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UNIVERSITY OF KENT

DOCTORAL THESIS

Willingness to Pay for Environmental Attributes

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A thesis submitted in fulfilment of the requirements
for the PhD in Agri-Environmental Economics
from the

School of Economics, University of Kent

July, 2022

Declaration of Authorship

I declare that this thesis, titled “Willingness to Pay for Environmental Attributes”, and the work presented in it are my own.

An earlier version of Chapter 3 was presented at the International Conference of Agricultural Economics (ICAE) 2021.

A collaboration version of Chapter 3 was presented by Dr Adelina Gschwandtner at the annual conference of the European Association of Agricultural Economists (EAAE) 2021.

A version of Chapter 5 was presented at the 2022 Agricultural & Applied Economics Association (AAEA) Annual Meeting 2022.

Jose Eduardo Carvalho RIBEIRO

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List of Abbreviations

2SLS	Two-Stage least squares
ANA	Attribute non-attendance
CE	Choice experiment
CVM	Contingent valuation method
GLM	Generalised linear models
GLS	Generalised least squares
GMM	Generalised method of moments
HBT	Hypothetical bias treatment
HP	Hedonic price
IIA	Independence of irrelevant alternatives
IID	Independent and identically distributed
LLR	Log-likelihood ratio
MIP	Marginal implicit prices
OLS	Ordinary least squares
RP	Revealed preference
RPSP	Revealed preference and stated preference combined
SP	Stated preference
SQ	Status quo
WTP	Willingness to pay

Chapter 1

Introduction

Increasing global production and consumption of meat have intuitively impacted human health, animal welfare and the environment. In the case of chicken meat, some of these implications can be seen as comparatively positive, given that substituting chicken meat is potentially reducing the demand for red meat, which is usually associated with relatively more negative externalities. However, such a large production of chicken meat has inevitable negative implications, both for the health of consumers and the welfare of the chickens, driven mainly by production intensification associated with the use of antibiotics, hormones and confinement. These issues might be mitigated by organic chicken consumption.

In general, organic food is advocated to have a wide range of benefits, including enhanced taste, less use of pesticides harmful to consumers, higher standards of animal welfare, and a more sustainable model of farming. These factors have shaped individuals' perceptions, thus driving demand for organic food in the past two decades when the average nominal growth reached 10% per year between 2002 and 2016. Global organic farmland has also been on the rise, growing 8% per year in the same period (SoilAssociation, 2018). Current research suggests that global consumers are willing to pay a significant premium for organic products, and this paper confirms this in the coming sections. Premiums, however, vary according to consumers' socio-economic characteristics, product type, and level of information provided to respondents. This thesis explores how these characteristics explain consumers' willingness to pay (WTP) a premium for organic food. Chapter 2 investigates WTP for 'organic' across different foods, while the rest of the thesis studies these attributes when associated with chicken meat.

Estimating the marginal utility provided by the attributes of chicken meat offers essential information to stakeholders and policymakers seeking to identify and quantify the welfare impact of potential intervention points designed to mitigate social costs and encourage social benefits. For example, considerations of the welfare impact from a change in environmental legislation favouring an environmental attribute. On the producer side, policies can go from narrowing the potential information gap about consumer preferences towards environmental attributes (e.g. health, animal welfare and environmental friendliness), the use of strategical labelling, to estimating the potential impact on welfare from alternative fiscal policies (e.g. subsidies to local, environmentally friendly and low chemical usage production processes, or taxation of socially undesirable attributes). From the consumer side, WTP estimates also offer an opportunity to identify potential misconceptions of the actual effects of production and consumption of conventional and organic products (or lack of understanding about their costs and benefits), educating consumers.

Therefore, the marginal utility and welfare estimations of socially desirable and undesirable attributes have increasingly been a target for environmental economists since the 1970s; thus, the valuation of attributes of environmental goods as a field has grown to become an important focus (Whitehead, Haab, and Huang, 2012). However, academics in the area have debated the different valuation techniques, given the strengths and drawbacks of the existing approaches.

The valuation of changes in environmental quality attributes relies on two main techniques: revealed preference (RP) and stated preference (SP) methods. RP techniques seek to estimate the 'ex-post' WTP for attributes of commodities from the observable choice behaviour of individuals. In contrast, SP methods are based on hypothetical scenarios posed by individuals to elicit their 'ex-ante' WTP for environmental change. This thesis applies different methods for different biases, enabling discrepancy comparisons across estimations.

As the name suggests, RP approaches are limited to information revealed and can be collected from the market. Although the RP data used in this thesis is very comprehensive, RP techniques are restricted to observable environmental changes and their respective scopes of policy change. As an 'ex-post' approach, it does not incorporate desirable attributes or possible future outcomes. Therefore, RP does not apply to new goods and services or estimation of non-use value. Statistically, unobserved characteristics imply that RP models potentially suffer from omitted variables bias and endogeneity. Multicollinearity is also a common issue in RP preference data. Since multiple attributes will vary across products simultaneously, one will not have sufficient independent variation to identify the effects of some attributes.

Meanwhile, SP techniques have the freedom to include any class of variables, including the non-use value of economic goods. SP can be 'ex-ante' and applicable to past events, thus overcoming most of the above-mentioned problems. However, due to their hypothetical nature, stated preferences are often challenged for being subject to bias. This issue is widely discussed in the literature[1], thus this thesis contributes to such a debate.

Hypothetical bias is usually more of a concern for contingent valuation methods (CVM), as respondents state their WTP more directly and are more susceptible to strategic bias in their responses, e.g. compliance bias, warm-glow and anchoring bias (particularly for open-ended WTP questions), as explored by List and Gallet (2001). This thesis applies a choice experiment for the SP study, which is somewhat less affected by hypothetical bias, as discussed in Chapters 3. Nonetheless, as an SP approach, one should not assume that choice experiments (CE) are free from hypothetical bias; thus, treatment is applied accordingly.

It is widely accepted that the SP and RP approaches have advantages and limitations. This thesis uses a method that combines SP and RP methods to elicit the WTP for key environmental attributes of chicken meat, mitigating the limitations of each approach when applied independently. Nonetheless, to maximise the benefits of the different methods, this thesis also carries out SP and RP studies independently, as some inputs are incompatible across the additional data and yet offer helpful information. Therefore, the idea is organised as follows.

Chapter 2 involves a meta-analysis that provides the latest consensus on the WTP for organic food and its attributes. It intends to set up the background for further studies in the field, identify gaps in the literature at the methodological level, and propose new explanations for patterns found in the literature. Its meta-regression includes 56 studies, contributing to 108 observations from around the world, which satisfy the criteria established by its protocol. The studies are published and unpublished papers that apply established environmental valuation methods, using both stated and revealed datasets. The results also enable

[1] Almost all valuation studies recognise this, but the argument stated preference is not reliable took the stage in the early 1950s with prominent economists such as Friedman (1953) and Samuelson (1953) and back in the 1990s with Hausman (1993) and others, see Whitehead, Haab, and Huang (2012).

one to investigate heterogeneity across different products, socio-economic characteristics, and influences from the different methodologies.

Using novel data, Chapter 3 applies a hedonic model (an RP approach) to estimate the implicit price of chicken meat attributes to identify what characteristics UK consumers value the most and identify potential areas of intervention and market opportunities. Focusing on 'organic', the study uses comprehensive scanner chicken meat data from UK shops. The chapter provides robust results estimating that 'organic' is associated with an average premium of 136%. In addition, the paper contributes to the literature on environmental valuation, demonstrating that household characteristics can be used as instruments to address the identified endogeneity of product characteristics and that the generalised method of moments (GMM) provides robust estimates of the hedonic price model. At the same time, two-stage least squares (2SLS) are likely to inflate results.

Chapter 4 consists of an SP study using a CE to elicit the WTP for 'organic' and other attributes not available from RP data. This chapter explores the behaviour and attitudes correlated with the choice of these socially desirable characteristics of chicken meat. This critical information was not available in Chapter 3. As the methods of estimation in the other chapters are alternative (attributes) focused, these could not be used in the joint estimation (Chapter 5) but are available in the chapter, thus justifying an independent set of results and discussion that offer more insight about consumers. The estimation model uses a conditional logit with interaction terms, relaxing the model's strong assumption of an independent and identically distributed error structure. The chapter also compares results with and without interaction terms and estimations from a mixed logit model for robustness.

Chapter 5 combines the two different types of environmental valuation, taking advantage of both approaches' benefits while addressing each method's statistical limitations. The joint SP and RP approach arguably offers the most robust WTP estimates. The econometric issues and bias from both approaches identified in the literature are addressed thoroughly. The chapter contributes with an application of joint RP and SP valuation and how to handle the most common issues that arise in the approach, something rarely done holistically in the literature. In particular, special attention is given to scale differences and the influence of different sources of unobserved factors, such as data collection, survey design, and intention versus behaviour choice structures. For this purpose, the RP data is made consistent with the SP in a consumer choice model. The model used in the SP and RP samples of the chapter is a conditional logit, and the joint estimations are carried out using a heteroscedastic conditional logit model. The latter aims to address scale differences between SP and RP data, while the estimation model with interaction terms also accommodates other issues found in joint estimations.

Chapter 2

Meta-analysis of WTP for Organic Attribute

2.1 Chapter introduction

Given the vast number of existing empirical research papers, meta-analyses are regarded as a valuable tool to synthesise studies that attempt to address a particular issue. They enable researchers to summarise results and explore the heterogeneity in available data and populations under analysis, thus identifying potential differences in estimations and increasing explanatory power. This is possible when there is sufficient quantitative evidence of the effect of certain explanatory variables on a particular dependent variable, such as the willingness to pay (WTP) premium (the case of this thesis).

In the literature, there are some meta-analyses that attempt to summarise results regarding whether organic products bring benefits to both consumers and the environment, including areas such as yields, soil quality, water, emissions, energy, biodiversity, and lifecycle assessment, e.g. Huylenbroek et al. (2009), Bengtsson, Ahnström, and Weibull (2005), and Lee, Choe, and Park (2015). However, I am unaware of meta-analyses on the WTP for organic products, i.e. a demand-side analysis. Overall, on the impact of organic food production and consumption, those studies conclude that, in comparison to its conventional counterpart, organic food contributes to biodiversity protection and has a relatively positive effect (or at least less harmful, one might argue) in terms of soil quality and energy use. These are usually attributed to the lower intensification of organic food production (less use of fertilisers and pesticides). The latter is also linked to higher land-use requirements, thus offering lower yields (Seufert, Ramankutty, and Foley, 2012). The emissions results can be considered mixed, with discrepancies mainly explained by product type heterogeneity and how they are produced, geographical area, methodology, and sample size. This meta-analysis, however, focuses on WTP; thus, it is a demand-side analysis, mainly concerned with consumers' perceptions of the benefits of organic food.

Generally, the WTP premium can be estimated using stated ('intention' to buy values, collected via a survey) or revealed (actual 'behaviour' purchase data) preference approaches. Revealed preferences (RP) are data retrieved from consumers' purchases, such as supermarket scanner data; thus, they are usually regarded as offering reliable WTP values. Stated preferences (SP), however, are retrieved from interviews in which consumers are asked about what would be their purchase behaviour in a hypothetical situation and are subject to hypothetical bias. However, the latter can offer preferences about product characteristics often unavailable from revealed datasets. The most common methods within the SP approaches are contingent valuation (CVM) and discrete choice experiment (CE). CVM studies are often questioned regarding external validity, as consumers state their WTP more directly than estimated through individuals' decisions and choices, as in CEs.

This meta-analysis synthesises the results of 56 valuation studies conducted worldwide. The results indicate that premiums in SP are (significantly) higher than in revealed preferences, thus adding to the current discussion around hypothetical bias. Other methodological characteristics positively correlated with WTP are face-to-face interviews and information given. This study also shows that consumers have increased their WTP for organic food in recent years. At the product level, consumers pay higher proportional premiums for lower price products (e.g. leaves and seasoning).

Regarding socio-economic characteristics, GDP per capita was not statistically significant. Still, results indicate that consumers in developing regions are willing to pay a relatively higher premium for organic food. At the same time, the average level of education has a rather unexpected negative correlation with WTP premium.

In addition to estimating the WTP premium for organic food worldwide, when addressing the research questions set in its protocol, this meta-analysis contributes to the discussion about the importance of socio-economic variables in studies of WTP for organic products, especially 'education'. The results also demonstrate the development of the organic food market, showing an increasing premium over time. In terms of methodology, results indicate that CVM provides significantly higher WTP premiums, adding that the method might be subject to hypothetical bias and that online surveys are associated with lower estimates, probably less influenced by compliance bias as respondents are not face-to-face with the surveyor. These form a strong background for future SP WTP studies to incorporate hypothetical bias treatment in their design.

2.2 Data

2.2.1 Protocol and paper selection

The protocol of this meta-analysis is in line with Moher et al. (2009) and Stanley et al. (2013) and is closely related to Clark et al. (2017). PRISMA protocol (Moher et al., 2009) is widely used within medical sciences and applies to most research areas, whilst Stanley et al. (2013) offers a guideline for meta-analyses more tailored to economic research. A protocol describes the searching strategy and data collection, including the criteria for selection and exclusion of studies, aiming to answer the key research questions of the meta-analysis, which in the case of this study are:

- On average, what is the premium consumers are willing to pay for organic food?
- What are the product characteristics driving consumers' WTP premium for organic food?
- What are the socio-economic factors shaping consumer preferences for organic food?
- Has WTP for organic food changed in time?
- Is the size of the WTP premium for organic food sensitive to the valuation methodology used?

To answer the above questions, a search and selection of the studies had to follow specific criteria, as indicated in the PRISMA Flow diagram (Figure 2.1). This offered robust results, addressing potential bias in publication and paper selection. The data selection followed four stages: 'identification', 'screening', 'eligibility', and 'inclusion' (final section).

The first step, as shown in Figure 2.1, was identifying studies. AgEcon, Web of Knowledge (WoK) and Scopus were the databases used. Additional records were added using Evri (a more specialised database) and Google Scholar. These were used as sources of grey literature, which generally intend to capture projects less likely to have an academic agenda,

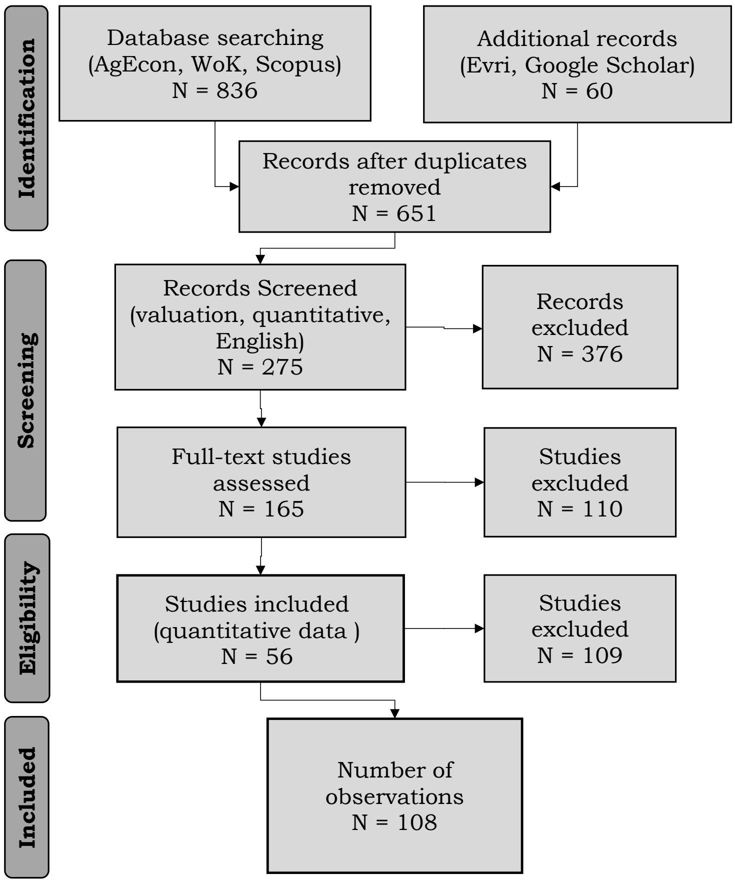

FIGURE 2.1: *Flow Diagram (PRISMA, 2009)*

e.g. policy projects. It was also important to include non-published papers because they are more likely to offer 'negative' results (bearing in mind factors such as representativeness, statistical significance, etc.), e.g. findings that consumers are not willing to pay a premium for 'organic', or even negative WTP. Generally, studies with negative results are highly under-represented; some papers suggest that this is driven by editors (Olson et al., 2002, Jannot et al., 2013, and Duyx et al., 2017), and others indicate bias from authors, who are more likely to submit manuscripts with positive results (Lent, Overbeke, and Out, 2014, Scherer et al., 2015, and Chong et al., 2016)[1]. These steps aimed to address or reduce the influence of academic publication bias.

The keywords used in the databases were mainly: Organic OR fair trade OR pesticide-free OR additive-free OR chemical-free OR non-chemical OR free-range AND (Type of study and outcome) valu* OR intention OR behav* OR purchas* OR WTP OR willingness to pay OR willingness to buy.

The data research was conducted in 2017; the search period was 2002 – 2017. Thus, papers published in that 15 years were selected. The objective was to cover enough variation in terms of WTP while capturing any change in taste and preferences over time. The papers were from the fields of economics and agriculture, environmental sciences, ecology, biodiversity, conservation, retail, and food. Studies included journal articles, working papers, book chapters, and reports. Only studies in English were included.

The data provided by the final list of papers were recorded and managed in Microsoft Access (please refer to Figure A.1 for illustration). The Access form was in line with Cochrane Data Collection Form (Moher et al., 2009) and tailored to this meta-analysis to certify the inclusion of all relevant variables and answer the proposed research questions stated in the introduction. The data extracted was organised into three areas: 'General Characteristics', 'WTP for Organic', and 'Socio-economic Information'. General data included information such as valuation method, data collection year, publication year, product type, country of valuation, and GDP in the year of the data collection. 'WTP for organic' section recorded the WTP premium (mean and median when available) and related information, e.g. coefficients, standard deviations, confidence interval, the unit of measurement, currency, etc. The third section was 'paper selection', which mainly included further socio-economic information about the sample, such as income and age averages, proportions of females, individuals

[1] in Mlinarić, Horvat, and Šupak Smolčić, 2017.

FIGURE 2.2: *Global distribution of studies*

with higher education, and consumers from urban areas. These factors are proven to influence the WTP of consumers, as discussed in the following sections.

The papers provided by the databases (651 in total, after removing duplicates and including grey literature) were recorded into RefWorks for screening. The first screening involved reading all titles and abstracts. Only valuation and quantitative papers were selected, resulting in 275 studies. Thus, 376 records were excluded without requiring text screening to indicate their qualitative approach explicitly. The following selection criterion involved text screening for another layer of quantitative eligibility check, as described below, resulting in 165 studies (110 excluded). The final stage was the full-text revision and data collection, which resulted in 56 papers (Figure 2.1) with WTP values, thus providing input to the meta-regression. At that stage, a further 109 articles were excluded for not offering WTP estimates. These papers did not explicitly give the WTP premium or the necessary information to calculate it.

Moreover, only valuation studies of organic food, as opposed to organic products in general (e.g. health and beauty), were used for data collection. As some studies involve the valuation of multiple products, each paper provided 1 to 6 observations, totalling 108 initially included in the meta-regression. The meta-regression was performed in STATA.

Meta-analyses are also analysed in the light of their risk of bias, inconsistency, indirectness, imprecision, and publication bias as proposed by Meader et al. (2014). These criteria can be summarised as follows:

- Risk of bias - selective results, not clear about treatment of potential limitations.

- Inconsistency - methodological heterogeneity, intervention in the data collection population.
- Indirectness - population, product, etc. How well does the evidence answer the research question?
- Imprecision - the size of effects, sample size, and confidence interval.
- Publication bias - it is widely accepted that the nature of the results found in a study determines whether it is publishable, in addition to the quality of the research.

