.

Table 2 provides a summary of household characteristics in the RP dataset: 78.3 per cent female, 29 per cent married, with an average age of 48.3 years and a household size of 2.93. Income and employment statistics reveal that respondents generally had above average gross income (£30,000–£39,999 annually) compared to the UK's 2016 average (£26,300). The percentage of unemployed respondents was notably low (2 per cent), and 43 per cent were in full time employment.

Table 2. Summary statistics RP data: households.

Variable	Description	Obs	Mean	Std.Dev.	Min	Max
Female	dummy = 1 if female	9948	0.783	0.412	0	1
Age	age of respondent	9948	48.3	13.9	18	95
Married	dummy = 1 if married	9948	0.292	0.455	0	1
Retired	65+, no children, 1 to 2 adults	9948	0.176	0.381	0	1
Employment FT	Full time employment (30h+)	9948	0.430	0.495	0	1
Employment PT	Part time employment (<30h)	9948	0.234	0.424	0	1
Unemployed	dummy = 1 if unemployed	9948	0.021	0.142	0	1
Household data						
Household size	Number of individuals	9948	2.930	1.256	1	10
Adults	Number of people aged 18+	9948	2.205	0.830	1	8
Children	Number of children	9948	0.725	0.995	0	7
Pre-family	age < 45 with no children	9948	0.123	0.328	0	1
Young-family	youngest child 0 to 4 years old	9948	0.189	0.391	0	1
Middle-family	youngest child 5 to 9 years old	9948	0.117	0.322	0	1
Older-family	youngest child > 10 years old	9948	0.115	0.320	0	1
Older dependents	44 + years old and 3 + adults	9948	0.134	0.340	0	1
Empty nest	45 to 65 years old and 1 to 2 adults	9948	0.184	0.388	0	1
Income level	from 1 (<£10K) to 8 (£70k+)	8312	4.226	1.944	1	8

Family structure among households is relatively evenly distributed, but the highest proportion of households are ‘young family’ (couple with youngest child younger than 4 years) and ‘empty nest’ (45–65 years old with no children in the household), forming 19 per cent and 18 per cent of the sample, respectively.

The smallest proportions (11 per cent) are for ‘middle family’ (families in which the youngest child is between 5 and 9 years old) and ‘older family’ (families in which the youngest child is above 10 years old). Statistics for the merged data are included in the next section.

4.3 Joint SP-RP data description

In this study, the choice experiment (CE) and its accompanying survey offered valuable insights into how consumers’ socioeconomic characteristics and behaviours influence the demand for specific socially desirable attributes. However, when estimating WTP, a joint estimation approach yields more robust results by leveraging a larger dataset and the complementary strengths of both data sources. As previously mentioned, RP data anchors SP hypothetical choices in real market transactions, while SP data isolates the impact of specific attributes and includes the ’non buy alternative’.

To make observations from the RP data consistent with the choice context presented in the SP data, a set of choice alternatives was constructed from the RP dataset. The RP data was sourced from Kantar Worldpanel, which provides weekly household purchase records for approximately 30,000 UK households at the product level. Only purchases of chicken breast were retained, as it is a widely consumed product with sufficient variation in attributes across brands and retailers. To align with the SP design, the RP data was filtered to include only a single purchase per household per week. If multiple purchases were made, one observation was randomly selected, ensuring comparability with the SP data where respondents evaluated a single choice card at a time.

To construct a realistic set of alternatives in the RP data, we identified instances where at least two chicken breast options were available at the shop during the purchase week. This was achieved by matching product attributes with the shop name, household ID, and postcode, and inferring availability based on purchases by other shoppers at the same location. Observations with only one chicken breast option were excluded to maintain consistency with the SP design, where consumers always faced three alternatives: two product options (A and B) and a ’no buy’ (status quo, SQ) option.

The SQ option in the RP data was carefully defined to represent situations where households chose not to purchase chicken breast, despite its availability. This was determined by tracking households that bought other products in the same store during the same week but did not select chicken breast. For these observations, all attribute dummy variables were set to zero, indicating the absence of specific product attributes, while household socioeconomic characteristics were retained.

This approach ensured that the SQ option in the RP data conceptually aligned with the SP data, where respondents could explicitly choose not to purchase any of the presented alternatives. Including the SQ option in both datasets is necessary, as it captures the preferences of the population segment that does not buy the product, thereby preventing the overestimation of WTP.

4.3.1 Parameter restrictions

To effectively combine the SP and RP datasets, it is necessary to harmonize variables and address inconsistencies in attributes, scale and choice contexts. The attributes in the RP data were derived from scanner data characteristics, such as ‘Organic’ labels or high-quality branding (e.g. ‘Tesco Finest’, ‘Asda Extra Special’). However, some attributes were unique to each dataset. For example, ‘Less Chemicals’ and ‘Environmentally Friendly’ were present only in the SP data, while ‘Healthy’ and ‘Offer’ (discounts and promotions) were exclusive to the RP data.