The above is discussed as publication, selection, and misspecification bias proposed by Stanley et al. (2013). This meta-analysis has included published and non-published studies, which should mitigate potential issues with publication bias. Furthermore, funnel plots, a common approach used to assess potential publication bias, were constructed and shown in Figure 2.3. The estimation of each study is plotted on the x-axis (lnPWTP) against their respective measurement of accuracy on the y-axis (standard errors). The most accurate studies are closer to the top of the triangle. The symmetric funnel plot, i.e. an even distribution of plots across both sides of the overall meta-analysis outcome, indicates no publication bias (Bown and Sutton, 2010). Furthermore, the selection process presented in the flow diagram and the use of a source of grey literature (as explained above) mitigate potential bias, as studies were not selected based on their results or where they have been published.

The dataset aggregated input from studies worldwide, with North America having the highest representation with 34.3% of entries, Western Europe (27.8%), and Asia (11.1%). Figure 2.2 shows the regional distribution of selected studies.

The year of publication should capture any changes in regulation, e.g. implementation of credentials and certification, such as the USDA Organic, and potential changes in consumers' perception. The observations include data collected between 1999 and 2016 and published between 2002 and 2017. Most observations (62.9%) are from papers published between 2008 and 2012.

2.2.2 Data description

Considering the 56 papers, consumers, on average, pay an extra 41% for organic food compared to conventional ones, which is quite substantial. However, heterogeneity is observed

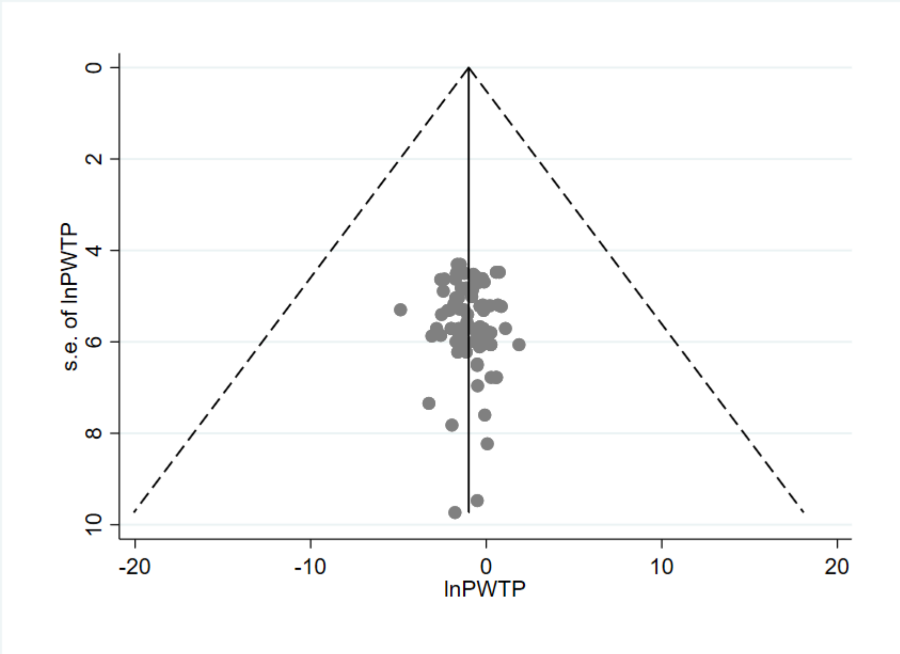

FIGURE 2.3: *Funnel plot (pseudo 95% confidence limits)*

and is explained in Section 2.3. Table 2.1 shows the selected papers, their respective number of observations, mean premium across observations, product types, and countries. Median WTP values are usually favoured as they capture the dominant option across the population, i.e. majority voting systems, and disregard outliers. However, these are not available in a significant number of studies.

The number of studies is not evenly distributed amongst product types, and the most extensive entries of WTP in the database are produce, dairy and meat (45%, 16% and 14%, respectively). The entries also indicate that leaves are associated with the highest premium, most likely due to their relatively low cost, followed by ornamental edible plants, such as indoor fruit-producing and foliage plants. The latter is probably observed because these may be perceived as superior goods, and consumers may be more concerned about more direct conventional production practices such as chemical usage. Beverage, eggs and ready meals are associated with the lowest premiums.

Instead of providing a WTP value, some studies supplied the coefficient of the 'organic' attribute. In those cases, the WTP was estimated from the ratio between the 'organic' coefficient and the 'price' coefficient (both from explanatory variables):

$$WTP = -\frac{(Organic \quad Coefficient)}{(Price \quad Coefficient)}$$

TABLE 2.1: *Eligible Papers*

Authors (Publication Year)	**N**	**MeanPremium**	**Product Type**
D'Amico, Vita, and Monaco (2016)	1	0.13	Beverage
Amirnejad and Tonakbar (2015)	1	0.68	Dairy
Bernard and Bernard (2010)	2	0.2	Dairy
Magistris and Gracia (2016)	1	0.27	Dairy
Griffith and Nesheim (2010)	1	0.17	Dairy
Kolodinsky (2008a)	4	0.39	Dairy
Rodriguez, Lacaze, and Lupin (2007)	1	0.14	Dairy
Roosen, Kottl, and Hasselbach (2012)	3	1.95	Dairy
Schröck (2014)	1	0.6	Dairy
Wier et al. (2003)	2	0.32	Dairy
Wong et al. (2008)	1	0.6	Dairy
Wong et al. (2010)	1	0.6	Dairy
Ara (2003)	2	0.92	Grains
Batte et al. (2004)	2	0.17	Grains
Boxall et al. (2007)	1	0.63	Grains
Thilmany, Bond, and Bond (2008)	1	0.04	Leaf
Rodriguez, Lacaze, and Lupin (2008)	5	2.98	Leaf
Chang et al. (2013)	1	0.07	Meat
Corsi and Novelli (2002)	2	0.52	Meat
Corsi and Novelli (2007)	2	0.23	Meat
Corsi and Novelli (2011)	4	1.3	Meat
Garcia-Torres, Lopez-Gajardo, and Mesias (2016)	1	0.44	Meat
Heid and Hamm (2013)	2	2.1	Meat
Villanueva, Lopez, and Dios Guerrero Rodriguez (2015)	1	0.22	Meat
Kalashami, Heydari, and Kazerani (2012)	1	0.01	Meat
Rihn et al. (2016)	2	2.35	Ornamental
Goddard et al. (2007)	4	1.06	Eggs
Emberger-Klein, Zapilko, and Menrad (2016)	2	0.97	Seasoning
Kalogeras et al. (2009)	1	0.7	Seasoning
Panico, Giudice, and Caracciolo (2014)	1	0.61	Seasoning
Vietoris et al. (2016)	1	0.07	Several
Arnoult, Lobb, and Tiffin (2010)	2	0.35	Produce
Bernard and Bernard (2009)	1	0.21	Produce
Cerda et al. (2012)	3	0.84	Produce
Cerda et al. (2015)	2	0.33	Produce
Chen and Gao (2016)	1	0.14	Produce
Chen et al. (2015)	3	1.8	Produce
Cicia et al. (2006)	1	0.86	Produce
Costanigro, Kroll, and Thilmany (2012)	3	0.89	Produce
Garcia-Yi (2015a)	1	1.23	Produce
Gschwandtner and Burton (2018)	2	0.32	Produce
Garcia-Yi (2015b)	6	0.27	Produce
Narine, Ganpat, and Seepersad (2015)	1	0.25	Produce
Nouhoheflin et al. (2005)	4	0.8	Produce
Owusu (2012)	2	6.48	Produce
Owusu and Anifori (2013)	2	1.31	Produce
Piyasiri and Ariyawardana (2002)	4	0.29	Produce
Scarpa, Spalatro, and Canavari (2007)	1	0.92	Produce
Shi, House, and Gao (2012)	1	0.21	Produce
Xie et al. (2016)	2	0.19	Produce
Yue and Tong (2009)	2	0.23	Produce
All (56)	**108**	**0.41**	**Several**

Table 2.2 shows the most important variables used in the meta-regression. Other variables were extracted, though they were not significant or could not be obtained across a significant number of studies. The variable PWTP indicates the mean WTP premium; the average premium consumers are willing to pay in the research. In other words, how much (in percentage so that entries can be compared and applied in the regression) individuals would pay extra/less for the 'organic' attribute concerning their conventional counterparts?

TABLE 2.2: *Descriptive statistics*

Variable	**Description**	**Mean**	**Std.Dev.**
lnPWTP	Dependent variable. Log of mean organic premium (Median: 0.333 - Min: -0.270 - Max: 6.480)	0.603	0.798
Study Characteristics			
Revealed	= 1 if revealed preference valuation method	0.130	0.338
Stated	= 1 if stated preference valuation method	0.870	0.338
CVM	= 1 if contingent valuation method	0.389	0.490
InfoGiven	= 1 if information about organic given	0.056	0.230
Online	= 1 if survey was taken online	0.083	0.278
HBT	= 1 if conducted hypothetical bias treatment	0.111	0.316
Product Characteristics			
Beverage	= 1 if product type is beverage	0.028	0.165
Fruit	= 1 if product type is fruit	0.139	0.347
Leaf	= 1 if product type is Leaf	0.028	0.165
Eggs	= 1 if product type is Eggs	0.028	0.165
Seasoning	= 1 if product type is seasoning	0.046	0.211
Ornamental	= 1 if product type is ornamental	0.019	0.135
Socio-economic Characteristics			
PubPrior2008	= 1 if published before 2008	0.241	0.430
Post2012	= 1 if data collected after 2012	0.130	0.338
HighEdu	Proportion of sample with a degree (Median: 0.517 - Min: 0.200 - Max: 0.830)	0.516	0.185
GDP	Gross domestic product per capita Year of the data collection (1/10,000) PPP Constant 2011 international $ (Median: 3.716 - Min: 0.170 - Max: 5.193)	3.086	1.696
Africa	= 1 if region is Africa	0.102	0.304
Asia	= 1 if region is Asia	0.111	0.316
NAmerica	= 1 if region is North America	0.343	0.477
WEurope	= 1 if region is Western Europe	0.278	0.450
UK	= 1 if region is United Kingdom	0.046	0.211
Weight	Sample Size	656 (15)	2057 (43)
	Grade	2.870	1.103

Sample size adjusted to population in parenthesis

The vast majority of observations (87%) are stated preference approaches, 45% of which are contingent valuation methods. From all observations, only 8.1% of responses were given through online surveys, whilst respondents were given information about organic products in 5.6% of the studies. Providing information about the potential benefits of the product under valuation is relatively common, but this may lead to an overestimation of the true WTP in those studies, as the researcher should not influence responses from consumers and exclusively report their behaviour based on the information they possess. A more diligent approach would provide information only to a treatment group within the sample and investigate whether information affects WTP. For this meta-analysis, the influence of information is analysed in the regression results. Also related to potential issues with stated preference approaches, 11% of studies conducted a type of hypothetical bias treatment.

For the characteristics of respondents, the average proportion of females in the studies was 66.6%, and those with higher education qualifications (i.e. college degree or above) was 51.6%. The higher proportion of females in the sample is consistent with the fact that, generally, women are responsible for grocery shopping in most cultures (e.g. Rihn et al., 2016, Wong et al., 2010 and Arnoult, Lobb, and Tiffin, 2010). Thus, studies aim to reflect this when selecting their samples to keep the representativeness of their respective populations. The only exception (in which respondents were predominantly male) in the sample was Iran (Kalashami, Heydari, and Kazerani, 2012 and Sabbaghi and Mahammadi, 2013), but this is consistent with the local culture about whom is responsible for the household shopping.

The sample level of education is substantially above global levels and may bias the true estimation of WTP. This is contributed by the fact that 65.7% of the sample comes from OECD countries with higher education levels, with approximately 36% of the population aged 24 to 65 (OECD, 2018). There is also an influence from lab experiments, which usually occur in universities.

Many studies do not provide information on education level. In some cases, other socio-economic data were not consistent or comparable across the sample, mainly due to differences in measurement. In fact, despite being central as WTP explanatory variable, meta-analyses of WTP studies rarely incorporate education in their regressions for this same measurement issue. Nonetheless, education level is necessary not only because it is highly correlated with income (thus serving as a proxy of such a central factor of WTP in general) but also due to the influence of information about the potential benefits of organic food, assuming that more educated individuals should have higher access to related information.

TABLE 2.3: *Average Premium by Product Type*

Product Type	Entries	Mean (PWTP)	Std.Dev.
Produce	45	0.56	0.45
Meat	19	0.58	0.60
Dairy	17	0.35	0.23
Grains	9	0.59	0.62
Seasoning	4	1.21	1.18
Eggs	3	0.19	0.76
Leaf	3	2.45	3.51
Beverage	2	0.16	0.04
Ornamental	2	1.55	1.14
Ready meal	1	0.21	0.00
Total	108	0.60	

Socio-economic data is challenging to be consistent in terms of measurement and scale. Thus, other variables such as income, rural/urban areas, and age, all with a theoretical background as a driver of WTP for organic products, could not be included due to a lack of similar information across the papers, so average values could not be computed to serve as input in the meta-regression.

In terms of mean WTP, Table 2.3 shows premiums by product type (in percentage) globally. The studies show that consumers are willing to pay 245% premiums for leaves, 155% for ornamental plants and 121% for seasoning, forming the highest values. In contrast, the lowest premiums are associated with ready meals (21%), eggs (19%) and beverages (16%).

Averaging WTP premium gives us an indication of the overall WTP for organic food. However, the results exhaustive, with substantial heterogeneity. They do not offer an insight into the contribution of each characteristic to premiums, which can be obtained by a meta-regression, as follows.

2.3 Meta-regression

This chapter investigates how the different environmental valuation methods, products, and socio-economic characteristics (independent variables) explain the premiums consumers are willing to pay for organic food. Thus, the dependent variable in its regression is the PWTP (y), expressed as the willingness to pay in percentage of the total price.

Meta-regression models of environmental valuation studies are generally simple, primarily because entries are accounted for equally, and ordinary least square (OLS) regressions are often estimated[2]. However, it is also understood that studies do have varying quality levels of evidence. Therefore, as explained in Section 2.2, papers were graded based on a careful assessment of their risk of bias and sample size. Grading the studies implies that OLS, core in meta-regression estimation, is inadequate in this case. Instead, this paper will apply a weighted least square (WLS) regression. In other words, the data points are not treated equally, as it gives preference to entries that have been more precisely measured, assuming that larger samples offer more robust results than smaller ones. In WLS estimations, weights are inversely proportional to the variance of the predictor, as:

$$W_i = \frac{1}{Var(x_i)} \tag{2.1}$$

Where W_i represents the weights and x_i some predictor.

Typically, the observations represent averages, and the weights are the number of elements that give rise to the averages. Papers with a higher risk of bias (such as studies with minor or less representative samples) are associated with larger variance, thus lower grade. In other words, the weight was given according to sample sizes divided by their respective population, thus giving higher weight to potentially more representative samples. The sample size had to be adjusted to the population to make sure the representativeness of the sample is more valued than the sample size per se[3]. Thus, relatively larger and more representative samples are associated with lower variance, receiving higher weight.

The caveat of weighting by sample size is that stated valuation methods and experiments are associated with lower samples, despite being representative. Thus, results may favour revealed preference methods, which usually can access thousands of observations from, for example, supermarket scanner data. However, revealed preference methods have a more robust theoretical background and are generally preferred amongst economists. Nonetheless, results can be compared with OLS regressions to investigate whether these are significantly different, and the coefficients of stated preference approaches also contribute to this discussion.

[2] Barrio and Loureiro, 2010; Brander, Van Beukering, and Cesar, 2007; Lindhjem, 2007; and Loomis and White, 1996, to name some key studies in the field.

[3] Samples from countries with large populations naturally require larger samples, which would not necessarily mean that these are more accurate than a sample from small populations.

The regression model using WLS is therefore equivalent to:

$$\frac{y_i}{\sqrt{g_i}} = \frac{\alpha}{\sqrt{g_i}} + \frac{\beta_s X_{si}}{\sqrt{g_i}} + \frac{\beta_p X_{pi}}{\sqrt{g_i}} + \frac{\beta_e X_{ei}}{\sqrt{g_i}} + \frac{\epsilon_i}{\sqrt{g_i}} \tag{2.2}$$

Where g is the grade given to each paper, based on sample size; α is the constant term, X_s groups the study characteristics, X_p product characteristics, and X_e socio-economic characteristics, and ϵ_i is the error term. Assuming variance is proportional to predictor g_i, i.e. $Var(x_i) = g_i\sigma^2$, $W_i = 1/g_i$.

In terms of functional forms, most meta-regression of WTP studies have used log-linear estimations. As an attempt to test this convention, Barrio and Loureiro (2010) conducted a Box-Cox test (which makes the residual sum of squares comparable in a meta-regression) and confirmed that the best model for their data was the semi-log (log-linear) model.

The main problem with semi-log functions is that negative WTP premiums would not be incorporated in the regression. However, there were only two negative WTP observations in the sample, which may not significantly affect the results. This study tested several function forms, following goodness of fit, heteroscedasticity, and misspecification tests (Table 2.4), and the best-suited one was confirmed to be the semi-log model.

TABLE 2.4: *Omitted variables and heteroscedasticity tests*

	Restricted Model (log-linear)	**Extended Model (log-linear)**
Ramsey RESET		
	F(3, 87) = 4.80	F(3, 36) = 0.40
	$Prob > F = 0.0039$	$Prob > F = 0.7571$
Null: Model has no omitted variables		
Breusch-Pagan Cook-Weisberg test for heteroskedasticity		
	chi2(1) = 0.34	chi2(1) = 0.56
	$Prob > chi2 = 0.5601$	$Prob > chi2 = 0.4540$
Null: constant variance		

The restricted model is presented as:

$$ln(y) = \beta_0 + \beta_1 Stated + \beta_2 CVM + \beta_3 InfoGiven + \beta_4 Online + \beta_5 PubPrior2008 +$$

$$+\beta_6 Post2012 + \beta_7 Beverage + \beta_8 Fruit + \beta_9 Leaf + \beta_{10} Meat + \beta_{11} Eggs + \beta_{12} Seasoning +$$

$$+\beta_{13} Ornamental + \beta_{14} Africa + \beta_{15} Asia + \beta_{16} NAmerica +$$

$$+ \beta_{16} WEurope + \beta_{17} UK + \epsilon \tag{2.3}$$

The extended model includes the average level of education within the studies, as justified in the previous section. Given that the dataset does have negative WTP premiums, results from a linear model will be presented for comparison. Not all variables in the data were included in the results in Section 2.4 due to issues of misspecification (as some variables were not relevant) and collinearity (Table 2.5).

TABLE 2.5: *Multicollinearity test (restricted model): Following that $Vif > 5$ as highly correlated*

Variable	**VIf**	**1/Vif**
North America	6.44	0.16
GDP per capita	5.98	0.17
Asia	2.72	0.37
Higher Education	2.05	0.49
Post-2012 Sample	1.61	0.62
Fruit	1.42	0.71
Contingent Valuation	1.40	0.71
Seasoning	1.37	0.73
Stated Preference	1.36	0.73
Information Given	1.32	0.76
Online	1.25	0.80
Leaf	1.08	0.93
Mean VIF	2.33	

2.4 Results

Results from the restricted model in Table A.1 (see Appendix) suggest that ornamental plants and eggs are associated with the highest proportional premiums amongst significant product types. In contrast, beverages are associated with the lowest premiums. A counter-intuitive result from this model is that, although narrowly significant, 'information given' has a negative impact on the 'organic' premium. Other variables associated with the methodology of the valuation studies were not significant in the first model. Regarding regional effect, Model 1 indicates that Africa has the highest positive impact on WTP for organic products, followed by Western Europe, and Asia in third. The UK has a negative effect. The coefficient for HBT indicates a negative impact from hypothetical bias treatment on WTP, although this is not significant in the restricted model.

As explained, the restricted model in Table A.1 does not include education to capture the highest number of observations possible, as this information was not available in all studies. Not surprisingly, one cannot reject the null of omitted variable in the restricted model (Table 2.4), and the goodness of fit (r-squared) is relatively low (66.5%) in comparison to other meta-analyses; thus, results from Model 1 should be analysed with caution, and focus should be placed on the extended model from Table 2.6.

Both restricted and extended models were tested with no evidence of heteroscedasticity (Table 2.4), but only the extended model showed no evidence of omitted variables. This is in line with the argument about the relevance of education in WTP estimates. In addition, the fact that other variables became significant in the extended model can be justified by the potential issue with omitted variables in the restricted model, which could bias the estimators. Finally, for the model selection, one can use the criteria from either the Akaike information (AIC) or the Bayesian information (BIC) from Tables 2.6 and A.1, which show substantially smaller values for the extended model (including education), thus confirming the better fit. Therefore, the discussion from this point is on results from the extended model.

Including education as a factor confirms that socio-economic information is central to WTP estimations. Table 2.6 shows results with 'Education', which then increases the explanatory power to 92.4% (suggesting a strong fit). The variable GDP per capita was dropped due to issues with multicollinearity (Table 2.5), and it was strongly (and significantly) correlated mainly with 'North America' (NAmerica), and moderately with Asia and CVM (Table A.2).

In the extended model, one can benefit from gaining more methodological insight, with variables such as CVM (valuation studies using CVM), 'online survey' (as opposed to face-to-face), and 'recent studies' (post-2012) then becoming significant. Concerning product types in the extended model 'leaf' and 'seasoning', geographically, Asia and North America are also significant variables. Amongst the variables related to the methodology used, 'stated' was significant in both models. At the same time, CVM was significant (99% confidence) only in the extended model, showing that CVM does offer higher WTP estimates.

TABLE 2.6: *Regression Results*

lnPWTP	Coef.	St. Err.	t-Value	p-Value	Sig.	Partial Effect if=1	Partial Effect Mean
SP (stated preference)	0.417	0.234	1.78	0.084	*	1.517	0.512
CVM (contingent valuation)	0.424	0.174	2.43	0.020	**	1.528	0.748
HBT (hypothetical bias treatment)	-1.019	0.349	-2.92	0.006	***	0.361	0.114
Information Given	1.521	0.394	3.86	0.001	***	4.577	1.053
Online Survey	-1.315	0.388	-3.39	0.002	***	0.268	0.075
Publication Prior 2008	0.114	0.194	0.59	0.560		1.121	0.270
Data Collected Post-2012	1.230	0.256	4.82	0.000	***	3.421	1.155
High Education (sample %)	-2.353	0.512	-4.59	0.000	***	0.095	0.018
Product type (Eggs as Baseline)							
Beverage	-0.101	0.409	-0.25	0.807		0.904	0.149
Fruit	0.549	0.286	1.92	0.064	*	1.732	0.602
Leaf	1.889	0.237	7.99	0.000	***	6.613	1.092
Meat	0.257	0.255	1.01	0.321		1.293	0.495
Seasoning	3.072	0.219	14.04	0.000	***	21.585	4.557
Ornamental	-1.437	0.653	-2.20	0.035	**	0.238	0.032
Region (Africa as Baseline)							
Asia	2.555	0.203	12.61	0.000	***	12.871	4.064
North America	1.870	0.212	8.80	0.000	***	6.488	3.094
Western Europe	0.605	0.452	1.34	0.190		1.831	0.776
UK	0.063	0.582	0.11	0.914		1.065	0.225
Constant	-2.217	0.229	-9.69	0.000	***		
R-squared	0.924	Number of obs: 52					
Akaike crit. (AIC)	7.548	Bayesian crit. (BIC): 40.72					

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

The results show that consumer WTP for organic seasoning, such as herbs and oil, increases the premium three times compared to other products. In contrast, organic leaf almost doubles the premium, and organic fruit increases the premium by 55%. This suggests that consumers may be willing to pay higher premiums for lower price products, as cheaper products can have a higher premium and remain inexpensive, thus having a relatively lower impact on consumers' budgets. This is also consistent with economic theory, as demand is expected to be less elastic when the product price takes a lower proportion of income; thus, higher production costs due to organic practices can be passed onto consumers. Concerning meat, although the data suggest that consumers are willing to pay an average premium of 58% for meat, the variable was not significant in the regression results. This was driven by the extensive scope of the study, with premiums ranging from 1% to 210%, and only four observations covering chicken meat, thus requiring a more detailed model and larger sample.

Some results, however, may sound counter-intuitive, most notably the negative effect of education on the WTP premium. One reason for this is that more educated individuals may have higher bargaining power and more information at their disposal; thus, they act more rationally and are less likely to overestimate their WTP. Another potential reason is the misrepresentation of the sample in terms of education, as discussed in the data section. Once more, it is important to stress that the coefficient of 'Education' does not indicate that educated individuals would offer negative WTP (which would mean they require compensation). Still, instead, they would pay a lower proportional difference in price between organic and conventional. From the data, some of the WTP studies that found a negative effect of education on 'organic' premiums include Govindasamy and Italia (1999), Gschwandtner and Burton (2017), Kolodinsky (2008b), and Misra, Huang, and Ott (1991), whilst others have mixed results, e.g. Hamzaoui-Essoussi and Zahaf (2012), Chen et al. (2015), and Rodriguez, Lacaze, and Lupin (2008). In other words, the latter argues that the lower the educational level, the higher the quality of risk perception. The higher the education level, the higher the confidence in production standards, thus driving the inverse relationship between education level and the organic food premium.

Regarding regions, results indicate that 'organic' premiums in Asian and North American countries are generally higher than the average WTP premium across all regions in the data (with a 99% confidence level). This might sound counter-intuitive for Asia. However, this is not the first time a meta-analysis of environmental valuation indicates this. Barrio and Loureiro (2010) found negative WTP for environmental amenities in Europe, while Clark et al. (2017) found in their meta-analysis that studies in Asia provide the highest average WTP for animal welfare, in contrast with, for example, the UK, the lowest WTP in their estimations.

At the methodological level, the results also contribute in terms of study characteristics. The positive coefficient of stated preference methods indicates that these provide relatively higher premiums, showing an average increase of 42% in premiums compared to the RP approaches. Within SP approaches, the positive coefficient of CVM supports the perceived idea that CVM might be relatively more likely to provide over-estimated WTP than CEs and other SP approaches. In the alternative linear regressions (Tables A.3 and A.4), the coefficient for 'stated' is also positive and significant (at 5% level)[4], but the other methodological variables are not significant. This can be interpreted as hypothetical bias potentially being an issue. The coefficient for HBT in the main model indicates that hypothetical bias treatment has a negative effect on WTP, which should encourage such an approach to SP methods.

Another insight comes from the variables generated from the year of data collection, which capture any trends over time. In other words, this intends to incorporate changes in consumer perception driven by new findings and commercial expansion. Results in the extended model show that studies carried out post-2012 are associated with higher premiums, showing an increase of 123% in the premium compared to the baseline period (2008 to 2011), which is in line with organic market expansion, i.e. demand-side pressure on prices. The increase should have a connection with the global economic recovery from 2012, assuming 'Organic' as 'luxury' compared to conventional; thus, more income elastic. Moreover, as explained in Section 2.1, several studies have indicated the benefits of organic food, fuelling information passed onto consumers, which may have contributed to an increase in the consumption of organic products and WTP premium.

The results also suggest that online surveys have a negative effect on WTP for 'organic'. This is not surprising, as respondents may feel encouraged to inflate their responses when in direct contact with the surveyor. Face-to-face interviews are more likely to be affected

[4]These models were used for robustness, showing results from linear models (unweighted) for both restricted and extended data.

by a 'social desirability bias' due to the interviewer's presence (Duffy et al., 2005). In contrast, the coefficient of 'information given' is positive, suggesting that WTP premiums are likely to be larger when consumers are more informed about the potential benefits of organic food, which also follows intuition. The two sides of this result are that, firstly, the information given is likely to bias WTP estimations; thus, survey-based valuation studies should consider this approach carefully. However, this also reinforces the prospective influence of information on consumers' WTP, notably for social marketing strategies and profitability.

2.5 Chapter conclusion

This meta-analysis summarises the current consensus about the WTP for organic food. It covers heterogeneity at the methodological, product characteristics, and socio-economic levels. After considering 651 studies of organic products, 56 valuation papers were selected to provide the required data for the meta-regression, contributing to an input of 108 valid observations (102 included in the extended model). On average, consumers across all studies were willing to pay 60% extra for organic products compared to conventional ones.

Regression results from this meta-analysis indicate that SP approaches (particularly CVM) estimate a relatively higher premium. This confirms that hypothetical bias should be addressed in SP valuations. Future research (meta-analysis in particular) may explore the effectiveness of treatment of hypothetical bias in such studies. Other methodological practices associated with higher WTP premiums are face-to-face surveys and providing information about attributes to respondents during the surveys. These factors should be considered when designing an environmental valuation study, as they are likely to inflate the WTP premium. At the application level, stakeholders should be confident that information is vital in raising awareness of the potential benefits of organic food and the revenue opportunities associated with such an influence.

About product type, fruit, leaf, and seasoning offer relatively higher premiums. The intuition can explain why consumers are more likely to pay extra for cheaper products, as the impact on their budgets would be relatively lower. For example, consumers are willing to pay almost three times the price of conventional seasoning for their organic counterparts. Even amongst these three products, one can observe a trend with an increasing coefficient (thus proportionate premium) from herbs, leaf and fruit, respectively. Generally, this would also be the ascending ordering price for these products. Another trend is about time, as older studies found that consumers would pay a lower proportionate premium. Over time, the increase in price premium is justified by the development of the 'organic' market, with more information and a greater variety of products available to consumers in recent years.

Another contribution of this meta-analysis is to identify the influence of socio-economic variables on WTP premium for organic food. The results indicate that level of education would have a negative effect on proportional premiums. In other words, despite paying a premium (an extra value for the 'organic' attribute), the price difference between organic and conventional food is relatively lower amongst more educated individuals. This might indicate that those individuals believe it is more rational or sensible to pay extra for organic food but at a more measured percentage. Concerning WTP for organic meat, this meta-analysis shows that average consumers pay a 58% premium for the product.

However, one of the limitations of this study is that the global scope and exhaustive list of products are associated with considerable heterogeneity and raise more questions about the value of the WTP for organic food. Therefore, the main contribution of this study is the analysis of the explanatory variables driving WTP, particularly product characteristics, valuation methodology, and socio-demographic insights. The following chapters will explore and inform the key consumer characteristics and product attributes in more details, and how these affect WTP but will be narrowed to a product type (chicken meat).

Another limitation is the number of studies. As discussed in Section 2.2.2, although this is a common issue faced by meta-analyses, socio-economic characteristics are not consistently provided across studies. Thus, the meta-regression loses some observations. In the case of this study, although with fewer observations, including key socio-economic characteristics benefited the study more than having more observations with less statistical quality (as shown by the tests). A future meta-analysis might benefit from a more extensive scope as new WTP studies arise and different selection criteria could be followed, so results are compared.

Finally, weighting studies can have an unintended effect on bias. This meta-analysis applies a robustness check by weighting WTP according to the grade of bias attached to the paper. Results were consistent with sample size per population, but another method may be applied. For example, the nature of the data (e.g. revealed or stated) might be an adequate weighting in a different dataset, assuming that revealed preference estimates of WTP are arguably more accurate than stated ones.

Chapter 3

Revealed Preference Estimation: Hedonic Price Modelling

3.1 Chapter introduction

There has been a significant increase in the breeding and consumption of chicken globally, with considerable adverse effects on the environment, consumers' health and animal welfare, compared to the previous breeding processes. The rise in chicken consumption has recently drawn the attention of consumers, suppliers, and the media (BBC, 2018, The Economist, 2019, The Guardian, 2018). Arguably, an organic approach to food production can offset many of the issues associated with increasing demand; thus, understanding consumer preferences is a necessary step forward. This chapter values the premium consumers pay for the 'organic' attribute, which can be used in policymaking considerations, from social marketing (assuming organic food as a merit good) to the valuation of the right supply incentive to match local demand.

As highlighted in Chapter 2 of this thesis, organic products are considered to have an overall positive impact on individuals (especially health), the environment (soil, pollination, and biodiversity protection), and animal welfare (humane farming). These perceived benefits have been pivotal to a significant increase in the production and consumption of organic products worldwide. However, in the UK, the picture looks somewhat different. While sales were increasing in line with the global trend up to 2008, there was a noticeable dip after the 2008–2010 financial crisis (Figure 3.1).

Despite six years of solid growth, sales are only regaining their 2008 level. In contrast,

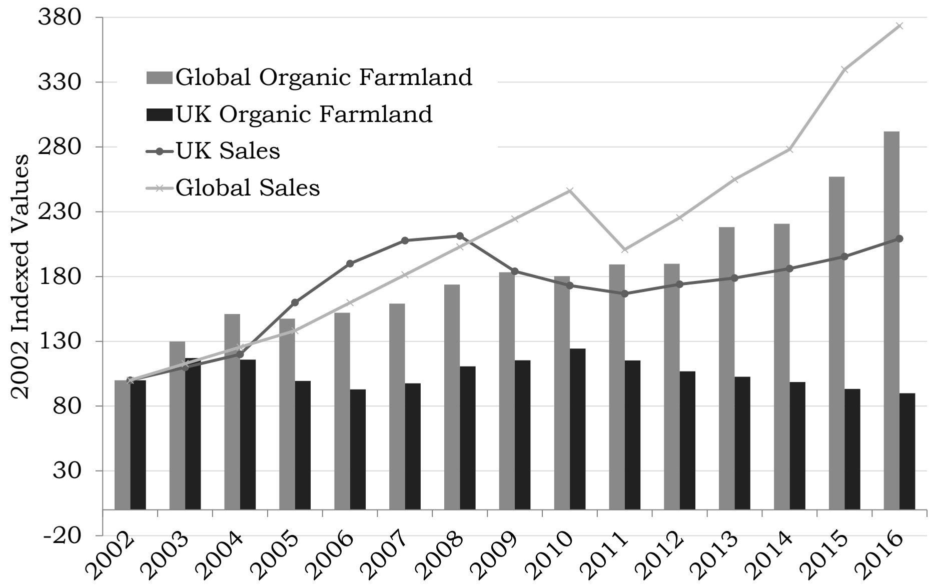

FIGURE 3.1: *Organic product: sales and farmland (2002 indexed values)*

organic farmland in the country has decreased 5% per annum since 2011 as farmers convert back to conventional production (SoilAssociation, 2018). Chapter 2 also shows that consumers are willing to pay a higher premium for lower-priced organic products; thus, indicating that lower prices enable consumers to pay a higher premium for their desirable attributes. For example, as a result of the current low chicken price, some consumers seem to be happy to pay a premium for altruistic attributes, such as animal welfare, which would previously have had a higher affordability effect. Therefore, a precise estimation of the organic attribute is central.

Specifically, chicken meat consumption has increased substantially in the last decades due to farming and processing intensification, but with a potential negative impact. ‘Organic’ is advocated as a possible way to offset some of these problems; thus, raising questions about consumers’ implicit value associated with organic production. According to the Organisation for Economic Co-operation and Development (OECD, 2017), global consumption of chicken has grown 134% since 1990. The bird accounts for 23 of the 30 billion land animals living on farms (Bennett et al., 2018). Intuitively, price is the primary driver of such an increase in consumption, as producers have reduced the average costs through methods

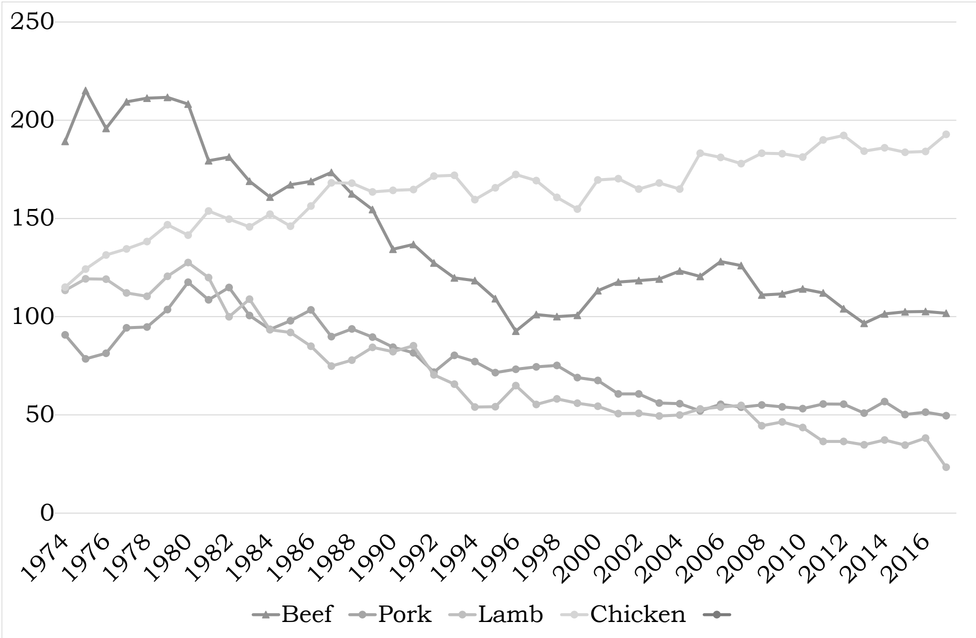

FIGURE 3.2: *Meat Consumption in the UK (g/person/week) - Source: Defra*

such as selective breeding. They are not only large in number but have also grown in size. The average weight of a 56-day chicken in 1957 was 0.9 kilograms, while in 2005, it was 4.2 kilograms (Zuidhof et al., 2014). As a result, chicken is the most consumed meat in the world, which also applies to the UK, as shown in Figure 3.2. Although this is mainly price-driven, it is helpful to understand the contribution of each attribute to the WTP for broiler chickens.

To better understand the trends in organic chicken sales and to appreciate the merits of different policy options, one needs to have a robust understanding of consumers' preferences for organic attributes. With the UK leaving the EU's Common Agricultural Policy (CAP), this is a pivotal time when the country designs its own agricultural policy. However, there are limited valuation studies on WTP for organic attributes, particularly in chicken meat. In addition, existing studies do not offer robust estimations or provide enough details about the socially desirable attributes of chicken meat.

Environmental valuation has been incorporated into decision-making in Europe and the UK, reaching a legal mandate status. This is particularly true for the housing market, forestry, agriculture, and carbon emissions (carbon trade). Altogether, estimations of the economic value of benefit transfers and WTP feeding decision-making. As summarised by Pearce and Seccombe-Hett (2000), some of these uses include cost-benefit analyses of projects and policies, pricing policy, design of environmental taxes, national accounting and management tool, and public participatory exercise. Cost-benefit analysis, green national income analysis, and environmental tax design are typical applications in Europe.

To estimate the premium consumers are willing to pay for the organic characteristics, this chapter applies a hedonic price (HP) model, using purchase information from British consumers to model how chicken meat characteristics explain changes in willingness to pay. However, it has been widely covered in the literature that the hedonic models suffer from econometrics issues often ignored in empirical work, notably the endogeneity of the product characteristics. Therefore, this paper uses the generalised method of moments (GMM), incorporating consumer characteristics as instruments, to address this issue and estimate the value added by the organic attribute to the marginal price paid for chicken meat.

The following section explains how the simultaneity of the marginal price and quantity of attributes implies that the product characteristics are potentially endogenous. Meanwhile, some studies use an inadequate approach, such as questionable instruments, to deal with this issue. This chapter illustrates that GMM offers a reliable alternative to address endogeneity in hedonic price models. In line with Wooldridge (1996), this study suggests that, whenever applicable, consumer characteristics can be used as instruments to address endogenous product characteristics in the HP model. In the case of this study, the price contribution of the 'organic' attribute to chicken meat was treated with instruments generated from the family structure of consumers. Backed by the literature, in line with economic intuition, and passing the required statistical tests, this paper estimates a 136% premium for the 'organic' attribute of chicken meat in the UK. The results also offer some insights into the heterogeneity of 'organic' premiums across chicken parts and the UK regions.

3.2 Theoretical background

This chapter uses the hedonic price method (HPM) for value estimation of attributes. HPM is suitable for the large sample and the vast number of attributes available in the data used for the chapter. Alternative to hedonic pricing, many studies using revealed preferences have applied consumer discrete choice-based random utility models to estimate willingness to pay for specific attributes, including environmental ones[1]. These studies follow McFadden et al. (1973) and (1974) multinominal logit model (MNL), and estimates how attributes (including price) explain the choice for a product. One of the main limitations of MNL is its assumption of independent and identically distributed (IID) random variables. These methods are further explored in Chapters 4 and 5. Some studies aim to relax such a strong assumption, incorporating heterogeneity or using more advanced mixed logit models. For example, Hilger et al. (2019) assumes IID and does not incorporate heterogeneity from individuals' characteristics. The paper indicates a correlation between unobserved attributes, the choice probability and error terms, and heterogeneity effects on individual choices from unobserved attributes.