Attributes common to both datasets, such as ‘Organic’, ‘Animal Welfare’ (‘Freedom Food’) and ‘Quality’, provided the basis for joint estimation. During initial model testing, we identified and addressed the following parameter inconsistencies:

Price and volume: The RP dataset included prices up to £26 per kilogram, significantly higher than the £10/kg cap used in the SP data (a ‘choke price’ for 400 g packs). To reconcile this, prices in the RP data were truncated at £10/kg, and volume was included as an explanatory variable, limited to a maximum of 1 kg to align with the SP design. While limiting the RP dataset to 400 g packs was considered, it resulted in insufficient variation in attributes and observations, reducing model reliability.

Status quo (SQ): Initial log likelihood ratio (LLR) tests revealed scale differences between the SQ choices in the SP and RP datasets, likely driven by differences in unobserved factors. For instance, SP respondents may have been more inclined to make a choice due to the hypothetical nature of the experiment and clearer attribute presentation, while RP shoppers could opt out by visiting another shop or choosing unrelated products. To account for this, separate variables (SQSP and SQRP) were introduced to represent the SQ option in each dataset.

Scale differences: The SP and RP datasets also exhibited significant scale differences in initial joint estimations, as evidenced by LLR test results (P-value = .000) for parameter equality in the RPSP CLogit model (Table A2 in the Appendix). These differences were addressed by incorporating the scale heterogeneity into the combined model using the CLHet approach. After the adjustments, the LLR test for the CLHet model yielded a P-value of 0.233, indicating that the SP and RP parameters were statistically equivalent when scale differences were accommodated; thus, justifying the use of the CLHet model (Table 4).

4.3.2 RPSP summary statistics

Table 3 provides a summary of the SP, RP and combined (RPSP) datasets, emphasizing the differences and overlaps in variables and observations. While

Table 3. Summary statistics joint RP and SP data.

	SP Data					RP Data					RPSP data variable				
	Mean	SD	Min	Max	*E*	Mean	SD	Min	Max	*E*	Mean	SD	Min	Max	*E*
Labels															
Price (£/Kg)	4.01	3.49	0	10	7,088	6.45	1.58	0	10	54,989	6.04	2.16	0	10	62,077
Volume (Kg)	0.27	0.19	0	0.4	10,632	0.67	0.40	0	9.2	54,989	0.63	0.38	0	9.2	65,621
Organic	0.17	0.38	0	1	1,827	0.00	0.02	0	1	31	0.03	0.16	0	1	1,853
AnimalWelfare	0.31	0.46	0	1	3,339	0.002	0.04	0	1	113	0.05	0.22	0	1	3,440
Quality	0.35	0.48	0	1	3,753	0.007	0.08	0	1	423	0.06	0.24	0	1	4,129
Healthy						0.00	0.02	0	1	12	0.00	0.01	0	1	12
Offer						0.48	0.50	0	1	26,825	0.40	0.49	0	1	26,825
LessChemicals	0.18	0.38	0	1	1,877						0.03	0.17	0	1	1,877
EnvFriendly	0.33	0.47	0	1	3,516						0.05	0.22	0	1	3,516
Socioeconomic characteristics															
Age	50.52	15.63	18	80	10,632	46.52	13.08	18	95	56,362	47.15	13.59	18	95	66,994
Income	3.33	1.96	1	8	10,632	4.39	1.95	1	8	56,362	4.22	1.99	1	8	66,994
Female	0.60	0.49	0	1	10,632	0.78	0.41	0	1	56,362	0.76	0.43	0	1	66,994
Unemployed	0.12	0.32	0	1	10,632	0.02	0.14	0	1	56,362	0.04	0.18	0	1	66,994
Married	0.68	0.47	0	1	10,632	0.28	0.45	0	1	56,362	0.34	0.48	0	1	66,994
Children	0.62	0.97	0	5	10,632	0.82	1.01	0	7	56,362	0.79	1.01	0	7	66,994
PreFamily	0.08	0.27	0	1	10,632	0.13	0.33	0	1	56,362	0.12	0.32	0	1	66,996
YoungFamily	0.01	0.07	0	1	10,632	0.21	0.41	0	1	56,362	0.18	0.38	0	1	66,994

Notes: SD = standard deviation, E = number of entries in the regression.
In the CE, each respondent was presented with 8 choice cards with 3 alternatives each.
Labelling: 'AnimalWelfare' is captured from the 'Freedom Food' RP label, 'Quality' from retailers' own-brand 'luxuries', the 'Healthy' attribute was only labelled in the RP, and 'Offer' denotes discounts and other promotions offered by the retailer. 'LessChemicals' denotes chicken produced with a low level of antibiotics and fed with organic feed free of artificial fertilizers and pesticides, 'EnvFriendly' is captured from the label with the same name in the CE.
Income is before tax per year and is measured in categories from 1 to 8, where $1 < 10{,}000$ and $8 \geq 70{,}000$. 'PreFamily' denotes a couple below 45 years without children and 'YoungFamily' denotes a family where the youngest child is less than 4 years old.

Table 4. Discrete choice model regression results factors impacting the choice probability of chicken meat using individuals' interaction terms.