Having price as an explanatory variable, it results that these methods are susceptible to endogeneity driven by unobserved consumer characteristics. This requires solutions such as simultaneous equation models proposed by Berry, Levinsohn, and Pakes (1995), which is not always feasible, as discussed in Section 3.2.1. Thus, most studies assume that each alternative's mean of unobserved factors is zero and independent across individuals (Berry, Levinsohn, and Pakes, 1995).

This chapter applies the hedonic price model to estimate the contribution of attributes associated with organic chicken, considering consumers' perception that such a product offers better results in terms of the environment, health, animal welfare, and potentially quality and taste. The hedonic price model is the most popular revealed preference approach to environmental valuation. It is widely used to estimate the added value of housing attributes, e.g., environmental amenities, but also has been applied to markets in the food industry, including dairy, produces, and eggs (Griffith and Nesheim, 2010; Kolodinsky, 2008a; Schollenberg, 2012; and many others, as detailed below). The method is derived from consumer theory, based on the assumption that a consumer's utility for a good or service is driven by its attributes (Garrod, Willis, et al., 1999). The theoretical framework of the hedonic method was proposed by Rosen (1974), which applies to a bundle of n products where several products provide each characteristic. Rosen's model has been applied to several products, durable and non-durable.

Hedonic price, however, whilst widely used, is often applied to ignore its econometric

[1] To name some: Berry, Levinsohn, and Pakes (1995), McFadden and Train (2000), Swait, Adamowicz, and Bueren (2004), Hilger et al. (2019).

issues, notably the simultaneity problems derived either from supply and demand equilibrium or marginal price and quantity of attributes, the latter being associated with the non-linear characteristics of the price function, as illustrated by Follain and Jimenez (1985), Wooldridge (1996), Bishop and Timmins (2011), and others. Closer to this thesis, Kim and Chung (2011) applies a GMM hedonic price model to estimate the willingness to pay for product characteristics of eggs, using egg size and the daily number of transactions (from scanner data) as instrumental variables. In another hedonic price study applied to the food industry, Berning and Sprott (2011) follow Wooldridge (1996) and considers the potential source of endogeneity of demographic dummy variables as unobserved factors to the researcher, including nutrition consciousness and nutrition label consciousness. The following paragraphs will explore these problems, explain why simultaneity is a problem in the case of this study, and it will explore a potential solution. This section demonstrates that the supply and demand simultaneity is not a problem in the hedonic price model applied to microdata. Thus, there is no need to incorporate supply-side information. However, the second simultaneity problem derived from the non-linear nature of the price function has to be addressed.

The two-steps baseline hedonic price model proposed by Rosen (1974) for a product with characteristics z, where $z = (z_1, \dots, z_n)$. Therefore, it is important to stress that z represents a vector of all product characteristics associated with a product i. Ladd and Suvannunt (1976) proposed a model of consumer goods characteristics applied to food purchases. The paper expresses that the total amount of product characteristics Q chosen by a consumer is a function of the quantity of products consumed (q) and the characteristics z. Thus:

$$Q_i = f_i(q_1, q_2, ..., q_n, z_{1j}, z_{2j}, ..., z_{nj}), for :$$

$$i = 1, 2, ..., n, andj = 1, 2, ..., m, and$$

$$Q_{m+1} = f_{m+i}(q_i, z_{im+i}),$$

where Q_i is the total amount of the ith product attribute embedded in all products, q_i is the amount of each product consumed, and z_{ij} is the quantity of the jth attribute in one unit of product i. $Qm + i$ represents the characteristics available from consuming the ith product.

$Qm + i$ can measure, for example, a particular vintage year or a presence of a particular sensory property of a fresh fruit for a wine in a hedonic estimation model (Huang and Lin, 2007).

It is assumed that the consumer aims to maximise their utility, given by a function expressed as:

$$u = u(Q_1, Q_2, ..., Q_m, Q_{m+1}, ..., Qm + n),$$

also expressed as:

$$u = u(q_1, ..., q_n, z_{11}, ..., z_{1m}, z_{21}, ..., z_{nm}, ..., z_{nm+n}).$$

The budget constraint posed to consumers would give income y, then be $y = \sum p_i q_i$. Where p_i is the price of the ith product. This can be written as $p_i = f_i(z)$.

The consumer utility function can be simplified as $u = u(z, v)$, where v is a unity price composite commodity.

Rosen's two-step approach estimates the hedonic price from Equation (3.1), then supply and demand functions. In the first step, the marginal price of z, given as $(p(z))$, is estimated using the best fitting function form by OLS. This would involve regressing observed differentiated product prices on their characteristics (z), and characteristics other than consumers or suppliers, e.g. geographical location, that may influence prices, given as x^h. The price function is defined as a function of its characteristics z_i, x^h and the stochastic error term ϵ, given as:

$$P = f(z_i, x^h, \epsilon) \tag{3.1}$$

From the results, for each buyer and seller, one can compute the marginal implicit price of attributes, i.e. $p(z)$ or the first-order condition of the hedonic price function. In Rosen's second step, the marginal implicit prices by each entry are used as an exogenous variable in both demand and supply functions. It is important to stress that firms and households are assumed to be price-takers. Thus p is defined by the market-clearing conditions, i.e. market equilibrium. It is also intuitive to assume that the Equation 3.1 is non-linear. We will come back to these assumptions and their implications later.

The first order condition (the marginal effect of attributes z on price) entails:

$$\frac{\partial p}{\partial z_i} \equiv p_i = u_{zi}/u_v, i = 1, ..., n$$

While the amount consumers are willing to pay for a characteristic z is given by the function:

$$\theta(z_1, u, y, \alpha)$$

Given their utility and income:

$$u = u(y - \theta, z, \alpha)$$

Where α is a taste parameter (differs across individuals). Therefore, the amount individuals are willing to pay for the characteristic z_i is given by:

$$\theta_i = u_z/u_v \tag{3.2}$$

As *p(z)* is assumed to be given, it represents the minimum price consumers are willing to pay to maximise their utility, i.e. only individuals who have WTP above or equal to the equilibrium price would consume the good; thus, this reveals their lower bound WTP, i.e. *p(z)* is the minimum price the consumer must pay in the market. The utility is maximised at the tangent point[2], where:

$$\theta(z^*, u^*, y^*, \alpha) = p(z^*) \tag{3.3}$$

* indicating optimum quantities.

It is important to note that $p(z^*)$ is also determined by supply. Thus, assuming firms are also price-takers and profit maximisers, they are willing to accept a value ϕ, subject to the potential profit π and its cost structure c(z,β), where β indicates the factor prices and production parameters. Thus, the firm's willingness to accept (WTA) is given by:

$$\phi(z^*, \pi^*, \beta) = p(z^*) \tag{3.4}$$

[2]Assuming consumers' indifference curves are convex, i.e. one should expect that higher income always increases the maximum attainable utility (Rosen, 1974).

The equilibrium price $p(z^*)$ is simultaneously defined by demand, and supply poses some econometric issues. In the hedonic pricing sorting, the product characteristics z are identified as endogenous, sourced in the simultaneity of $p(z^*)$. The second possible source of endogeneity comes from the simultaneity of z and $p(z)$. When individuals maximise their utility, attributes z and $p(z)$ affect their choices simultaneously. Thus, the price function needs to be non-linear so that z remains in the first-order condition (supply and demand functions). Therefore, either way, z needs to be instrumented, as shown in more detail in the following subsections.

3.2.1 First simultaneity problem: supply and demand

The equilibrium point (price and quantity) is reached when supply equals demand. Thus, $p(z^*)$ is defined simultaneously by (3.3) and (3.4). This poses practical problems in inferring preference structures from the price equilibrium and data from households and firm characteristics, as error terms are correlated with explanatory variables in either the demand or supply functions (Follain and Jimenez, 1983). Thus, simultaneous supply-demand estimation is necessary when the hedonic price depends on the observed units demanded. Rosen's two-step approach can be used to estimate this system. However, as Follain and Jimenez (1985) demonstrates, an individual's demand (and error terms) for a particular good would not affect the market hedonic price function in microdata. Microdata studies explore individuals' behaviour. Therefore, a demand-side analysis does not need to incorporate supply equations and a simultaneous price determination approach to estimate consumers' WTP. Similarly, Kahn and Lang (1988) demonstrate that in different markets, the distribution of consumers and firms does not influence supply and demand equations, as they do not affect the relationship between demand for the product attribute, consumers' characteristics and marginal prices.

Follain and Jimenez (1985) have also argued that several studies have addressed a non-existent problem (simultaneity in microdata). Meanwhile, Bishop and Timmins (2011) show that supply-side shifters, commonly used as instruments to address the endogeneity problem, including Kahn and Lang (1988), are not valid to justify the demand equation (not relevant), and some other researchers have chosen weak instruments based on assumptions often difficult to justify. It is better to use OLS than two or three-stage regressions with weak instruments when the correlation between the instruments and z is low (Wooldridge, 2010).

Therefore, a simple linear hedonic price model that attempts to estimate the determinant of demand for the product attributes z is commonly used. Usually, the WTP for the attributes z is simply inferred from the coefficients of the hedonic functions estimated with linear regressions.

Several studies have applied the hedonic price model to investigate the price premium consumers are willing to pay for the 'organic' attribute; thus, offering only a demand-side analysis. These studies include Nouhoheflin et al. (2005), Kolodinsky (2008a), Blow, Browning, and Crawford (2008), Griffith and Nesheim (2013) and Schröck (2014). These studies have in common that they, at least partially, have applied linear regressions, assuming the price is in equilibrium and an individual consumer cannot affect the market price, to avoid dealing with the first simultaneous problem. It is also argued that consumers face the same choices and hold the same level of information about the product.

Adapting from Equation (3.2), and following Griffith and Nesheim (2013) applied to consumer basket of goods, a household with characteristics x_h chooses an organic product if the utility (shown by preference θ) generated by the organic product o is greater or equal to the one associated with the conventional counterpart n, given as:

$$\theta(x_h, z^o, p^o) \geq \theta(x_h, z^n, p^n) \tag{3.5}$$

The mean value theorem would indicate that there is a $p^* \in [p^o, p^n]$ which would satisfy the following equation:

$$\theta(x_h, z^o, p^o) + [\frac{\partial\theta}{\partial p}(x_h, z^o, p^*)](p^o - p^n) \geq \theta(x_h, z^n, p^n)$$

Given that:

$$\frac{\partial\theta}{\partial p}(x_h, z^o, p^*) > 0$$

Therefore, we would have:

$$\frac{\theta(x_h, z^o, p^n) - \theta(x_h, z^n, p^n)}{\frac{\partial\theta}{\partial p}(x_h, z^o, p^*)} \geq (p^o - p^n) \tag{3.6}$$

Similar to Follain and Jimenez (1985) in Equation (3.2), the left-hand side of Equation (3.6) represents the WTP for the organic characteristics, while the right-hand side represents the 'organic' premium.

3.2.2 Second simultaneity problem: non-linear price function

Although the problems associated with the simultaneous supply and demand system may not be an issue in microdata (which is the case of this study), the second source of simultaneity with hedonic price models might arise from the non-linear characteristic of the hedonic function, i.e. p is non-linear in z. The hedonic price model is estimating the marginal effect of the attributes z on price (as in Rosen's step one), i.e. the first-order condition $(\partial p/\partial z)$ of the price function. However, this marginal price paid by consumers, following the demand function, is simultaneously determined by the choice of the quantity of the attribute z, which can be at any point along with the price function, and is affected by unobserved consumer characteristics shaping preferences. Therefore, the implicit price of an attribute is also affected by the amount of consumption of the attribute z, as it will remain in the marginal price function, i.e. z also affects p_i^z. The logic here is that the non-linear nature of the price function implies simultaneity, which for instance, makes the attributes z endogenous, as further explained below.

Starting with the non-linearity of the price function, in the utility maximisation process, the marginal price (first-order derivative) and quantity of attribute consumed change simultaneously, given that the utility maximisation point change according to consumers' preferences (and budget constraints). So, this simultaneity happens due to the non-linearity of the hedonic price function.

The theoretical modelling proposed by Rosen (1974) considers markets for a class of commodities of attributes z, and avoids complexity associated with re-sale thus assuming that the goods represent "pure consumption", therefore with more approximation to some markets than others. Nonetheless, Rosen's approach has been particularly popular in the housing market, and Follain and Jimenez (1983) offers a detailed theoretical framework of the second simultaneity problem existing in Rosen's model before applying it to the sector. Adapting from Rosen (1974) and Follain and Jimenez (1983), the issue can be seen in Figure 3.3. The graph shows two observation points, A and B, on the same price function for an attribute i, which represents different marginal prices faced by two individuals with varying structures of preference θ_i^1 and θ_i^2, respectively. Their preference structures are assumed to be the same, apart from one socio-economic characteristic (e.g. income). Both individuals

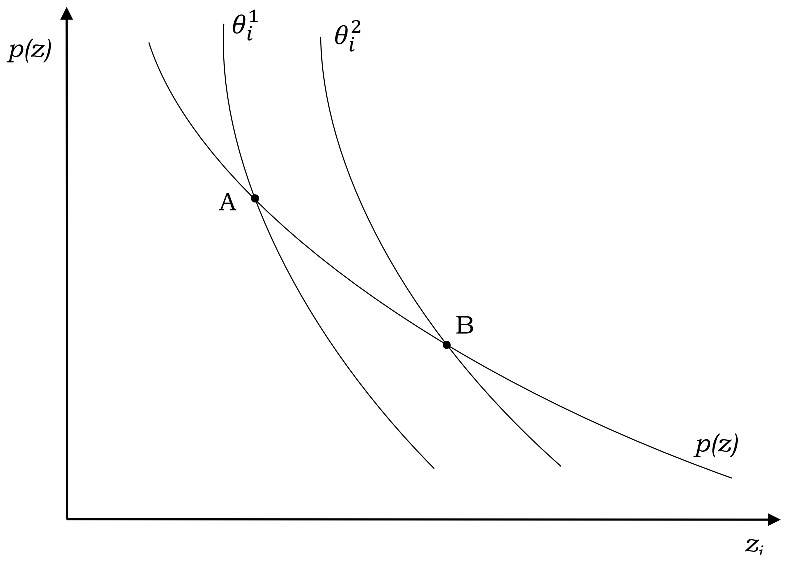

FIGURE 3.3: *Simultaneity in microdata: non-linear hedonic price*

face the same price function, which they take as given, but the implicit price is not fixed. The consumer accepts the price structure but can choose any point on the curve simultaneously with the quantity of attribute z. Thus, a regression of z_i and the hedonic price p_i using OLS generates biased results, as this does not incorporate unobserved consumer characteristics that define their preferences; thus, variations on the quantity of z.

The simultaneity acts as a source of endogeneity of characteristics z simply because in the first-order condition, p_i^z changes with z_i. If the hedonic price function were linear, in the first-order condition, only quantities would be defined in the individuals' utility maximisation points because the marginal price would be a constant. Intuitively, $p(z)$ changes with z in the first-order condition, so the hedonic price function (Equation 3.1) has to be non-linear. To illustrate this, in a simple linear hedonic price function $p_i = \delta z$, the marginal implicit price would be:

$$p(z) = \frac{\partial p_i}{\partial z} = \delta$$

Thus, consumers' preferences would only affect their choice for the quantity of the attribute, i.e. only z changes across consumers, and $p(z)$ is constant, as shown in Figure 3.4.

Mathematically, adapting from Kahn and Lang (1988), and Bishop and Timmins (2011),

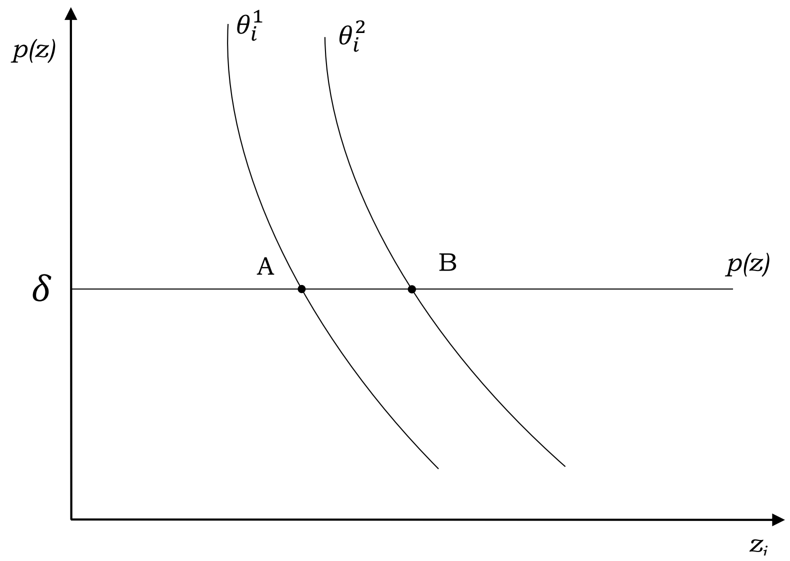

FIGURE 3.4: *Simultaneity in microdata: linear hedonic price*

consider a non-linear (quadratic for simplicity[3]) hedonic price model with one characteristic z_i:

$$p_i = \delta_0 + \delta_1 z_i + \frac{\delta_2}{2} z_i^2 + \varepsilon \tag{3.7}$$

Where $i = 1, \ldots, N$ items, p_i measures the price of item i, and z_i measures the attribute level associated with item i. The implicit marginal price (first step of Rosen's hedonic price estimation) of the above hedonic function is:

$$p_i^z \equiv \partial p_i / \partial z_i = \delta_1 + \delta_2 z_i \tag{3.8}$$

The demand and supply equations for z_i, in line with step two of Rosen's hedonic price estimation, from (8) would be, respectively:

$$p_i^z = \alpha_0 + \alpha_1 z_i^d + \alpha_2 x_i^d + \nu_i^d \tag{3.9}$$

$$p_i^z = \gamma_0 + \gamma_1 z_i^s + \gamma_2 x_i^s + \nu_i^s \tag{3.10}$$

[3]Please note that here I use a quadratic function for simplicity of illustration, and although the function form used in the empirical section is non-linear, the variable of interest is a dummy. Thus a quadratic form for z would not be justified.

Where, x_i^d and x_i^s represent characteristics of buyers and sellers of item i, and ν_i^d and ν_i^s attempts to incorporate unobserved idiosyncratic shocks to tastes and marginal costs, respectively[4]. Equations (3.9) and (3.10) are the respective Marshallian forms of Equations (3.3) and (3.4).

The problem explored here arises from the fact that, in the hedonic sorting (a price equilibrium process), z_i^d must be correlated with ν_i^d. If the demand function (3.7) were linear, its first-order condition (3.8) would be constant, i.e. not influenced by z_i^d, as illustrated above.

However, as $z_i^d = z_i^s = z_i$, in the hedonic equilibrium, i.e. combing (3.8) and (3.9), gives:

$$z_i = [1/(\delta_2 - \alpha_1)][(\alpha_0 - \delta_1) + \alpha_2 x_i^d + \nu_i^d] \tag{3.11}$$

Therefore, Equation (3.11) shows clearly that z_i is correlated with ν_i^d, i.e. z_i is endogenous in Equation (3.9). Combining (3.8) and (3.10) would result in the same conclusion for z_i and ν_i^s in the supply function. Thus, when estimating the demand function (3.9) and the supply function (3.10), one must find instruments for z_i.

For the application in this thesis, given that 'organic' as the attribute of interest, is a dummy variable in the hedonic function; it would not have a non-linear relationship with price[5]. For Rosen's two stages, this would imply that 'organic' would not appear in the second stage and would shift $p(z)$ through a constant α_0, but with no price differentiation across preference structures θ_i, as shown in Figure 3.4. Therefore, the WTP for 'organic' would be equal to the difference in the intercept between 'organic' and conventional price functions. Although this would imply that non-linearity may not cause endogeneity for the 'organic' attribute, it is unrealistic that the implicit price of 'organic' is constant across individuals. These would classify as omitted variables instead[6].

Nonetheless, one should also note that z is a set of all attributes often correlated. Thus, one specific attribute should appear in both stages. This is the central simultaneity problem making z appear in both demand, supply and HP functions, which is intuitive. In addition, this thesis uses an exponential hedonic price function which implies that z_i stays in the first

[4] ν_i^d is not a function of z_i^d, and ν_i^s is not a function of z_i^s.

[5] If 'organic' is in the base of the exponential function; and only if it has its power independent of other attributes, e.g. $p_i = \delta_0 + \delta_1 Organic^n + \delta_2 Z_i$, for any n).

[6] Thus, z_i (organic) should still be endogenous potentially caused by omitted variables, such unobserved consumer characteristics (not included in hedonic price models), e.g. socio-economic characteristics, tastes, and behaviours associated with consumption of organic food.

order condition[7], thus z is correlated with the error term in the HP function, as $z_i^d = z_i^s = z_i$, illustrated in Equation 3.11, and needs to be instrumented.

3.2.3 Estimation model

In the literature, when the endogenous attributes in the demand function estimation are not ignored, the dominant approach is to use supply-shifters. These follow Rosen's recommendation to address supply and demand simultaneity with step two of his model, when x_i^d and x_i^s are used as instruments for z in the supply (3.10) demand (3.9) functions, respectively. This, however, has some conditions. In the market equilibrium, hedonic sorting induces that x_i^s is also correlated with ν_i^d, i.e. x_i^s cannot be used as instruments in the demand equation, neither can x_i^d be used in the supply function.

Nonetheless, one can observe from the system above that x_i^d (consumer characteristics) is exogenous in (3.9) and is correlated with the amount of attribute z_i in Equation (3.11). In other words, the demand for the attribute z depends on the price consumers are willing to pay for it and their tastes and preferences. Therefore, as argued by Follain and Jimenez (1983), Wooldridge (1996), and Ekeland, Heckman, and Nesheim (2004), x_i^d and x_i^h may be used as instruments for z_i^d. Similarly, x_i^s and x_i^h may be used as instruments for z_i^s in the supply function, and x_i^d and x_i^s can be used as instrument for z_i in the hedonic price function. However, finding valid instruments is relatively complex. It might be challenging for some applications; thus, implying that researchers have overwhelmingly ignored this endogeneity issue, mostly because of the lack of available strong instruments in revealed datasets.

As argued in the previous section, in microdata, supply estimation is not required in demand-side estimations; the most challenging aspect is addressing endogeneity from the second simultaneity problem, or omitted variables. Thus, an extension of Rosen's two-step approach would involve a three-stage estimation with instruments for the endogenous characteristics. The conclusion that characteristics of individuals (x_i^d) are exogenous in the hedonic price function implies that, unless these characteristics are used as supply-shifters (in price discrimination), when relevant, they can be valid instruments in the hedonic price model.

[7] For simplicity, if $y = e^{z+c}, dy/dz = e^{z+c}$.

This study addresses the endogeneity of the z attribute, adapting the two-step approach proposed by Rosen (1974) and further improved by other researchers. Rosen's two-step approach is only applicable when regressing the first stage using marginal price depends on variables that are not incorporated in the demand and supply functions (Kahn and Lang, 1988, and Wooldridge, 1996), e.g. x^h in Equation (3.1). Otherwise, the demand and supply regressions in the second step of Rosen's estimation might only replicate results already found in the first stage of the hedonic price (Brown, 1983). Alternatively, if only one step (OLS hedonic estimation) takes place, it would provide inefficient results because of unobserved shocks of preferences affecting the quantity or combination of attributes chosen by the individuals. In other words, z_i still needs to be instrumented because the hedonic price equilibrium is defined in the maximisation of consumers and suppliers, as they choose their marginal prices $p(z)$ and z simultaneously, and z_i is endogenous also in the original hedonic price function. Similarly to the illustration of endogeneity in the demand and supply functions (Rose's step two) - in the hedonic sorting using the equilibrium of Equations 3.8, 3.9 and 3.10 - by firstly integrating Equation 3.9, so that:

$$p_i = \gamma + \alpha_0 z_i^d + \frac{\alpha_1}{2}(z_i^d)^2 + \alpha_2 x_i^d z_i^d + V \tag{3.12}$$

Where V is a constant of integration and should include ν_i^d. Then, combining (3.12) and (3.7) with a new system similar to that shown in (3.11), but now for p_i as opposed to p_i^z. Thus, Equation (3.13) shows that z_i is also correlated with ϵ from the original hedonic price function, i.e. Equations (3.7) and (3.1).

$$z_i = \frac{(\delta_0 + \gamma + \varepsilon + V)}{[\delta_1 + \alpha_0 + \alpha_2 x_i^d + 0.5 z_i(\delta_2 + \alpha_1)]} \tag{3.13}$$

Considering the abovementioned issues, Kahn and Lang (1988) applied demand-shifter instruments in a three-stage least square (3SLS) for the simultaneous equations' estimation system. However, Wooldridge (1996) demonstrates that the hedonic model does not fit into situations where a 3SLS would be asymptotically efficient. Hence, he suggests that the generalised method of moments (GMM) should be used to estimate the parameters in the hedonic price system. In addition, Cameron and Trivedi (2005) also demonstrates that GMM is more efficient than 2SLS/3SLS in addressing the identified endogeneity and non-linear functions underlying the hedonic price system. GMM also performs better when the model is over-identified and under heteroscedasticity, a common problem in revealed data, especially when estimating system equations (Arellano and Bond, 1991). Therefore, this paper applies the GMM method to a hedonic price function, as in Equation (3.1), using consumer characteristics x_i^d as instruments to treat the endogenous product characteristics z, following the theoretical framework above, which shows that x_i^d can be a valid instrument for z in both the demand and hedonic price functions.

Given the sample's comprehensive characterisation, a substantial number of available variables are expected to explain the price variation comprehensively. However, the primary hedonic model does not consider consumer characteristics, as demonstrated in Section 3.2. In addition, again, consumers are assumed to be price-takers, and their characteristics should not change the price available to them in most cases. As explained in Section 3.2, following Rosen (1974), most studies focus on the product's characteristics (z) and do not consider factors such as time influence and geographical information. These are sometimes used to generate instruments, which is difficult to justify, as these characteristics are expected to influence price (dependent variable).

Considering z as the vector of all product characteristics (mostly discrete elements, e.g. chicken part, organic, retailer, etc.), the model includes dummies for special offer (ζ_{i_t}) and region (ϕ_r), and a monthly vector (δ_t).

Therefore, the household maximises utility by choosing a product with price p explained by:

$$ln(p_{irst}) = \alpha_1\delta_t + \alpha_2\zeta_{it} + \alpha_3\phi_r + \beta z_{is} + \epsilon_{irst} \tag{3.14}$$

Where: i, r, s and t are, respectively, item, region, store and time, and ϵ is the error term. Thus, δ varies with time, ζ varies with item and time, ϕ with the region and β are specific to each item and store. The vector of characteristics allows one to calculate utility by considering all the information given rather than looking at things one at a time. It is essential to mention that t, in this case, will mainly explain seasonal variations rather than capture broader shocks. A more extensive annual panel data study would be required for the latter.

The appropriate function-form for the hedonic method depends on the data used in the study. The predominant approach in the literature is the log-linear, but double-log is also used, as it facilitates the interpretation of results (Martínez-Garmendia, 2010 and Kim and Chung, 2011). Given that all explanatory variables are dichotomous, this study uses an exponential semi-log function. The function form will be applied in a GLS estimation (model 1), in the first stage of the GLM (model 2), and the GMM (model 3) estimations. The latter attempts to address any bias from endogeneity, using socio-economic characteristics as instruments. As justified in Section 3.2, the GMM estimation will be the primary approach used in the estimations for its ability to address endogeneity; thus, it will be the primary source of results discussion.

The extended and exponential version of the model for the GMM regression can be expressed as:

$$\begin{aligned} lnP_{irst} = exp(&\beta_0 + \beta_1 Organic_{it} + \beta_2 FreedomFood_{it} + \beta_3 Offer_{it} + \beta_4 Branded_{it} \\ &+ \beta_5 BudgetLabel_{it} + \beta_6 Halal_{it} + \beta_7 Healthy_{it} + \sum_{j=2}^{7} \beta_j ChickenPart_{ijt} + \sum_{k=2}^{5} \beta_k Size \\ &+ \sum_{l=2}^{13} \beta_l Retailer_{ilt} + \sum_{m=2}^{7} \beta_m Region_{imt} + \sum_{n=2}^{12} \beta_n Month_{int}) + \epsilon_{irst} \end{aligned} \tag{3.15}$$

Where, in addition to the variables previously described, 'organic' represents an organic label, 'freedom food' represents a label for freedom food, 'offer' denotes any type of promotion, and 'branded' and 'budget label' indicate external and own low price labels. 'Quality' indicates own brand product advertised as superior quality (e.g. Tesco Finest, Asda Extra Special, etc.), 'halal' indicates halal chicken, and 'healthy' denotes the presence of a health label. From the remaining five types of dummy variables included in the model, 'chicken part' indicates the part sold (or whole chicken), 'size' indicates the package weight, 'retailer' the shop/supermarket (from 13 leading companies), 'region' denotes the UK region, and 'month' represents the monthly dummies.

The exponential GMM format is widely used in applied work as an alternative to linear regressions when the dependent variable uses log-transformed values. This avoids transformations from the original format for predicted values (Baum, Schaffer, and Stillman, 2003). The two-step optimum GMM regression was estimated using Stata (heteroscedasticity assumed in the second step). The instruments tested in the GMM approach process were income, age, gender, BMI, employment status, and variables associated with family structure, e.g. number of children, age of children, etc. Validity tests, discussion around the best-fit instruments, and regression results are shown in Section 3.4. Instrumental variables from the family structure of households provided the best results from statistical tests and were used in the analysis and discussion.

Choice of instruments

In the literature on hedonic price models, there are some applications of instrumental variables to estimate coefficients of attributes of interest. Combris, Lecocq, and Visser (1997) tested sensory variables as an instrument in a hedonic price estimation of attributes (notably 'quality') of Bordeaux wine but did not identify any endogeneity, concluding that the OLS function was consistent when estimating their parameters of interest. Follain and Jimenez (1983) replaced the marginal price by an instrument generated via regression of the marginal house price against variables such as income and household size. Meanwhile, Gopalakrishnan et al. (2011) used spatial varying coastal geological features as an instrument to estimate the amenity value of beach width to coastal properties in a 2SLS estimation. Despite the different endogeneity addressed, those studies have revealed a significant effect from the instrumental variables. Other examples include Kahn and Lang (1988), which treated geographical locations as characteristics included in one of the vectors other than product characteristics in the first stage hedonic price model. More recently, Martínez-Garmendia (2010) used (endogenous) quantity in a hedonic price model to incorporate price volatility across retailers and regions. In the case of this study, discrimination across regions is also controlled with the regional dummy variables.

This chapter uses the socio-economic characteristics of households as instruments to treat the organic characteristic of chicken meat as the variable of interest. For the socio-economic characteristics to be valid instruments, they must be both exogenous and relevant to the choice of the treated attribute. The discussion in Section 3.2.2 gives the theoretical background that demonstrates why consumer characteristics can potentially be used as instruments, given that they should be exogenous to the marginal price. This section discusses the validity of each potential instrument and, most importantly, the relevant tests that need to take place; firstly, about the relevance of socio-economic variables in explaining the choice for 'organic' (here, the z attribute of interest); secondly, the possibility that suppliers may be able to discriminate amongst individuals when some characteristics are observable.

Several studies confirm that socio-economic characteristics are relevant to organic food consumption, i.e. socio-economic characteristics drive the WTP for organic food. Chapter 2 of this thesis (meta-analysis) highlights the importance of these variables in explaining the price premium across different types of organic products worldwide. Just to name some other studies, Griffith and Nesheim (2010) explore heterogeneity WTP for organic products across different family structures; Costanigro, Kroll, and Thilmany (2012), Gschwandtner (2018), Yue, Alfnes, and Jensen (2009) and Wong et al. (2010) show the contribution of individuals' characteristics on consumption level of organic food attributes, these include income, age, gender, level of education, family structure, employment status, etc.

Given the high number of attributes in the database, particular attention is given to addressing the endogeneity of the 'organic' attribute as the primary variable of interest. The Kantar data sample used in this study offers several household variables which are not expected to explain the dependent variable (p), while should be relevant to a preference for 'organic' consumption, assuming that individual households are price-takers – thus potentially exogenous to the price equation – and that retailers cannot discriminate across households.

For being associated with microdata, it is assumed in this study that suppliers may not discriminate between individuals across their residual demand. Therefore, consumers are likely to face the same price for the same item. By the same item, here it means the same combination of attributes, including chicken part, labels, package, etc., as well as retailer characteristics. However, the non-discriminatory assumption may not hold for some consumer characteristics available in the data under certain circumstances.

The potential instruments present in the data, thus considered in this study, are investigated in the light of theoretical framework, data analysis, statistical tests (showed in Section 3.4.3), and economic intuition. The main variables under investigation were income, age, gender, BMI (body mass index) and family structure. The rationale driving the choice of instruments is to evaluate whether suppliers would be able to use information about their customers as a source of price discrimination. As discussed above, microdata makes this possibility difficult for suppliers, as they cannot charge different prices to customers based on those characteristics once they enter their premises. However, retailers have access to socio-economic information about their local or average customers and may use this as a source of discrimination across different locations within regions. Based on purchase data, they also offer voucher discounts and promotions associated with quantity bought, though the variable 'offer' would capture this variation.

Disregarded instruments

Some social-economic characteristics have strong theoretical relevance in terms of 'organic' consumption but may be used as supply-shifters. For example, retailers can observe information such as income and age, so they should be able to charge a higher price from wealthy neighbourhoods and select higher price items to market in those areas. Similarly, a price strategy might take place in areas close to universities. Thus, retailers might be able to discriminate at this level. In other words, consumer characteristics can be used in supply strategy and be correlated with price.

The same argument could be used against the choice of gender as an instrument. Suppliers understand that most shoppers are women (as confirmed in Chapter 2, and several other studies[8]), and can use this information in a screening process. Online shopping might mitigate these caveats, but retailers should be able to increase prices through delivery charges, for example. The main purpose here is to control for consumer characteristics influencing the price. One might argue that it is unfeasible, however, that suppliers would charge different prices to men and women in the stores or online[9]. Nonetheless, other available variables are more restrictive, and other factors are considered when choosing the best instruments.

From the dataset, BMI, pre-family (young couple with no children), young-family (family with the youngest child aged below five years old), and middle-family (family with the youngest child aged between 5 and 9 years old) were tested. As explained later, particularly for family structure variables, there is no suggestion that these are correlated with the price equilibrium. Again, suppliers should have access to individual information from, for example, loyalty cards. Still, it is unlikely that retailers would assess this micro-level of data (e.g. age of the children in the household) to use in price discrimination. However, tests and further discussion is needed. In addition, these potential instruments have also to be correlated with the endogenous treated 'organic' attribute.

[8] Rihn et al. (2016), Wong et al. (2010), Arnoult, Lobb, and Tiffin (2010), and Gschwandtner (2018), to name some.

[9] This is also a conservative approach, as this trend is likely to be consistent across neighbourhoods, so with limited space for price discrimination.

The first stage regressions (OLS and probit) are used to test the significance of consumers' characteristics on the choice of organic chicken. Table B.1 (Appendix) shows results from the probit first-stage estimation[10], and indicates that the socio-economic characteristics are relevant ($p>0.01$) individually and combined. This is not trivial because the lower the correlation between the instrument and the instrumented variables, the potentially more significant is the bias of the IV estimators (thus, it would be better to use OLS instead), even though numerous observations may offset the effect of a slight correlation (Wooldridge, 2010).

These variables, however, cannot be correlated with price, as explained in Section 3.2.2. A simple regression as a correlation test in Table B.2 (Appendix) indicates that, within the socio-economic variables, income and age have the highest correlation with price. Furthermore, when added to the baseline model (OLS) (Table B.4 - Appendix), income, age, number of children and pre-family are significant in explaining price variations. At the same time, female, BMI, retired, young-family, middle-family, and older-family dummies are insignificant. Although this does not prove that the variables in the latter group are exogenous (as the model includes endogenous variables, which would bias the regressors), it is an indication of possible instruments.

Adding robustness to the choice of instruments, several studies have indicated health as one of the mains perceived attributes driving the consumption of organic products. In the case of meat, it is related to the risk aversion to antibiotics and hormones used in the conventional counterparts. Also, it is widely accepted that BMI is a strong indicator of a healthy diet. Therefore, it is intuitive that a 'healthy BMI range' would have a positive correlation with organic food consumption. Medical studies have reported a causal relationship between individuals' health and their diet (West et al., 2002), as well as BMI (Laxy et al., 2018), so BMI is commonly used when determining public health policies (Nuttall, 2015).

The key issue is that a healthy and balanced diet is also more costly, driving a negative correlation between price and BMI, implying that BMI would not be a valid instrument. Further data analysis shows that the correlation between BMI and price is the highest among the potential instruments (Table B.2). Table B.3 (Appendix) and Figure 3.5 show more clearly

[10]Given that the option for purchasing 'organic' is dichotomous, Table B.1 shows results from a probit regression. This might differ from the first stage of the simultaneous GMM regression but add extra robustness, as results from the probit estimation are more reliable for latent dependent variables. The primary purpose of the regression is to illustrate that the exogenous socio-economic variables are relevant to the system of equations.

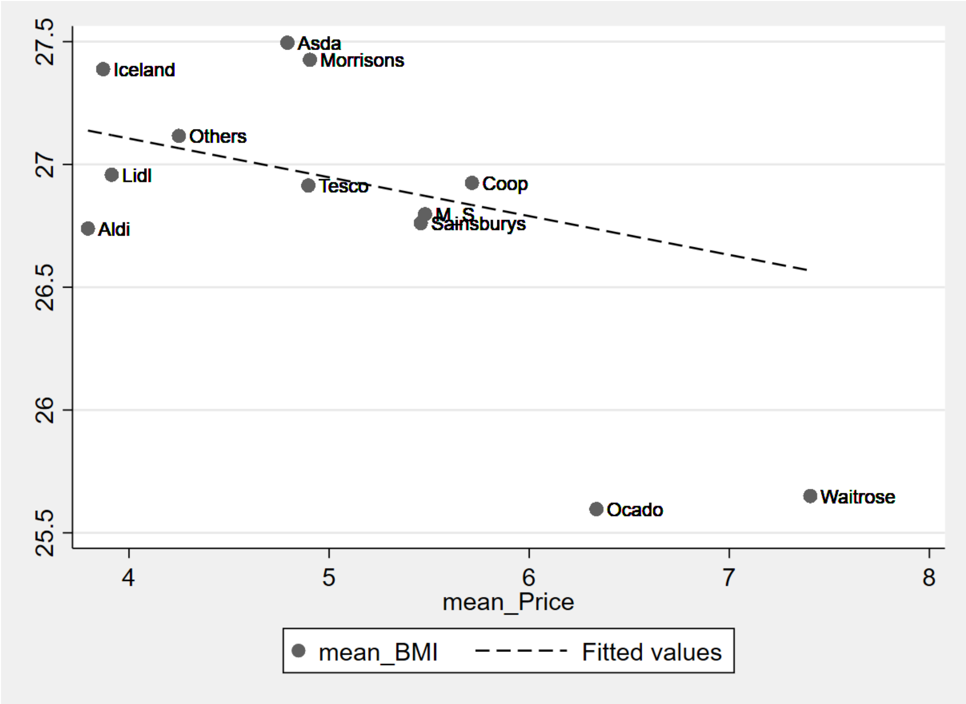

FIGURE 3.5: *Correlation BMI and Average Price: leading retailers*

the inverse correlation between the most prominent suppliers' average price and the average BMI of their consumers. On average, shoppers from cheaper retailers are suggested to have relatively higher BMI. Cameron, Waterlander, and Svastisalee (2014) also show a strong correlation between store size (which intuitively are the most affordable retailers due to economies of scale) and national obesity prevalence in the UK. Thus, given such a potential correlation, despite the strong relevance, BMI would not qualify as a valid instrument and the family structure variables are the strongest IV candidates.