Variables	(1) SP CLogit	(2) RP CLogit	(3) RPSP CLHet
Price	−0.243***	−0.554***	−0.234***
	(0.023)	(0.018)	(0.017)
Volume		−0.760***	−0.318***
		(0.029)	(0.026)
Organic	0.963***	0.995	1.009***
	(0.234)	(1.831)	(0.219)
AnimalWelfare	0.295***	0.958***	0.318***
	(0.069)	(0.263)	(0.057)
Quality	0.408***	0.385	0.330***
	(0.086)	(0.395)	(0.072)
LessChemicals	−0.209**		−0.206**
	(0.088)		(0.082)
EnvFriendly	0.183***		0.180***
	(0.041)		(0.040)
Healthy		−0.376	−0.157
		(0.837)	(0.350)
Offer		−0.220***	−0.092***
		(0.023)	(0.012)
SQRP (No buy RP)		−2.809***	−1.173***
		(0.041)	(0.085)
SQSP (No buy SP)	−2.112***		−2.096***
	(0.100)		(0.088)
AgeXOrganic	−0.020***	0.004	−0.020***
	(0.004)	(0.041)	(0.004)
UnemployedXQuality	0.387***		0.399***
	(0.119)		(0.117)
IncomeXQuality	0.030	0.226***	0.056***
	(0.021)	(0.075)	(0.016)
IncomeXPrice	0.007*	0.008**	0.004***
	(0.004)	(0.004)	(0.001)
Scale Parameter (RP)*			0.873***
			(0.072)
LLR	−3235.137	−14195.506	−17434.680
LLR Test			8.07
			(0.233)
Observations	10,632	56,362	66,994
Number of groups			22,470

Standard errors in parentheses; *** $P < .01$, ** $P < .05$, * $P < .1$ except for the row below the LLR test, where there are P-values in parentheses.
*The scale parameter is the exponential the term (RP) = 2.39.

certain attributes, such as ‘Healthy’ and ‘Offer’ were unique to the RP data, and others, like ‘Less Chemicals’ and ‘Environmentally Friendly’, were exclusive to the SP data, common attributes to both datasets were ‘Price’, ‘Volume’, ‘Organic’, ‘Quality’ and ‘Animal Welfare’. The joint RPSP approach ensures that the combined model reflects purchasing intentions and behaviours more accurately than either dataset alone.

Table 3 provides a summary of the SP, RP and joint RPSP datasets. Key variables such as Price, Volume and socioeconomic characteristics show consistency across the datasets. However, discrepancies such as the low representation of the attribute ‘Healthy’ in RP data highlight dataset specific limitations that are addressed in the modelling approach. It is expected that scale differences will not have an additional effect on the results, as this is controlled by the scale parameter, making it an RP dataset specific limitation. The combined dataset provides the foundation for the subsequent econometric analysis.

Combining the RP data with the SP data increases the percentage of married respondents to 48 per cent, which we believe is more realistic. The national average in 2016 was 50.9 per cent in England and Wales (ONS n.d.) and 47 per cent in Scotland (Scottish Household Survey 2016: Annual Report n.d.). These figures differ from both the SP and RP statistics but are close to the average of the two samples, making the joint data more representative in this regard.

SP data provides controlled insights into consumer preferences, while RP data reflects actual purchasing behaviour. Pooling the datasets improves representativeness and allows for the exploration of relationships between socioeconomic characteristics and WTP for organic attributes.

5. Results

This section presents results from the heteroskedastic conditional logit model (CLHet), used to jointly estimate preferences from SP and RP data. For completeness, results from separate conditional logit models estimated on the SP and RP datasets are reported in Table 4; however, all discussion and interpretation focus on the joint estimation model, which accounts for scale heterogeneity across data sources.

5.1 Results from the joint model

Table 4 presents the discrete choice model results: conditional logit (CLogit) estimates from the SP and RP data (columns 1 and 2), and the joint estimation using the heteroskedastic conditional logit model (CLHet) in column 3. The joint CLHet model identifies a significant scale parameter of 0.873 (last row), indicating the presence of differences in scale between SP and RP data, likely due to sample characteristics and survey design and confirming the need for correction in joint estimations. These differences, if unaccounted for, could lead to misleading coefficient estimates. The inclusion of interaction terms in the CLHet model captures within-sample heterogeneity by incorporating individual-specific interaction terms and allowing for scale heterogeneity across respondents, improving the precision of preference estimates (Vass *et al.*, 2018). The model's post-regression log-likelihood improvement of 117.8 (compared to Table A2 in the Appendix) further supports its robustness.

The estimated scale parameter (using RP as a baseline) confirms that the RP data has a significantly greater scale, with a scale difference of 2.39 between RP and SP. This aligns with expectations, given that the RP dataset is more than five times larger than the SP dataset. The lower error variance in RP data likely results from the greater sample size and fewer unobserved influences on consumer choices compared to the SP data. Notably, several attribute coefficients differ substantially between the SP and RP conditional logit models, particularly for 'Price', 'Organic', 'Animal Welfare' and 'Volume', reinforcing the necessity of adjusting for scale differences to avoid biased estimates.