Selected instruments

Instrument exogeneity: To further support the exclusion restriction, one can test whether the potential instruments are correlated with price, i.e. investigate a direct effect of instruments on the dependent variable (price). There might also be a concern that the household variables would be correlated with some variables, such as retailers, parts and regions. However, these are controlled as explanatory variables, and households are not necessarily correlated with the error term. Another potential issue would be reverse causation between attributes such as retailers and price. These would indicate that the assumption that households are price takers would be too restrictive. As an illustration, depending on their household structures, consumers would choose where to buy driven by price, and suppliers would adjust their price strategies based on this information. Although this response should be unrealistic within regions, retailers might adjust their price strategies between regions. However, it is worth mentioning that the selected family structures are defined mainly by the age of the children; thus, suggesting a correlation between, for example, 'middle family' and shops would imply that when the youngest child reaches a higher age (above nine years old), the parents will change their preferred shop. This is possible but probably not significant.

A simple exclusion restriction test can tell us if household variables are jointly significant, which partially affects the price. Using the model in Table B.4 (Appendix), one cannot reject the null that coefficients of excluded household variables equal zero. However, individually, when using the main model in results (OLS), one would reject the null if 'young family' is excluded, but not 'pre family', 'middle family' and 'older family'[11]. Thus, regardless of the model, these household variables would pass the test, with or without other socio-economic variables. Nonetheless, in a more conservative approach, the model uses a fixed effect (FE) for shops, regions and parts. In these fixed effects, the identification assumption will now be that, conditional on these controls, the instruments affect price only through the treated endogenous variable ('organic'). Although this remains an assumption, the arguments above and the post-regression tests support this notion.

Instrument relevance: Within variables related to family structure, health remains a crucial factor for households with children. However, this is subject to affordability. Using a Bayesian inference method to estimate the demand system for food in the UK, Tiffin and Arnoult (2010) have concluded that the presence of children in a household negatively correlates with their dietary quality, e.g. fresh meat, fruit and vegetables. The study also estimates that couples with children have the highest negative impact on meat consumption, compared to one or two adults only in a household. This is explained by the estimated expenditure elasticity of such products, as the paper shows, which does not explore the specific food attributes. Households should be expected to demand attributes such as quality,

[11]Results using 'pre family', 'middle family' and 'older family':

$$F = \frac{R_r^2 - R_u^2}{Df_r - Df_u} / \frac{1 - R_u^2}{Df_u} = (\frac{(0.8370 - 0.8370)}{3}) / \frac{(1 - 0.8370)}{336893} = 0.000$$

Where: Df_r and Df_u are the degrees of freedom of restricted and unrestricted models (with tested instruments), respectively.

taste and nutrition but are subject to their budget constraint. Maguire, Owens, and Simon (2004) show that parents are willing to pay a significant premium for the 'organic' attribute of baby food, and meat positively affects the premium. Thus, parents do place value on organic meat.

For young couples with no children, concerns about children's health would not play a part. Still, other factors such as higher affordability (given smaller household size, thus higher grocery expenditure per head, ceteris paribus), aesthetic focus and higher exposure to social media may nudge them towards consuming organic products. The latter may result in social compliance in line with motivators beyond own health, e.g. animal welfare and a positive attitude towards the environment. As far as this paper is concerned, the primary outcome of these ideas is that household structures influence individuals' choices of attributes associated with health and dietary quality of food. Therefore, these should influence individual choices for 'organic', justifying their use as instruments for the attribute in the GMM regression. Section 3.4.3 carries out statistical tests for further verification.

3.3 Data description

This chapter uses a revealed (actual purchase entries) dataset in a hedonic price model to estimate the marginal effect of a list of attributes on chicken price, with emphasis on 'organic' characteristic. As explained in the introduction, the demand for chicken has increased consistently in the past decades, enabling consumers to pay a premium for the characteristics they perceive as beneficial. Using scanner purchase information from UK households collected in 2016 by Kantar Worldpanel, this paper investigates the product's characteristics, consumers and retailers that might have driven such strong demand.

3.3.1 Chicken purchase data

The sample contains 336,970 chicken purchases from 26,658 households, representing the UK population. This chapter explores 40 variables containing product characteristics (chicken part, price, volume, packing, labelling, etc.), store information (e.g. retailer name and location), and socio-economic characteristics of the households. These allow for the investigation of heterogeneity across regions, education level, class, etc. Table 3.1 shows the sample distribution, which should be compared to the usual buyer (the household member responsible for the grocery shop) rather than the average characteristics of the UK population.

The average age of the household member responsible for the grocery shop in the sample is 49 years old, 78% of whom are female. On average, households have one child and an average gross income within category 4 (£30,000 to £39,999 per annum), which was above the national average income in 2016 (£26,300).

Family structure amongst households is fairly distributed, but the highest proportion (18.6%) if 'empty-nest', i.e. 45-65 years old with no children in the household, and the smallest number (10.2%) are 'pre-family', i.e. below 45 years old with no children.

TABLE 3.1: *Sample socioeconomic description*

Variable	Description	Mean	sd	Med	Min	Max
Adults	Number of adults	2.273	0.852	2	1	9
Age	Respondent's age	49.250	13.680	48	18	95
Female	Dummy = 1 if female	0.780	0.411	0	0	1
Income	Household income level	4.210	1.960	5	1	8
Children	Number of children	0.733	1.006	0	0	7
BMI	Respondent's BMI	26.990	5.700	26	10	66
PreFamily	Housewife $<$ 45; No Children	0.102	0.302	0	0	1
YoungFamily	Youngest Child 0-4	0.175	0.380	0	0	1
MiddleFamily	Youngest Child 5-9	0.123	0.328	0	0	1
OlderFamily	Youngest Child 10+	0.119	0.324	0	0	1
OlderDependents*	No Children 3+ Adults	0.153	0.360	0	0	1
EmptyNest*	No Children 1-2 Adults	0.186	0.389	0	0	1
Retired*	No Children 1-2 Adults	0.141	0.348	0	0	1
Scotland	Region dummy	0.075	0.263	0	0	1
Wales	Region dummy	0.046	0.210	0	0	1
North	Region dummy	0.256	0.437	0	0	1
Midlands	Region dummy	0.173	0.378	0	0	1
South	Region dummy	0.247	0.431	0	0	1
East	Region dummy	0.114	0.318	0	0	1
London	Region dummy	0.089	0.285	0	0	1
Jan	Month dummy	0.081	0.273	0	0	1
Feb	Month dummy	0.083	0.277	0	0	1
Mar	Month dummy	0.097	0.296	0	0	1
Apr	Month dummy	0.083	0.276	0	0	1
May	Month dummy	0.080	0.272	0	0	1
Jun	Month dummy	0.098	0.297	0	0	1
Jul	Month dummy	0.074	0.261	0	0	1
Aug	Month dummy	0.071	0.257	0	0	1
Sep	Month dummy	0.097	0.297	0	0	1
Oct	Month dummy	0.078	0.269	0	0	1
Nov	Month dummy	0.081	0.273	0	0	1
Dec	Month dummy	0.076	0.264	0	0	1

*Housewife 45+

Concerning regional distribution, it follows as North (25.6%), South (24.7%), Midlands (17.3%), East (11%), London (8.9%), Scotland (7.5%), and Wales (4.6%). Thus, above half of the chickens sold in the country are to attend demand in the North and South regions. These are similar to the regional population distribution in the UK, but not exactly. However, one should not expect the socio-economic distribution to match the national numbers precisely, as the data only includes households from the panel that bought chicken in 2016. Therefore an approximation of the representativeness of the total population should be sufficient.

Table B.5 (Appendix) illustrates the number of purchases by region and total expenditure, which are consistent with the representation of each region. At the same time, the average price paid per kilogram of chicken is relatively persistent across regions, ranging from £4.13 (Wales) to £4.32 (London). Table B.4 (Appendix) illustrates how preferences (given their affordability) for chicken parts vary between regions and might justify the difference in average price paid in each region; this is further discussed in Section 3.3. Supply could also be considered, For example, differences in costs such as transportation, retail presence, and product availability, which would need a supply-side investigation.

The dataset has entries from 35 different retailers across the country. Figure 3.6 shows the sample distribution by leading retailers (in shares of chicken purchases in the UK). The sample indicates that approximately 23% of chicken purchases in 2016 were made from Tesco, which is the UK's largest grocery retailer, substantially higher than the second-ranked Aldi, with 15% of the market, which might be surprising that it sells more broiler chicken than Asda, Sainsbury's and Morrisons. Table B.6 (Appendix) shows the market shares by region. For example, Tesco has 33% of the market share in the East region, whilst Aldi, which is associated by some with good quality meat, holds 21% in London.

The distribution in Figure 3.6 differs from the market shares of the supermarkets for all products in 2016, which were respectively Tesco (28.3%), Sainsbury's (16.8%), Asda (15.6%), Morrisons (10.9%), Aldi (6%), The Cooperative (6%), Waitrose (5.3%), Lidl (4.4), and Iceland (2.3%) (Kantar, 2018).

The data also allows for an investigation of the market for each chicken part. As indicated in Table B.7 (Appendix), breast is the most popular chicken part in the UK, formed by 48.81% of entries in the panel. Chicken breast is also associated with the highest price, costing on average £6.67/Kg. Wings are the cheapest part sold, on average only £2.23/Kg.

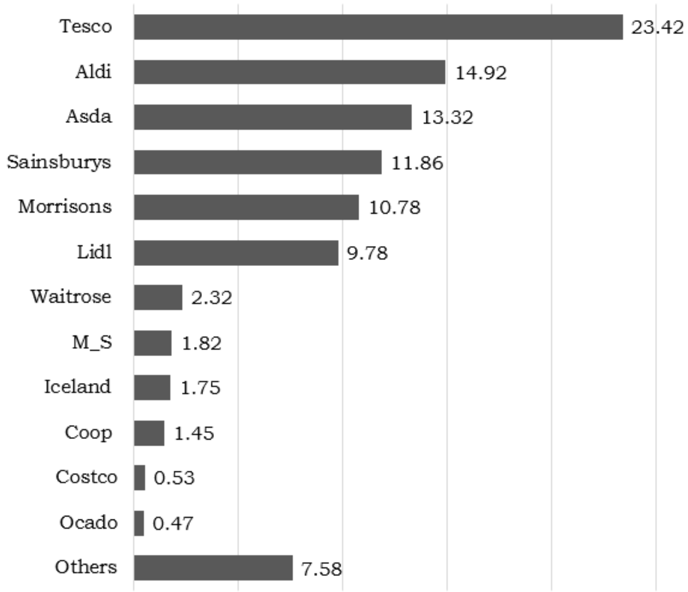

FIGURE 3.6: *Entry distribution by retailers (%)*

3.3.2 Organic chicken market

Figure 3.7 shows how sellers charge much higher prices for organic chicken. As the main target of this research, the market for organic chicken is relatively more consolidated, with only eight sellers: Sainsbury's (40.4% of entries), Waitrose (25.3%), Tesco (15.3%), Morrisons (6.4%), Mark & Spencer (M&S) (5.9%), The Black Farmer (5.8%), Ocado (0.8%), and Asda (0.1%). Market shares in terms of expenditure are shown in Table B.5 (Appendix). Table B.8 (Appendix) shows the average price also among the bottom 1% (p1) and 10% (p10) and top 1% (p99) prices per retailer. It shows, for example, that Ocado is the most expensive across all price distribution and does not sell low-price products. The seller only supplies organic thighs, the second most costly part. M&S, usually perceived as relatively more expensive and the third most costly conventional chicken, has the lowest mean price for organic chicken. However, 44% of its organic chicken sold was on offer, on average 56% cheaper than the original prices (the highest discount amongst suppliers). Most of its organic chicken sold were legs associated with relatively low cost. M&S also sells the average most expensive whole chicken and the third most expensive chicken breast.

Asda conventional chicken is, on average, the cheapest in the sample. However, it has minimal 'organic' sales, thus driving its price up. Table 3.2 gives more insight into which chicken part the retailers sell the most. The average organic whole chicken is sold at Waitrose, while the cheapest breast at Morrisons and thigh at Sainsbury's, suggesting a certain

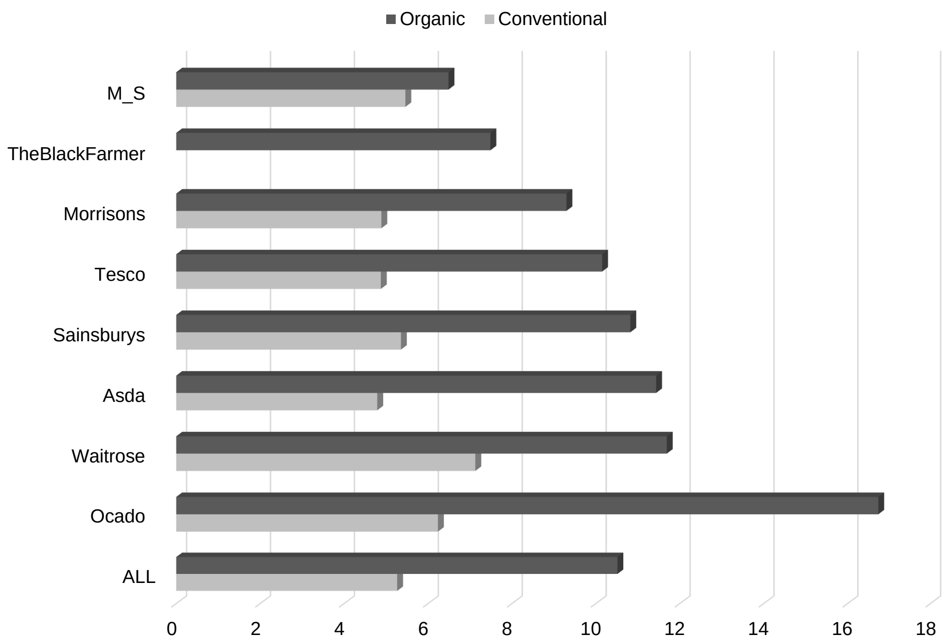

FIGURE 3.7: *Prices Organic vs Conventional Chicken (£/Kg)*

TABLE 3.2: *Retail price by organic chicken parts (£/Kg)*

	Chicken Part					
Retail	Breast	Drumstick	Legs	Thigh	Whole	Wings
Ocado				16.74		
				(15)		
Waitrose	19.49	7.69		11.38	6.01	5.78
	(121)	(17)		**(193)**	(128)	(15)
Asda	11.44					
	(2)					
Sainsburys	18.55		5.68	6.84	6.53	
	(279)		(163)	(135)	(182)	
Tesco	11.01		12.42	10.00	7.40	
	(155)		(41)	(10)	(82)	
Morrisons	10.04		4.97		6.90	
	(103)		(17)		(1)	
TheBlackFarmer			7.49			
			(108)			
M&S	11.65		3.85		7.87	
	(29)		**(65)**		(16)	
Sample Average	15.44	7.69	6.55	9.83	6.6	5.78
	(689)	(17)	(394)	(353)	(409)	

Number of observations in parentheses.
Numbers in bold represent the highest chicken part proportion.

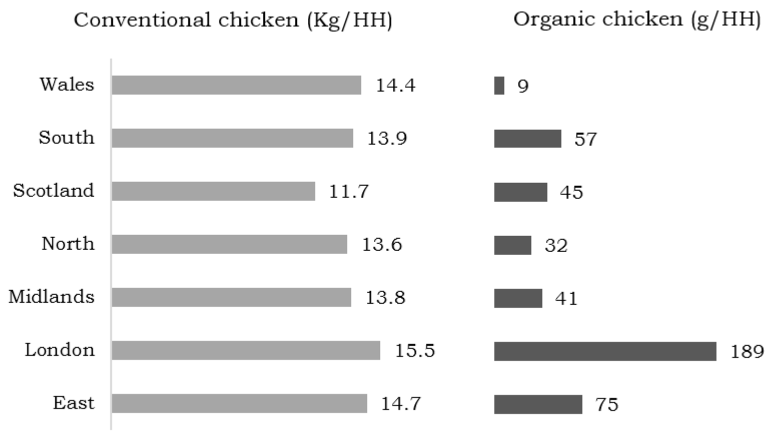

FIGURE 3.8: *Chicken consumption by region*

specialisation level.

As illustrated in Tables 3.2 and B.9, organic chicken breast is the most popular (37% of entries) and the most expensive part. It was bought on average for £15.44 per Kg. Note that it is generally sold in smaller packs (400g on average, as opposed to 1000g for the total sample). Thus, consumers may have a lower price perception when buying. On the other hand, drumsticks and wings are the cheapest (sold only at Waitrose) and the least popular chicken parts, though they are substantially more expensive than their conventional counterparts.

Overall, the price distribution for organic chicken is illustrated in Figure B.1 (Appendix), which shows the broad distribution, despite a relative concentration of prices at around £6 per kilogram. The price paid for organic chicken varies substantially across retailers and regions. Figures B.2 and B.3 (Appendix) show the 'organic' price distribution across retailers and chicken parts. Figure B.2 (Appendix) suggests that Waitrose and Sainsbury's offer the widest variety of chicken products in their stores, which is natural given their market shares, in contrast with Tesco and The Black Farmer. Ocado is not on the chart but was found to be highly consolidated, in line with Table 3.2, indicating only one type of organic chicken part sold by the retailer in the sample. Concerning chicken parts, breasts and thighs are the only ones associated with a wide price range.

The data also suggests a heterogeneous level of consumption of organic chicken across the UK. Figure 3.8 shows a relatively even distribution of chicken consumption in 2016 between regions. On average, households (HH) within the sample consumed 13.9 kilograms of chicken in that year, ranging from 11.7 Kg in Scotland to 15.5 Kg in London. With much fewer purchases (only 0.6% of total entries), the average consumption of organic chicken per household in the UK was only 57g, and quantities are much more discrepant across regions. Consumption of organic chicken in London (the highest consumption) was 21 times the consumption in Wales. This should not be interpreted as purely driven by consumer preferences or affordability but also by the availability of supply in the retailers, which would require further supply investigation and may form a market opportunity.

3.4 Regression results and discussion

3.4.1 Descriptive statistics

Following Equation 3.13 (Section 3.2), Table 3.3 shows the descriptive statistics of the main product characteristics (z), the promotion dummy, region, and the monthly vector included in all regression models. On average, consumers paid £4.71 per kilogram of chicken, buying approximately 1 kg per purchase. Perhaps surprisingly, 45.3% of the items were on some kind of offer, and 25.2% were budget labels (retailers' low-value items). Chicken breast is the most popular part, forming 48.8% of the observations, whereas half chicken and wings are the least popular amongst consumers. Only 1% of chicken sold was from a brand other than the retailers', and only 0.2% of entries had a 'healthy' label. Consumption across the months does not vary significantly. Still, July and August (summer in the UK) are suggested to be the period during which households consume the least amount of chicken, while consumption in the winter is relatively higher. December appears to be an exception, when possibly substitutes (such as turkey) are more prevalent during end-of-year celebrations. Further descriptive analysis is found in Section 3.3.

3.4.2 Regression results

As discussed in Section 3.3, most HP studies involve OLS regressions. However, endogeneity leads to biased and inconsistent estimates of parameters in OLS models. As explained, family structures (Pre-Family and Middle-Family) are used as instruments in the GMM estimation. All models use the semi-log model specification, but the GLS model is estimated without the exponential form. Table 3.4 shows the regression results from the GLS, GLM, and GMM estimations.

Given that the dependent variable in the GLS is the logged transformation of price per kilogram and that the main attributes are dummies, the interpretation of the coefficients

TABLE 3.3: *Descriptive statistics: attributes*

Variable	Description	Mean	st	Min	Max
LnPrice	Natural log of price paid per kg	4.706	2.459	-2.303	3.32
Freedom_Food	Freedom food label	0.006	0.077	0	1
Organic	Organic label	0.006	0.074	0	1
Offer	Any type of offer	0.453	0.498	0	1
BudgetLabel	Budget/low cost label	0.252	0.434	0	1
Branded	Not retailer's brand	0.010	0.101	0	1
Quality	Retailer high quality label	0.027	0.162	0	1
Healthy	Health label	0.000	0.015	0	1
Halal	Halal chicken	0.002	0.047	0	1
Size1	Package weight $<$ 400g	0.117	0.325	0	1
Size2	Weight 400-799g	0.323	0.468	0	1
Size3	Weight 800-1199g	0.223	0.417	0	1
Size4	Weight 1.200g-3000kg	0.334	0.472	0	1
Size5 (baseline)	Package weight $>$ 3kg	0.002	0.049	0	1
OtherParts (baseline)	Part 1	0.314	0.464	0	1
Drumsticks	Part 2	0.033	0.179	0	1
Half	Part 3	0.000	0.015	0	1
Legs	Part 4	0.040	0.195	0	1
Breast	Part 5	0.488	0.500	0	1
Thigh	Part 6	0.108	0.310	0	1
Wings	Part 7	0.015	0.123	0	1
Whole	Part 8	0.314	0.464	0	1
OtherShops (baseline)	Shop 1	0.075	0.264	0	1
Asda	Shop 2	0.133	0.340	0	1
Coop	Shop 3	0.014	0.120	0	1
Costco	Shop 4	0.005	0.072	0	1
Iceland	Shop 5	0.017	0.131	0	1
Lidl	Shop 6	0.098	0.297	0	1
M_S	Shop 7	0.018	0.133	0	1
Morrisons	Shop 8	0.108	0.310	0	1
Ocado	Shop 9	0.005	0.069	0	1
Aldi	Shop 10	0.149	0.356	0	1
Sainsburys	Shop 11	0.119	0.323	0	1
Tesco	Shop 12	0.234	0.423	0	1
TheBlackFarmer	Shop 13	0.000	0.018	0	1
Waitrose	Shop 14	0.023	0.151	0	1
London (baseline)	Region 1	0.089	0.285	0	1
East	Region 2	0.114	0.318	0	1
Midlands	Region 3	0.173	0.378	0	1
North	Region 4	0.256	0.437	0	1
Scotland	Region 5	0.075	0.263	0	1
South	Region 6	0.247	0.431	0	1
Wales	Region 7	0.046	0.210	0	1

Number of Observations: 336,940

TABLE 3.4: *Regression Results*

	Linear Form			Exponential Form					
	GLS			**GLM**			**GMM**		
$Y = LnPrice$	coef	se	MIP[1]	coef	se	MIP	coef	se	MIP
Organic	0.718***	(0.005)	4.94	0.355***	(0.002)	1.67	1.361***	(0.104)	6.40
FreedomFood	0.562***	(0.005)	3.54	0.325***	(0.003)	1.53	0.395***	(0.009)	1.86
Size1	0.347***	(0.008)	1.95	0.231***	(0.006)	1.09	0.197***	(0.011)	0.93
Size2	0.271***	(0.008)	1.46	0.193***	(0.006)	0.91	0.176***	(0.011)	0.83
Size3	0.141***	(0.008)	0.71	0.129***	(0.006)	0.61	0.099***	(0.011)	0.47
Size4	0.017**	(0.008)	0.08	0.024***	(0.006)	0.11	-0.016	(0.011)	-0.05
Offer	-0.059***	(0.001)	-0.23	-0.032***	(0.001)	-0.14	-0.015***	(0.004)	-0.05
Branded	0.053***	(0.004)	0.26	0.047***	(0.003)	0.22	0.027***	(0.005)	0.13
BudgetLabel	-0.117***	(0.006)	-0.49	-0.125***	(0.007)	-0.56	-0.091***	(0.009)	-0.42
Quality	0.393***	(0.003)	2.26	0.263***	(0.002)	1.24	0.341***	(0.010)	1.60
Halal	0.231***	(0.009)	1.22	0.123***	(0.006)	0.58	0.165***	(0.010)	0.78
Healthy	0.030	(0.026)	0.14	-0.000	(0.013)	0.00	-0.013	(0.029)	-0.05
Drumstick	-0.243***	(0.009)	-1.00	-0.254***	(0.009)	-1.18	-0.244***	(0.009)	-1.13
Half	0.106***	(0.027)	0.53	0.150***	(0.019)	0.71	0.219***	(0.027)	1.03
Legs	-0.162***	(0.009)	-0.69	-0.148***	(0.009)	-0.66	-0.196***	(0.011)	-0.89
Breast	0.703***	(0.009)	4.79	0.499***	(0.009)	2.35	0.506***	(0.009)	2.38
Thigh	0.077***	(0.009)	0.38	0.094***	(0.009)	0.44	0.072***	(0.009)	0.34
Whole	-0.013	(0.009)	-0.05	-0.048***	(0.009)	-0.19	-0.035***	(0.009)	-0.14
Wings	-0.341***	(0.009)	-1.35	-0.350***	(0.010)	-1.65	-0.328***	(0.010)	-1.50
Asda	0.044***	(0.002)	0.21	0.049***	(0.001)	0.23	0.011***	(0.003)	0.05
Coop	0.158***	(0.003)	0.8	0.129***	(0.002)	0.61	0.086***	(0.003)	0.40
Costco	0.154***	(0.006)	0.78	0.148***	(0.004)	0.7	0.132***	(0.004)	0.62
Iceland	-0.109***	(0.003)	-0.45	-0.056***	(0.003)	-0.24	-0.111***	(0.005)	-0.52
Lidl	-0.009	(0.006)	0.00	0.059***	(0.008)	0.28	-0.017*	(0.009)	-0.05
M&S	-0.072***	(0.004)	-0.32	0.013***	(0.003)	0.06	-0.136***	(0.016)	-0.61
Morrisons	0.112***	(0.002)	0.56	0.093***	(0.001)	0.44	0.045***	(0.005)	0.21
Ocado	0.151***	(0.006)	0.77	0.122***	(0.003)	0.57	0.058***	(0.007)	0.27
Aldi	-0.015**	(0.006)	-0.05	0.058***	(0.008)	0.27	-0.023**	(0.009)	-0.09
Sainsburys	0.086***	(0.002)	0.42	0.076***	(0.001)	0.36	0.001	(0.009)	0.00
Tesco	0.037***	(0.002)	0.18	0.045***	(0.001)	0.21	-0.002	(0.004)	0.00
TheBlackFarmer	0.278***	(0.022)	1.51	0.371***	(0.011)	1.74	-0.597***	(0.097)	-2.77
Waitrose	0.383***	(0.003)	2.19	0.251***	(0.002)	1.18	0.104***	(0.021)	0.49
East	-0.000	(0.002)	0.00	0.001	(0.001)	0.00	0.021***	(0.004)	0.10
Midlands	0.002	(0.002)	0.01	0.002**	(0.001)	0.01	0.022***	(0.004)	0.10
North	0.001	(0.001)	0.00	0.003***	(0.001)	0.01	0.023***	(0.004)	0.11
Scotland	0.008***	(0.002)	0.04	0.007***	(0.001)	0.03	0.014***	(0.003)	0.07
South	0.006***	(0.001)	0.03	0.005***	(0.001)	0.02	0.025***	(0.004)	0.12
Wales	-0.009***	(0.002)	0.00	-0.005***	(0.002)	0.0	0.017***	(0.004)	0.08
Constant	0.896***	(0.012)	6.81	-0.096***	(0.011)	-0.42	-0.062***	(0.014)	-0.28
Observations	336,940			336,940			336,940		

*All models include monthly dummies; robust se in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$)*

IV in the GMM model: ***PreFamily*** *and* ***MiddleFamily****.*

Marginal Implicit Price (£/Kg): $MIP = \frac{\partial p(z)}{\partial z_i}.\overline{P}$, *where* $\overline{P} = 4.71$.

1. MIP estimation adapted to log-linear function: $MIP = [exp(\frac{\partial p(z)}{\partial z_i}) - 1].\overline{P}$

in the log-linear GLS function, following the price change when a given dummy variable equals one, is expressed as:

$$\frac{\partial p}{\partial z} = exp(\beta) - 1$$

The results show that the MIP attributes across the GLS and GLM models can differ significantly, thus raising awareness about the validity of both sets of results. The 'organic' MIP in the GLS is also substantially higher than the GLM estimates. As explained in Section 3.3, GMM estimations are considered the most reliable for addressing endogeneity. Intuitively, the main significant difference between GLM and GMM results is about the parameters for 'organic', with GMM reporting a coefficient almost four times greater than one from the GMM, in absolute terms. Nonetheless, the results presented in this section mainly involve GMM estimates.

In the GLM and GMM estimates, as the models use the exponential form of the explanatory variables and the dependent variable is log-transformed, the interpretation of the coefficients is straightforward, and represents the marginal effect of the respective variables, i.e. these indicate the price change when the attribute increase by one unit, or equals one for dummies. Therefore, the estimations for the marginal implicit prices (MIP) were given by: $MIP = \frac{\partial p(z)}{\partial z_i} x\overline{P}$, where $\overline{P}$ is the sample mean price paid per kilogram of chicken (£4.71).

The GMM estimation indicates that for UK consumers, the MIP for 'organic' attribute per kilogram, ceteris paribus, is £6.40, for 'freedom food' £1.86, for 'quality' £1.60, and halal £0.77 (2016 values). Consumers' implicit price for branded chicken products is £0.13 per kilogram, while the budget label gives a discount of £0.43. The coefficient for 'healthy' is insignificant in any regression model. Compared with 'other' chicken parts, breast has an MIP of £2.38, the highest added value amongst the parts, as expected. The other parts with a positive implicit price are half chicken (£1.03) and thigh (£0.34), while all the others have a negative marginal effect, with whole chicken being associated with the lowest premium (-£1.54).

The MIP increases as package weight decreases; smaller packages ($< 400g$) increase the MIP by £0.93 compared to packs larger than 3 kg, while 'offers' on average contribute to a decrease of only £0.07 per kilogram of chicken. This indicates that, at least for chicken, offers are mainly retailers' marketing strategy to influence shopping behaviour through their discount perception rather than an actual price reduction.

Unlikely the descriptive section, which shows the average price paid for each product characteristic across sellers, the MIP shows how much individuals would pay for the shopping experience at that specific supplier, with all other attributes held constant. As an illustration, despite its relatively high average price, The Black Farmer has the lowest MIP (-£2.80/kg), most probably because of its specialisation; thus, the higher price is driven by other variables, notably 'organic'. M&S (-£0.64) and Iceland (-£0.53) are associated with the lowest implicit prices. Costco (£0.62) and Waitrose (£0.49) have the highest implicit prices, followed by Coop (£0.41) and Ocado (£0.27).

Although statistically significant, there is no considerable variation in MIP across regions, and price differences are, in this case, driven mainly by product differentiation. With London as the baseline, all regions are associated with a positive effect on WTP. Consumers in the South pay the highest implicit price, followed by the North region. Further regional heterogeneity is explored in Section 3.4.4.

3.4.3 Instruments validity tests

Table 3.5 shows the results from the instruments statistical tests, following the GMM estimation. The adjusted R^2 from the first-stage regression indicates the squared partial correlation between the endogenous regressor and the instruments only, which is usually low. For the endogeneity test of the 'organic' attribute, this study applies the C Difference-in-Sargan endogeneity test. With 99% confidence, one can reject the null that 'organic' is exogenous, justifying the use of instrumental variables in the models.

For instrument validity, Table 3.5 shows an F-test, which tests when one endogenous variable (as only 'organic' is treated) is weakly identified in the presence of multiple endogenous variables (which is possible for this study), indicating that the instruments are valid, with F-statistics substantially above 10 (35.7); thus, it shows that the instruments are jointly significant.

Shea Partial R2 tests the instrument relevance of instruments when there are multiple endogenous variables; thus, this result is not relevant for this model.

For the over-identification of instruments test, Table 3.5 shows the Hansen's J test for the GMM estimation. Over-identification occurs when the number of additional instruments

TABLE 3.5: *Instruments Validity (Pre-Family and Middle-Family)*

Test	*GMM*	
Endogeneity		
C Difference-in-Sargan	98.520	***
First stage regression		
Adjusted R2	0.088	
Shea's Partial R2	0.0003	
F-statistic	35.663	***
Over-identification		
Hansen's J x2-test	0.074	
P-value	0.785	

*** $p < 0.01$

(conditional to at least one exogenous instrument) exceeds the number of endogenous variables. The test checks whether the instruments are uncorrelated with the error term, the model is misspecified, and any endogenous variables should be added. In other words, a significant test indicates invalid instruments or model misspecification. The results suggest that the instruments pass the test in all models; hence, one can reject the null of over-identification and cannot reject the null that the instruments are valid.

3.4.4 Heterogeneity

Heterogeneity across regions and chicken parts was identified through a series of regressions. In the GMM estimation, the socio-economic characteristics x_i^d (Equation 3.11) include measured and unmeasured heterogeneity and shocks in preferences of households, which should cause variation in WTP. In addition, spatial units (regions in the case of this study) have to be defined exogenously to rely on an analysis of the variations across space (Helbich et al., 2014). The same applies to chicken parts, which are treated as different products. Chapter 2 explores various sources of heterogeneity in 'organic' price premiums across different products and countries (ranging from -27% to 177%). Griffith and Nesheim (2010), who have applied a similar log-linear model to all grocery products in a basket of goods, have also revealed a large amount of WTP heterogeneity across organic products in the UK (ranging from approximately -50% to 140%). Further heterogeneity is explored in this section from GMM regressions. Results are shown in Tables B.11, B.12 and B.13 (see Appendix).

For consistency, the same variables are incorporated as regressors and coefficients of chicken parts and regions. Similar to the main model, variables derived from family structures were used as instruments. However, segmentation has implied that different valid instruments were used across sub-samples, and subsequent statistical tests have been applied to justify the use of instruments for each region or part and validate results. For the regions, 'Pre-family', 'Young-family', 'Middle-family', and the number of adults[12] were used, according to the strongest F-statistics. Almost all the models used 'older family' as an instrument for chicken parts, except for legs, for which the strongest instrument was 'young family'.

Across regions, consumers in the North and East regions pay the highest premium for the 'organic' attribute (above 150%), while households in Scotland pay only 35%. The price premium for 'freedom food' does not vary significantly between regions (ranging from 27% to 43%), and there is no substantial variation within the 'quality' attribute. The latter is explained by the fact that most observations containing the 'quality' attribute are associated with the retailers' own-brand label, which should be consistent in most parts of the country. Consumers also pay more for the halal attribute in the East. The marginal value of the budget label has the most significant effect in Scotland but is very consistent in London, the East, and North of England. The results also show that the marginal value from retailers varies in the country. The marginal effect of retailers on price in London is the lowest for Aldi, Lidl, and M&S. Meanwhile, the marginal effect is relatively higher in Scotland for Waitrose, in the Midlands, Morrisons and Waitrose have the highest implicit prices, and in the North, the leading retailers have similar MIP, apart from M&S, which is associated with a negative value. The non-weighted average implicit value across regions is 87% for the GMM model results. These results are particularly relevant for retailers and their respective market strategies.

Heterogeneity involving chicken parts confirms that the marginal effects of attributes vary with the parts, as shown in Table B.12[13]. 'Organic' has the highest marginal effect on all chicken parts, varying from 126% for legs to 298% for a whole chicken. This indicates that consumers place lower aggregated value on the 'organic' attributes when associated with parts of the chicken, i.e. a higher marginal value for organic chicken suppliers when the chicken is not cut into pieces, all other factors being equal. 'Freedom food' certification has the highest value for consumers of chicken breast and whole chicken (35% and 82%, respectively). In contrast, consumers of whole chicken and thighs negatively affect branded

[12]Consistent with the discussion in Section 2.3.1, and Tiffin and Arnoult (2010), 'adults' was statistically significant but omitted in Tables B.1 and B.2 due to collinearity.

[13]'Half chicken' is not included in the table as there is no 'organic' entry for the attribute in the sample.

products. Concerning the other attributes, although not in Table B.12, package weight has a negative effect on the price per kilogram of breast, wings, and whole chicken, which is intuitive, as a discount is expected when higher volume or larger packages are bought. However, the same is not valid for drumsticks and thighs.

A counter-intuitive result is the negative effect of 'quality' for drumsticks, despite the significant and high implicit values for all the other parts. Branded items have a mixed average effect, but there is an indication that consumers prefer thighs and whole chicken associated with the retailers' labels. As expected, a budget label has a negative effect on implicit values, except for breast and whole chicken. The 'healthy' label was only available for chicken breast, which was intuitively positive and with a marginal effect of 13%. Consumers also place the highest value of the halal attribute on thighs and legs, 37% and 11%, respectively. Compared with GMM results, MIP for the 'organic' attribute of chicken parts ranges from 57% for thighs to 136% for the whole chicken.

In terms of Heterogeneity within retailers, Table B.13 show results from the GLM model, given that instrumenting across brands were not consistent, thus comparison would have been biased. The results show that premiums for 'organic' range from 12.3% (M&S) to 57.1% (Ocado). This heterogeneity was consistent with results from the main model, though more significant for the organic market now, given some wider range of specialisation across retailers. For example, in the data Ocado has only 15 entries of one chicken part (thighs). Another seemly surprising result is the negative 'quality' premiums from M&S and Waitrose chickens. However, it may not be a coincidence that these two supermarkets are usually perceived as selling relatively higher quality (and higher average general price of) products. Thus, customers might rely on the quality of their conventional products compared to their premium lines. Retailers are also suggested differentiate their prices across regions, thus confirming the need to control for this in the main model. The regional influence on price for chicken was statistically significant in 22 out of 42 coefficients. However, most of the regional premium (compared to the South) were at around only 1%, with a maximum -3.6% for M&S Wales.

3.5 Chapter conclusion

This chapter attempted to elicit the implicit marginal effect of the organic attribute of chicken meat. Backed by the current literature and statistical results, the study suggests that chicken attributes in the hedonic model, particularly 'organic', were identified to be endogenous, and hence needed to be instrumented. The endogeneity of WTP for the organic attribute in the HP model is potentially generated either by the simultaneity caused by the non-linear nature of the price function or by potentially omitted variables. This study argues that at the micro-level, some individual characteristics are unlikely to be observed by suppliers, implying that these are exogenous to the marginal price, preventing them from discriminating across their customers; they could not be used as supply-side shifters and can be used as instruments. This chapter applied the GLS, GLM and GMM estimation methods to address such an issue and other econometrics limitations, such as the identified heteroscedasticity. The results suggest that the premium consumers are willing to pay for 'organic' is 136%, and is equivalent to a marginal implicit price of £6.40 per kilogram (2016 values). The average premium for organic meat covered in the meta-analysis (Chapter 2) is 58%, though ranging from 1% to 210%. None of these is RP estimates for chicken meat. Closer to this thesis, applying hedonic price models to 2004 scanner data, Griffith and Nesheim (2010) estimate a WTP premium of 125% for fresh organic meat and vegetables, but with no insight about chicken meat.

One of the main contributions of this paper is to demonstrate how socio-economic variables can be used as valid instruments in the application of HP models. The GMM estimations passed all required statistical tests of the instruments used, adding to the theoretical demonstration and discussions about the intuition behind the model. 'Organic' contributes substantially to the marginal price of chicken across all types of chicken meat. However, there is a noticeable heterogeneity across sub-product types (chicken parts) and regions in the UK. Furthermore, although the models include Month variables, these should mainly capture the seasonal trends, while analysing the influence from broader market shocks would require yearly time series data. It would be particularly interesting to investigate the influence of the pandemic on the WTP for environmental attributes.

This chapter also uses a series of previous studies to support the findings in the first-stage regression of instruments that consumer characteristics are central drivers of the demand for the 'organic' attribute (as the endogenous treated variable). The instruments used to treat the endogenous 'organic' variable were from family structure (mainly number and age of children), supported by economic theory and statistical tests, showing that these are valid instruments, i.e. they are both exogenous to the price function, and relevant to the choice for organic chicken. The validity of instruments is always a source of debate; thus, the exclusion restriction of instruments was addressed conservatively with the use of fixed terms for possible variables included in the model (e.g. shops). In theory, 'organic' can still be correlated with the instruments, but there is no empirical evidence in the data used. For example, although family structure may be correlated with where they shop, it is unrealistic that families would change where they shop as their children move up the age groups, which was the level of information used as instruments.