The CLHet model also accounts for within-sample heterogeneity, as it does not assume uniform preferences across individuals. Interaction terms capture variations across consumer groups, addressing the limitations of simpler models. Since the model normalizes the scale to the SP sample, the estimated coefficients primarily reflect the SP data, while the RP contributions are adjusted proportionally through the estimated scale parameter (Davis *et al.*, 2019). 'Price' has a strong, significant negative effect on choice probability, with RP estimates nearly double those of SP. The joint estimation moderates this effect, yielding a coefficient closer to the SP estimate. This has important implications for the interpretation of willingness-to-pay estimates derived from the joint model.

For 'Volume', interpretation is constrained by the SP dataset, which only includes 400 g packs. However, consistent with expectations, larger package sizes in the RP data are associated with a lower choice probability, likely due to consumer preference for smaller portions. The 'Organic' attribute has a significant positive impact on choice probability, with similar SP and RP estimates. While joint estimation often yields coefficients between those observed in the individual models, this is not always the case due to scale correction and interaction effects. Nevertheless, in the case of 'Organic', all three estimates remain close in value.

'Animal Welfare' has a positive and significant effect on choice probability, with a notably larger impact in the RP data. The CLHet joint estimation moderates this difference, yielding a coefficient closer to that observed in the SP model. 'Quality' also has a positive and significant effect, although it is statistically insignificant in the RP model. The coefficient of, 'Quality' becomes significant in the joint estimation, aligning with findings in the literature (Griffith *et al.*, 2010; Guenther *et al.*, 2015; Gschwandtner and Burton, 2020), further supporting the reliability of joint estimation results.

Attributes exclusive to the SP data, such as 'Less Chemicals' and 'Environmental Friendliness', exhibit similar coefficients in the joint model. 'Less Chemicals' has a counterintuitive negative coefficient, consistent with the SP results. In contrast, 'Environmental Friendliness' has a significant positive effect, as expected. 'Healthy' is only measured in the RP data and is not statistically significant, likely due to unclear labelling in the dataset. A better label would probably be needed to measure the impact of this important attribute.

Products on 'Offer' consistently show a negative and significant effect on choice probability, suggesting that discounted products are associated with lower perceived quality, possibly due to nearing expiration or reduced freshness. Finally, the 'Stauts Quo (no-buy) alternative has strong negative effects in both SP and RP, confirming the expected negative impact.

Interaction terms between product attributes and individual characteristics are used in the CLHet model to capture systematic preference heterogeneity. These capture preference heterogeneity by accounting for differences in how individual traits influence the valuation of attributes. For these interaction terms ('AgeXOrganic', 'PriceXIncome', 'QualityXUnemployed', 'QualityX-Income'), the coefficients must be interpreted jointly with consumer characteristics. The effect of 'Organic' on utility declines with age, as shown by the marginal effect: $1.009 - 0.020 \times Age$. Similarly, the effect of 'Price' is $-0.234 + 0.004 \times Income$, and for quality, $0.330 + 0.399 \times Unemployed + 0.056 \times Income$. Using Table 3 values, the average marginal effects are 0.066 for 'Organic', −0.217 for 'Price', and 0.580 for 'Quality'.

The interaction terms confirm the presence of consumer heterogeneity. Prior research highlights the role of demographic factors such as age, income, employment status, gender and household structure in shaping organic food preferences (Yue *et al.*, 2009; Griffith *et al.*, 2010; Wong *et al.*, 2010; Costanigro *et al.*, 2012; Gschwandtner, 2018). In this study, 'Age', 'Unemployment' and 'Income' emerged as most robust predictors of heterogeneity. Older consumers display lower marginal utility of 'Organic', while income is associated with greater WTP for 'Quality' and 'Price'. Additionally, the unemployed exhibit a higher marginal utility for 'Quality', a result consistent with the descriptive statistics.[9]

5.2 WTP estimates

WTP estimates were calculated as the ratio of the attribute coefficient to the price coefficient, using Equation (8) below. These values, derived from the heteroskedastic conditional logit CLHet joint model, reflect the trade-offs between price and each product attribute. Table 5 reports WTP for key attributes, including organic, animal welfare and environmental friendliness. Because WTP estimates are unaffected by heteroskedastic errors (Vass *et al.*, 2018), normalizing scale differences ensures unbiased comparisons:

$$\text{WTP} = -\frac{(\text{Attribute} - \text{Coefficient})}{(\text{Price Coefficient})}. \tag{8}$$

9 All demographic factors were tested but only significant ones were kept in the final model.

Table 5. WTP for chicken meat attributes estimates using interaction terms (£/unit).

Attributes	(1) SP	(2) RP	(3) RPSP (CLHet)
Volume		−1.37	−1.36
Organic	3.96	1.80	4.31
AnimalWelfare	1.21	1.73	1.36
Quality	1.68	0.70	1.41
LessChemicals	−0.86		−0.88
EnvFriendly	0.75		0.77
Healthy		−0.68[i]	−0.67 [i]
Offer		−0.40	−0.39

i: Statistically insignificant.
The unit for volume is 1 kg, all other variables are dummies.

Consumers are willing to pay less per unit for larger package sizes, which is consistent with the standard expectation that price per unit declines with volume. For the ‘Organic’ attribute, the WTP is approximately £4 in SP, £2 in RP and £4.31 in the joint CLHet estimation. The higher joint WTP estimate reflects a smaller absolute price coefficient, adjusted for scale heterogeneity. These figures are consistent with prior findings (Ribeiro *et al.*, 2024) and confirm that SP estimates typically exceed RP estimates due to hypothetical bias or survey framing effects.

WTP for ‘Animal Welfare’, is £1.21 (SP), £1.73 (RP) and £1.36 (CLHet joint), indicating a lower valuation relative to ‘Organic’, likely due to perceived overlaps between the two. Similarly, WTP for ‘Quality’ is £1.68 (SP), £0.70 (RP) and £1.41 (joint), supporting the hypothesis that consumers associate ‘Organic’ with multiple quality-related attributes. Summing WTP for attributes linked to organic production (namely ‘Animal Welfare’, ‘Quality’, ‘Environmental Friendliness’ and ‘Less Chemicals’) yields £2.68, aligning with WTP for ‘Organic’, suggesting bundled valuation. This supports the interpretation that consumers value organic chicken meat for the attributes traditionally associated with it, such as higher animal welfare, environmental friendliness and higher quality.

The CLHet model highlights the importance of accounting for scale heterogeneity in estimating reliable WTP. The negative coefficient and associated negative WTP for ‘Less Chemicals’ in the joint model remain counterintuitive but mirrors SP results. ‘Environmental Friendliness’ shows a positive WTP of £0.77, reinforcing expectations. The WTP for ‘Healthy’ is not statistically significant, likely due to poor labelling clarity in the RP data. This points the need for more transparent and standardized attribute information in retail settings.

Products on ‘Offer’ exhibit reduced WTP (−£0.40 in RP, −£0.39 in joint), as consumers associate lower utility with discounted products. These findings illustrate that relying solely on SP and RP data may yield biased or inconsistent WTP estimates. For key attributes such as ‘Organic’, ‘Animal Welfare’ and

'Quality', joint estimation under the CLHet framework offers a more robust valuation by correcting for differences in scale and unobserved heterogeneity.

As a robustness check, Table A3 (Appendix) replicates the CLHet estimation using SP as the baseline scale parameter. The results remain consistent, reinforcing the validity of joint estimation in addressing scale differences and improving inference reliability.[10]

6. Conclusions

As highlighted by much of the food marketing press, since its rise in popularity in the 1990s, the attribute 'Organic' has been perceived by consumers to reflect sustainability and quality. This is because organic products, which are free from synthetic pesticides, fertilizers, genetically modified organisms and artificial additives, have become synonymous with healthy and ethical consumption.[11] [12] [13] Given the increasing importance of organic meat, particularly chicken, this article focuses on preferences related to organic chicken meat.

Despite the positive attributes mentioned above, the press continues to question whether the organic label remains important to consumers and if they are willing to pay more for it. Understanding this is important for producers currently in the organic market, as well as for those interested in entering the market.

In this context, this study focuses on estimating the WTP for the organic label, whilst considering that this label covers several different attributes. We therefore estimate consumer preferences for various attributes of chicken meat using a robust joint approach. This method addresses the shortcomings of both RP and SP techniques to accurately elicit WTP.

The results related to WTP indicate that individuals are willing to pay £1.36 (22 per cent premium) per unit for better animal welfare and £0.77 (12 per cent premium) for being more environmentally friendly. The relatively lower WTP for environmental friendliness suggests that meat consumers are more concerned about animal welfare than the environment. Thus, the WTP for more 'humane' treatment of chicken in the production process is higher. At the same time, consumers appear willing to pay an average of £1.41 (23 per cent premium) for better quality, indicating that their own welfare is even more valued. The results also reveal that consumers are willing to pay a premium of £4.31 (71 per cent premium) for the attribute 'Organic', which encompasses several of these attributes simultaneously.

The interaction terms available in the main econometric model reveal the consumer characteristics driving WTP for the organic label and show that age, income and employment status are the main sources of heterogeneity, with very large variations. The joint estimation results show that the WTP for the

10 A code with the estimation procedure can be found in the Supplementary Material.

11 https://www.foodnavigator.com/Article/2024/08/14/Is-organic-still-important-to-consumers

12 https://tinyurl.com/yp96cjcw

13 https://www.thegrocer.co.uk/download?ac=358995

organic label would decrease by 2 per cent per year of age. These findings reveal market and intervention opportunities. For example, organic sales might increase if sellers target younger generations, while policy making could focus on educating the older generation about the benefits of organic food. More effective promotion of the characteristics conveyed by the organic label may contribute to increased consumer demand for organic products.

In terms of econometrics, this study shows that the heteroskedastic CLogit (CLHet) model, as a panel data study with interaction terms applied to different SP and RP samples, offers a viable way to simultaneously address issues such as unobserved heterogeneity effects, state dependence and scale differences.

To our knowledge, this is the first study to apply CLHet with interaction terms to address the assumption of homogeneous preferences and other problems associated with joint estimation.

The results show that after accounting for heterogeneity and considering the scale effect, the preferences in the two datasets are similar and can be meaningfully combined. When combining the RP and SP information, consumers appear to be willing to pay a larger amount for the organic attribute than when the SP (by 9 per cent) and RP (by 139 per cent) approaches are applied separately.

The results of the present paper yield several implications for product labelling, consumer education and regulatory decisions. Regarding labelling, the substantial WTP premium for the 'Organic' label (£4.31 in the joint model), supports continued policy efforts to strengthen official organic certification schemes such as the Soil Association in the UK. The WTP for the 'Organic' attribute appears to be driven by a 'bundled valuation' of associated attributes, including 'Animal Welfare', 'Quality' and 'Environmental Friendliness', indicating that the organic label effectively conveys multiple ethical and quality standards through a single, trusted mark.

Education programs could clearly define the full spectrum of benefits guaranteed by organic certification. This means moving beyond 'organic' to explicitly explain the link to animal welfare, highlighting the 'free-range' status of organic chicken, for example, or detailing the requirements for less chemical usage and environmentally friendly practices. Education efforts could also be designed to address the concerns of different consumer groups. Since older consumers appear to display lower marginal utility for the 'Organic' label, education could focus on the health and safety aspects of organic food.

With respect to regulation and government support, the significant WTP premiums to attributes like 'Animal Welfare' (£1.36 WTP) and 'Quality' (£1.41 WTP) imply that regulators could justify targeted financial support or grants for non-organic farmers who invest specifically in these attributes, without requiring full organic certification. The joint SP-RP estimates appear to be more robust than those derived from either dataset alone, making them ideal for determining the appropriate level of subsidies or financial support for organic farming and informing the structure of taxes or market mechanisms aimed at steering consumer behaviour towards sustainable consumption.

Finally, future research could build on the present work and compare the heteroskedastic conditional logit results with other models, such as the Mixed Logit or Latent Class models, to identify distinct, unobserved consumer segments and potentially offer deeper insights into why different consumer groups value attributes differently. Allowing the scale parameter to vary across contexts or over time could also provide insights into how experience and information affect consumer decision-making. Further applied work could also follow the guidance provided in the present paper on how to harmonize SP and RP data before modelling.

In terms of limitations, two should be mentioned: first, regarding the data, household level scanner data and household level survey data did not include some population groups in the sample (e.g. 18-year-old consumers). Additionally, the SP data only included individuals who signed up to take the survey. Nevertheless, care in the construction of the dataset were put to reduce the effects on the results. Second, some socially desirable attributes, such as 'Local Production' and 'Safety', which are usually associated with 'Organic', could not be included due to their limited availability in the data. These attributes should be incorporated into future studies.

Despite these limitations, it is important to note that the joint estimation approach used in the present paper and the insights derived from it are not only applicable to the chicken market but also can be extended to other markets, providing a versatile framework for further research.

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Supplementary data

Supplementary data are available at *ERAE* online.

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Appendix

Based exclusively on the household socioeconomic characteristics outlined in Table 2 from the RP data, Table A4 illustrates the influence of these variables on the choice of the organic attribute. The estimation model employs a linear form of a discrete choice function with ‘Organic’ as the dependent variable. The results show that many socioeconomics have a significant impact, justifying their use in the regressions.

There is extensive literature showing how various characteristics impact organic consumption. Griffith *et al.* (2010) explore the heterogeneity of the WTP for organic products across different family structures. Yue *et al.* (2009),

Q1 Background Information

This questionnaire is part of a research project concerned with consumer buying behavior in UK supermarkets. In this survey we will ask you to choose between different products that can usually be found in supermarkets. We want you to select the product that you most prefer. The questionnaire should take no more than 20-30 minutes to complete. Your answers will be treated anonymously and strictly confidentially and will be used for research and academic purposes only. Your anonymity will be safeguarded at all times. Your answers in this experiment will help the design of supermarket pricing policy and may have important consequences for the future. Important: We would like the person who usually does the food shopping for the household to answer the questionnaire. The questionnaire consists of three main parts. The first one (A) is about your actual purchases, the second one (B) is about your purchases in an experiment and the last part (C) consists of questions about you and your lifestyle.

Q67 Concluding Remarks: Dear Participant! Thank you for taking the time to complete this survey. If you have any questions, comments or feedback, please contact Dr Adelina Gschwandtner by email: a.gschwandtner@gmail.com We welcome any comments on the questionnaire. Please feel free to write these comments in the space below.

Fig. A1. Survey extract.

Attributes

Attribute	Description	Image	coding
Label	Organic label	EU UK	1
	Conventional label	No label	0
Chemical Usage in Production (i.e. antibiotics for animals)	Average		0
	Low		1
Environmentally Friendly	Average	No label	0
	High		1
Animal friendly (for chicken only)	No Freedom Food	No label	0
	Freedom food		1
Quality	Average		0
	High		1
Price (£) of Chicken Breast 400 Gramm (0.88lbs)	3.00, 3.50, 5.75, 6.64, 8.32, 10		cardinal

Fig. A2. Attributes used in the CE.

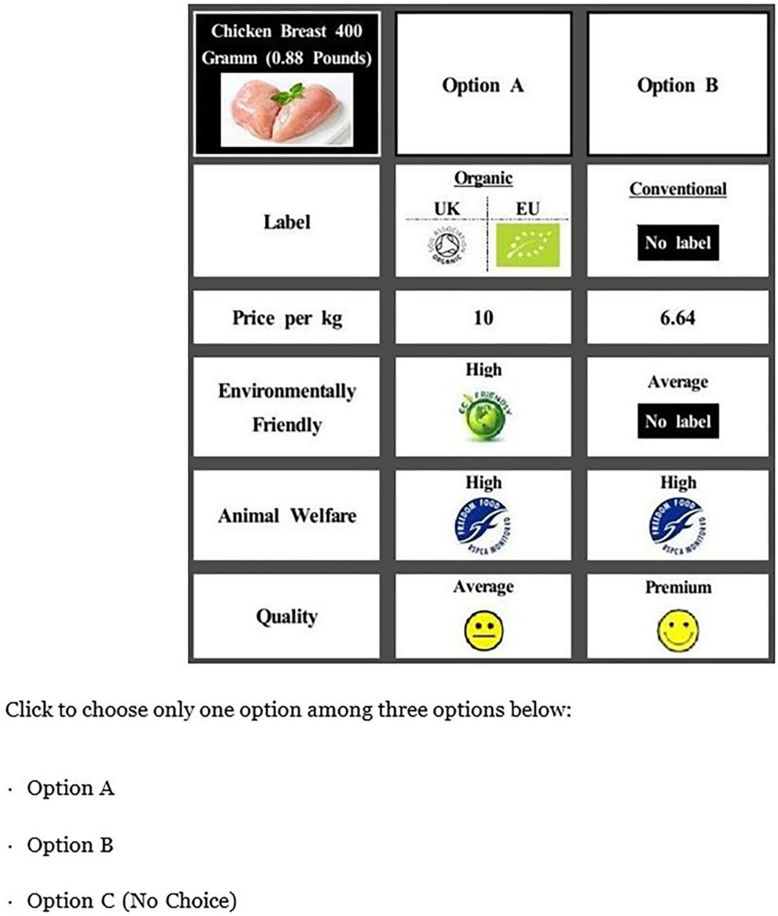

Fig. A3. Example of choice card.

Wong *et al.* (2010), Costanigro *et al.* (2012), and Gschwandtner (2018) are just a few of the many studies that demonstrate the influence of individual characteristics such as income, gender, family structure, employment status, and more on organic food consumption.

It is generally acknowledged that organic consumption is highly correlated with income. The association between consumer characteristics and consumption has led to these characteristics being used as instrumental variables in he-

Table A1. Summary statistics: choice cards (12,120 choices).

Variable	Description	Mean	Std.Dev.	Min	Max
Organic	dummy for organic label	0.172	0.377	0	1
Chemical usage	dummy = 1 if 'average" or = 0 if 'low"	0.177	0.382	0	1
Env friendly	dummy for Eco Friendly label	0.332	0.471	0	1
Animal Welfare	dummy for animal welfare label	0.315	0.464	0	1
Quality	=1 if 'premium" or = 0 if 'average"	0.352	0.478	0	1
Price	£3/£3.5/£5.75/£6.64/£8.32/£10	4.015	3.496	0	10
Status quo	alternative C, no purchase	0.333	0.471	0	1
HBT0	no hypothetical bias treatment (HBT)	0.253	0.435	0	1
HBT1	dummy for 'cheap talk" HBT	0.277	0.448	0	1
HBT2	dummy for 'honesty priming" HBT	0.234	0.423	0	1
HBT3	dummy for both HBT	0.236	0.424	0	1

donic pricing regressions, sometimes utilizing datasets similar to the present ones (Follain *et al.*, 1985; Bishop *et al.*, 2011; Ribeiro *et al.*, 2024).[14] This is also why they are used as interaction terms in the regressions in the present analysis.[15] However, as pointed out above, only significant interaction terms were used in the final results.[16]

14 Note that consumer characteristics can enter CLogit regressions only as interaction terms with the product attributes. This is because CLogit estimates the utility consumers derive from the choice of a product with specific attributes and is only interested in consumer characteristics insofar as they impact this choice. More fundamentally, the sociodemographics do not vary across the alternatives in the choice set and hence cannot identify why an alternative is chosen. Therefore, they *have* to be interacted.

15 All possible interactions were tested statistically to find the present (best fit) function form.

16 Even though we have a rich dataset, some variables are missing. For example, consistent information about the rural/urban status of the consumers in the two datasets (SP/RP) is not available even though some studies show that this may impact the availability and hence choice of organic food.

Table A2. Joint regression (with individuals' interaction terms RPSP CLogit).

Variables	RPSP _CLogit
Price	−0.481***
	(0.013)
Volume	−0.747***
	(0.029)
Organic	1.762***
	(0.236)
AnimalWelfare	0.898***
	(0.055)
Quality	0.389***
	(0.084)
LessChemicals	0.401***
	(0.081)
EnvFriendly	0.214***
	(0.042)
Healthy	−0.400
	(0.820)
Offer	−0.222***
	(0.023)
SQRP (No buy RP)	−2.688***
	(0.039)
SQSP (No buy SP)	−3.162***
	(0.077)
AgeXOrganic	−0.023***
	(0.005)
UnemployedXQuality	0.376***
	(0.122)
IncomeXQuality	0.070***
	(0.020)
IncomeXPrice	0.003
	(0.003)
Scale Parameter (RP)*	
LLR	−17552.434
LLR Test	243.58
	(0.000)
Observations	66,994
Number of groups	22,470

Standard errors in parentheses; *** $P < .01$, ** $P < .05$, * $P < .1$ except for the row below the LLR test, where there are P-values in parentheses.
*The scale parameter is the exponential the term (RP) = 2.39.
Labels: 'AnimalWelfare' is captured from the 'Freedom Food' RP label, 'Quality' from retailers' own-brand 'luxuries', the 'Healthy' attribute was only labelled in the RP, and 'Offer' denotes discounts and other promotions offered by the retailer. 'LessChemicals' denotes chicken produced with a low level of antibiotics and free of artificial fertilizers and pesticides; 'EnvFriendly' is captured from the label with the same name in the CE; SQRP: no buy option if the revealed preference data; SQSP: no buy option if the revealed preference.

Table A3. Robustness check: joint regression using interaction terms and SP as a base (scale parameter = SP).

Variables	RPSP CLHet	WTP using CLHet
Price	−0.560***	
	(0.017)	
Volume	−0.761***	−1.36***
	(0.029)	(0.13)
Organic	2.417***	4.31 ***
	(0.521)	(1.83)
AnimalWelfare	0.761***	1.36***
	(0.115)	(0.40)
Quality	0.790***	1.41***
	(0.178)	(0.61)
LessChemicals	−0.493**	0.88**
	(0.213)	(0.75)
EnvFriendly	0.432***	0.77***
	(0.0100)	(0.35)
Healthy	−0.376	−0.67
	(0.837)	(2.93)
Offer	−0.221***	−0.39***
	(0.023)	(0.08)
SQSP	−5.019***	
	(0.278)	
SQRP	−2.808***	
	(0.041)	
AgeXOrganic	−0.048***	
	(0.010)	
UnemployedXQuality	0.955***	
	(0.291)	
IncomeXQuality	0.133***	
	(0.038)	
IncomeXPrice	0.010***	
	(0.003)	
Scale Parameter (SP)*	−0.873***	
	(0.072)	
LLR	−17434.68	
LLR Test	8.07	
	(0.233)	
Observations	66,994	
Number of groups	22,470	

Standard errors in parentheses; *** $P < .01$, ** $P < .05$, * $P < .1$. Except for the row below the LLR test, where there are P-values in parentheses.
*The scale parameter is the exponential, the term (RP) = 2.39.
Labels: 'AnimalWelfare' is captured from the 'Freedom Food' RP label, 'Quality' from retailers' own-brand 'luxuries', the 'Healthy' attribute was only labelled in the RP, and 'Offer' denotes discounts and other promotions offered by the retailer.
'LessChemicals' denotes chicken produced with a low level of antibiotics and free of artificial fertilizers and pesticides; 'EnvFriendly' is captured from the label with the same name in the CE; SQRP: no buy option if the revealed preference data; SQSP: no buy option if the revealed preference.

Table A4. Impact of socioeconomic characteristics on the organic attribute (dependent variable).

Variables	Probit	OLS
Income	0.062***	0.001***
	(0.005)	(0.000)
Female	0.024	0.000
	(0.022)	(0.000)
BMI	−0.027***	−0.000***
	(0.002)	(0.000)
PreFamily	0.159***	0.002***
	(0.042)	(0.001)
YoungFamily	0.204***	0.003***
	(0.037)	(0.001)
MiddleFamily	0.294***	0.005***
	(0.038)	(0.001)
OlderFamily	−0.024	−0.000
	(0.045)	(0.000)
EmptyNest	0.263***	0.004***
	(0.038)	(0.001)
Retired	0.383***	0.006***
	(0.040)	(0.001)
Constant	−2.289***	0.009***
	(0.077)	(0.001)
Observations	238,860	238,860
R-squared		0.002

Robust standard errors in parentheses.
*** $P < .01$, ** $P < .05$, * $P < .1$.
Notes: Income is before tax per year and is measured in categories from 1 to 8 where 1 < 10,000 and 8 ≥ 70,000; BMI: 2 digits respondent's body mass index; 'PreFamily': a couple below 45 years without children; 'YoungFamily': a family where the youngest child is less than 4 years old; 'MiddleFamily': youngest child 5 to 9 years old; 'OlderFamily': youngest child > 10 years old; 'EmptyNest': 45 to 65 years old and 1 to 2 adults.