Another possible limitation of HP models is that, beyond the instruments, consumer characteristics are not included; thus, many questions about the individuals' socio-economic characteristics, attitudes and behaviours driving WTP are not within the scope of HP methods. There are other attributes not available in the market that remain of interest. Regarding other common issues in RP data, although heteroscedasticity is accommodated in the GLM and GMM models, multicollinearity may have an effect on the GLM estimators and the non-treated explanatory variables in the GMM model. The following chapters will retrieve and incorporate these in a survey and joint (stated and revealed) estimations.

Chapter 4

Stated Preference Estimation: Choice Experiment

4.1 Chapter introduction

Understanding consumer preference is a core field in economics and pivotal in assessing the welfare impact of environmental change and government interventions. This chapter applies a stated preference (SP) method to estimate the willingness to pay (WTP) for environmental attributes usually not labelled in the products available in the market, beyond 'organic'. This impact, however, is not homogeneous across individuals. In addition to WTP estimates for the attributes, this chapter explores the individuals' characteristics and behaviours driving, and affected by, these attributes.

To elicit consumers' preferences for chicken meat attributes, the SP data used in this chapter comes from individuals' responses to a choice experiment (CE). This is a discrete choice method which can also suffer from hypothetical bias but appears more shielded, as respondents do not explicitly give their WTP bids. Instead, WTP is estimated from a series of consumer choices, arguably more likely to be how they act in real circumstances. Nonetheless, the CE of this study included 'ex-ante' treatments to hypothetical bias, as discussed later in this chapter.

CE is still state-of-the-art when it comes to SP approaches. For most environmental economists, RP methods are more reliable, given that they are derived from individuals' actual behaviour. However, SP methods can expand the range of behavioural responses to the market of environmental change (Whitehead et al., 2008). In the case of this study, there are attributes proven to be significant to consumer preferences but are not usually labelled on the product at the supermarkets. Also, RP does not account for potential characteristics that current products may lack. This is relevant for the impact assessment of new products and the introduction of socially desirable attributes.

This chapter aims to elicit the WTP for the attributes of chicken meat by exploring the choice probability of individuals and how these are influenced by their socio-economic characteristics, behaviour and attitudes towards their health, the environment, their happiness and how they perceive organic food. The chapter also explores the effect of two hypothetical bias treatments (HBT) at attribute and individual levels. Closely related to Gschwandtner and Burton (2020), it contributes to the discussion about the population's WTP heterogeneity, however, at the individual level as opposed to latent classes explored in the former.

The CE estimation model that best suits the objectives of this study and the characteristics of the choice experiment applied in the survey is the conditional logit (C-logit). Given the strong assumption of homogeneity in the traditional method, interaction terms between attributes, consumer characteristics, and behaviours were included in the model, offering heterogeneity and essential information about consumer preferences. In addition, relaxing the same assumption, a novel mixed logit is applied for robustness and further analysis.

Results suggest high heterogeneity in terms of WTP for 'organic', which can be explained by individual characteristics, mainly age and income, behaviour towards organic food and the environment (pro and con), and 'healthy' lifestyle. They show a negative effect of HBT (honesty priming) on the choice of 'organic' (mixed logit) and 'quality' (combined HBT). Therefore, suggesting that individuals shift the price they are actually willing to pay for these attributes in the CE; thus, future studies should include HBTs.

However, the overall WTP for 'organic' in the main model (without the interaction terms) was not significant. For the CE used in this chapter, the intuitive explanation is that the most socially desirable attributes associated with organic food were available in the experiment for the subjects to choose independently of the 'organic' label. The coefficients for 'low chemical usage', 'environmentally friendliness' and 'animal welfare' are all significant. This indicates that individuals do not necessarily value the organic label per se but what it represents, and it has implications for future experiments. For policymaking and marketing purposes, this suggests a gap to enhance information for consumers, as one might argue that the individual would be better off by choosing a label which embeds all these characteristics, considering they are desirable. Another potential issue can be a lack of trust in the label or accreditation, but this would need further investigation.

4.2 Theoretical background: Choice Experiment

This section presents the theoretical background of choice experiments (CEs) and the best suited empirical models to elicit the marginal utility for this data.

A choice experiment (CE) is a survey-based stated preference approach used to elicit consumers' WTP for goods and their attributes. The CE used in this study collected data from British residents, including their socio-economic characteristics, behaviours and attitudes towards chicken meat, and their choices from a set of attributes presented to them in the experiment. In a CE, the surveyor presents respondents with choice cards, describing the attributes associated with the product they would buy and their respective prices. Options are then tracked to estimate the relationship between WTP and the attributes.

CEs are used to understand consumer behaviour in their utility maximisation, based on inferences of their choices of products, usually posed in a hypothetical scenario. The method has a common theoretical framework with the dichotomous contingent valuation method and is viewed as a more sophisticated and reliable SP alternative (Hanley, Shogren, and White, 2007) compared to CVM. CEs involve a random set of alternatives for individual selection. Each set is associated with several attributes assigned in the design of the experiment. CEs facilitate estimation of single attributes and sensitivity control of scope, which are more challenging under multicollinearity, often encountered in revealed data, as in Chapter 3.

The limitations of the method include the fact that incentive properties for WTP responses can be unclear (Carlsson and Martinsson, 2001) in the negative impact of choice complexity on preferences and the use of CEs in developing benefits transfer systems. In other words, estimation of economic values via transfer information from studies completed in a different context (Hanley, Shogren, and White, 2007), thus deviating from their potential purchase behaviour in real life. Although these limitations can be mitigated by incorporating revealed preference data, for example, to capture the impact of the CE design on the choices of respondents, and this is explored in Chapter 5, this section will present alternative solutions to these issues, given that the inclusion of RP data will contribute to broader aspects in the next chapter.

4.2.1 Experiment design

The CE design used in this study followed Hensher, Rose, and Greene (2005), which proposes a guideline with eight stages when setting up a stated choice experiment. These are problem definition refinement, stimuli refinement, experimental design considerations, generating experimental design, allocating attributes as a blocking variable, generation of choice sets, randomising choice sets, and survey construction.

1. **Problem definition refinement**

   This stage is related to the establishment and understanding of the problem being studied and thus the questions that need to be asked. In a CE, the researcher presents respondents with a hypothetical scenario that must reflect the market realities. In the case of this study, the objective is to understand consumer preferences for chicken meat, e.g. estimate the WTP for organic chicken. Therefore, some key questions one may ask to understand this include: What types of chicken meat do consumers have available in the market? What are the key attributes? What are the determinants of demand (behavioural, habit, socio-demographic, etc.)?

2. **Stimuli refinement**

   After considering an extensive list of alternatives and the market availability and attributes from stage 1, in this stage, the researcher needs to identify all relevant alternatives to be included in a random sample to be presented to the decision-maker (the experiment subject). The chosen attributes are those associated with the research question, i.e. WTP for 'organic' and its associated attributes, but also all relevant attributes of demand determination. Failure to include relevant attributes compromises the utility maximising outcome, i.e. results from estimations will be biased. This stage involves a key advantage of CEs over other valuation methods, mainly RP, as these attributes can include characteristics not commonly available in the market or not established certificates and labels.

3. **Experimental design considerations**

   The choice experiment of this study uses alternative levels of chicken attributes to elicit their implicit price, addressing the potential correlation between them. The different choices (options given to subjects) have a limited number of attributes. This number needs to be defined, their levels, e.g. low, medium and high (the more levels are added, the higher will be the researcher's ability to capture more complex utility relationships), and finally, their respective labels are determined.

Therefore, one of the first considerations in the experimental design is the number of options and how respondents will select them. These can be a 'factorial design', where all attribute combinations are enumerated, or 'conjoint analysis', where a fraction of a factorial design is considered. For the nature of this study, choice-based CEs (factorial design) are more suitable, as they are more comparable with what a revealed dataset provides[1], i.e. the individual has bought the product with only one set of observable characteristics or decided not to buy. Thus, the researcher cannot observe the products available to the shopper at that specific time and how they ranked their options.

Then, the next consideration is the type of 'factorial design'. A complete enumeration of choice sets is called 'labelled' instead of a design with only a set of choices presented to subjects, called 'unlabelled'. In the labelled CE, the researcher labels each of the alternatives, whilst 'unlabelled' experiments use generic titles (e.g. A or B) for the alternatives. The enumeration of sets is then equal to L^{MA} for 'labelled', and L^{A} for an 'unlabelled' experiment, where $L =$ the number of levels (e.g. low, medium and high), $M =$ number of alternatives and $A =$ number of attributes.

4. **Generating experimental design**

   The generation of the experiment is a complex task, requiring an expert for its design. This is because there are numerous possible combinations of choices, and these have to efficiently elicit the consumer preferences, i.e. enough variation within a feasible survey time. However, this can be done using a computer software (e.g. SPSS and Ngene). The software generates the most efficient design, i.e. the least variance (the shortest time possible not to exhaust the subject) and the number of treatment combinations. In addition to using the main effects of attributes in the choice process, the researcher can also include interaction terms. In the design of the choice card, the alternative (columns) has a set of attributes (rows).

5. **Allocating attributes as a blocking variable**

   The respective attributes are then allocated, including their levels, to the different

[1] Also having in mind that the SP and RP datasets are aimed to be joined in Chapter 5.

questions. The efficiency of design, referred to as 'D-optimal', is measured by the standard error of its parameters using 'D-error'. This D-error employs the determinant of the asymptotic variance-covariance matrix of the respondent, i.e. a design with the lowest D-error is associated with the lowest standard errors, thus is defined as D-optimal.

6. **Generation of choice sets**

   In this stage, the options generated by allocating attributes and attribute levels are grouped in pairs to form the choice cards for respondents. The specialised software can generate the choice sets (with the lowest 'D-error'), from which respondents can choose an alternative. The choices from respondents give a variation used as input to be used in the regression. From the coefficients, the researcher can construct the implicit price for each attribute, i.e. the results give the best outcome of the trade-off between the price paid and the preference for the attributes.

7. **Randomising choice sets**

   Subjects in an experiment can have diminished levels of concentration, thus potentially biasing responses towards the end of the experiment. Therefore, randomisation in the allocation of choice cards to respondents should be applied to address this. In addition to randomisation, the hypothetical bias treatment described in the following sections further mitigates this issue.

8. **Survey construction**

   The last stage involves the construction of the questionnaire. This consists in providing respondents with instructions, example task choices, potential issues with compliance bias, and general information such as the independence of how choice cards will be treated. The survey for this choice experiment is detailed in Section 4.2.2.

4.2.2 Data collection: survey

The choice experiment used in this study was conducted in April 2016 and involved interviews of a maximum of 30 minutes, with respondents across Great Britain, outsourced from a market research company. The interview was divided into four sections: a collection of data about recalled purchases, provision of instructions, a choice experiment, and collection of socio-demographic information, including attitudes towards organic food, the environment, health and happiness.

In the first section of the survey, respondents were given general information about the experiment and were asked about their purchasing behaviour. More specifically, they were asked about their past shopping experience, including product information such as quantity, shop, price, labels (e.g. organic), quality, and expiry date.

In the second section, respondents were asked a few warm-up questions. This section, combined with the fourth, is intended to incorporate elements of the treatment of potential hypothetical bias. Firstly, the respondents were made aware that people generally overstated their true WTP and reminded about their budget constraints. This approach is called 'cheap talk'. Following, the warm-up questions were a series of positive statements with obvious true or false words, which is an approach called 'honesty priming' (asking respondents to complete). These two measures aimed to reduce potential overstatement of WTP, as demonstrated by Farrell and Rabin (1996), Cummings and Taylor (1999), Carlsson, Frykblom, and Lagerkvist (2005), Jacquemet et al. (2011), Tonsor and Shupp (2011), and others. In the experiment, these treatments were randomly assigned to respondents; thus, forming four combinations of treatment: 'cheap talk' + 'honesty priming', 'cheap talk' only, 'honesty priming' only, and 'no treatment'. These treatments are used as regressors in the model to show if these are statistically relevant in influencing WTP.

The third section was the experiment, i.e. the choice task. Respondents were posed with choice cards such as Figure 4.1, on which each attribute is attached to a value, and respondents were posed with different combinations of product characteristics, from which they would choose one option (option A or option B), or none, defined here as status quo (SQ). Using this 'unlabelled' fractional factorial design described in Section 4.2.1, there were 2^5 x 6^1 (192) possible alternatives for chicken breast, given that there are five dichotomous attributes plus six levels for 'price'. It would be unfeasible to confront individuals with all possible alternatives within 30 minutes. Therefore, subsets of 16[2], randomly assigned choice cards, were allocated for the interview. A fractional factorial design was obtained using a software called 'Ngene', which chooses a subset (fraction) of the whole design such that it enables the estimation of the parameters with low errors, as explained in Section 4.2.1.

[2] This is the typical number of choices used in the literature, e.g. Adamowicz, Louviere, and Williams (1994) and Burton, Rogers, and Richert (2017).

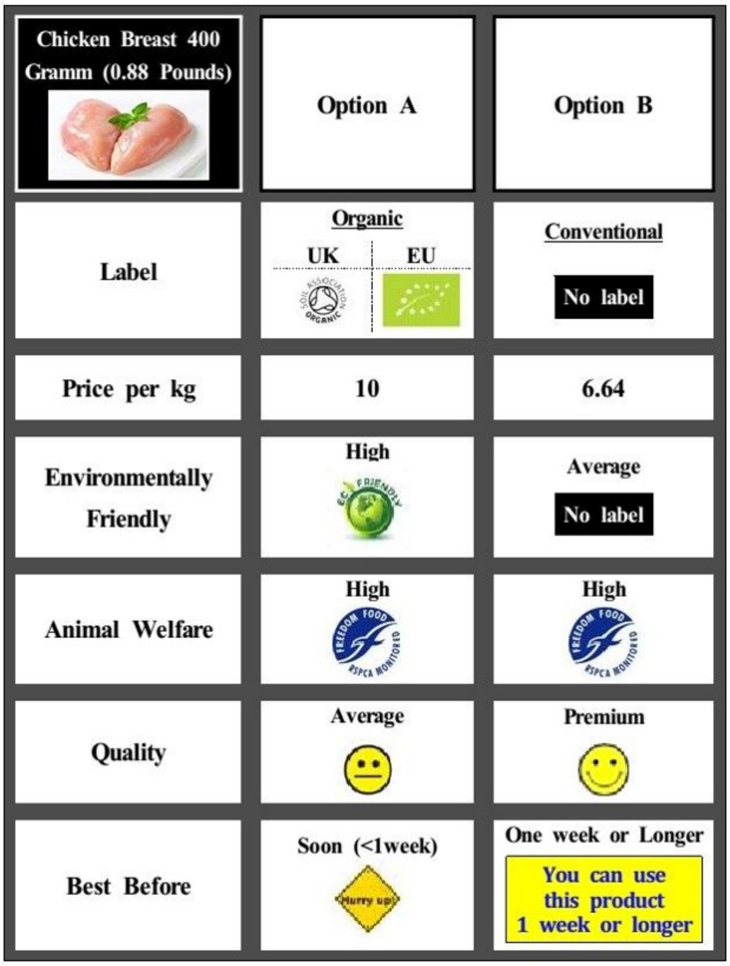

FIGURE 4.1: *Example of choice card*

In the final section, the questionnaire collected information about socio-economic characteristics, lifestyle, general behaviour towards organic, diet, frequency of exercise, and self-assessment of health and happiness. As illustration, Figure C.1 (Appendix) shows the questions about the motivations driving consumption of organic food. The responses were used for internal validity checks or detection of protest bids (from individuals who may place a higher/lower value than average but refuse to provide true WTP for ethical reasons) and outliers. Moreover, this thesis uses these to analyse individuals' characteristics, behaviour, respective demand, and WTP for organic and its associated attributes. These are also used as regressors in the estimation models.

4.3 Data

This section explores the data provided by the CE and used in this chapter, formed by collecting information from 505 households. The data includes socio-economic characteristics (household size, income, education, etc.), behaviour towards the environment and organic food, health status, lifestyle, and happiness, offering 12,120 choice observations. Each alternative (in each round of 3 alternatives) counts as one observation. Therefore, subjects provided the survey with an average of 8 rounds of choice cards ($505x8x3 = 12,120$). These were collected online by a professional survey company in 2016 after a pilot project was conducted with 60 subjects.

4.3.1 Data description

The summary statistics of the variables used from the dataset provided by the choice experiment are described in Tables 4.1 and 4.9.

As shown in Table 4.1, the experiment collected choices from 505 individuals, from which 60% were female, on average 50 years old, 67% were married, one with one child per household. On a scale from 1 (below high school) to 8 (professional degree), respondents, on average, placed their education level just below 4 (2-year college education, or 13.5 years in education). In terms of income, the average gross income of respondents was £2,454/month. Compared with UK demographics from the Office of National Statistics (ONS), these figures differ in age, education and gender. This is intuitive because these three variables refer exclusively to the respondents, not their households. Thus, they are expected to be different

TABLE 4.1: *Summary statistics: individuals (N=505)*

Variable	**Description**	**Mean**	**sd**	**Min.**	**Max.**
Female	gender dummy	0.602	0.49	0	1
Age	age of respondent	50.447	15.636	18	80
Married	dummy for marital status	0.667	0.472	0	1
Children	number of children in household	0.614	0.98	0	6
Vegetarian	dummy for vegetarian	0.044	0.204	0	1
Education	$<$ high school to professional degree	3.782	1.589	1	8
High education	dummy for high education	0.392	0.489	0	1
Income	net income	2,454	1,918	250	10,500
High Income	income $>$ UK average (£2,336*)	0.251	0.434	0	1
Professional	occupation dummy	0.206	0.405	0	1
Services	occupation dummy	0.051	0.221	0	1
Sales	occupation dummy	0.087	0.282	0	1
Farmer	occupation dummy	0.002	0.044	0	1
Construction	occupation dummy	0.016	0.125	0	1
Transports	occupation dummy	0.028	0.164	0	1
Government	occupation dummy	0.024	0.152	0	1
Retired	occupation dummy	0.269	0.444	0	1
Other	occupation dummy	0.19	0.393	0	1
Unemployed	occupation dummy	0.127	0.333	0	1
Pro-Environment	'green behaviour'	54.473	8.609	16	70
Pro-Organic	positive attitude	44.368	12.581	10	70
Con-Organic	do not buy organic	40.372	10.384	10	70
Happy 1	feeling happy	3.547	0.885	1	5
Happy 2	satisfied	3.606	0.951	1	5
Healthy	healthy lifestyle, $>$50 (10-70)	0.921	0.270	0	1
Diet	dummy for respondent on diet	0.156	0.363	0	1

*average monthly net income in 2016, source: ONS from the average national figures, including all individuals, not only the household member responsible for the grocery shopping. Most studies show that the primary shoppers are primarily adult women; thus, shifting upwards also age and years of education. Therefore, similar to Chapter 3, one should explore the characteristics of primary household shoppers on product choice.

Chapter 2 shows that the average proportion of females in the 56 studies was 67%. The sample should be consistent with the household's primary shopper (as opposed to national census data) because of their decisive role in the shopping and consumption behaviour of the household, especially organic and healthy food, as reported by Lea and Worsley (2005) (Australia), Arbindra and Wanki (2005) (USA) and Stobbelaar et al. (2007) (Netherlands). The latter shows that the influence of other household members, adolescents in that case, in food purchase depends on the type of product involved, and that only a proportion of them would take such a role (50% for meat). Again, education and gender are also central, with girls and those in higher education more influential than boys and in lower education, respectively.

The choice experiment that feeds the SP data also explored the attitudes and behaviours of respondents towards organic products, the environment, their health and happiness. The main objective was to better understand consumer behaviour correlated with environmental attributes. These are beneficial information for intervention purposes, e.g. education of individuals about the benefits of these attributes and marketing and price strategies for suppliers. During the experiment, the surveyor asked subjects ten positive questions about organic food, the environment, their health and their lifestyle, and also ten negative questions about organic. These were ranked from 'strongly disagree' to 'strongly agree', and the values were assigned to the respondent so that individuals with scores above the average were considered respectively 'pro-organic'[3], 'pro-environment'[4], with a 'healthy lifestyle' (*Healthy*), happy (*Happy1*) and satisfied (*Happy2*), and 'con-organic'[5].

'Healthy' and 'healthy family' derived from answers (dummies = 1 for 'good' and 'very good') to the questions: 'how is your health?' and 'how is your family health history?', respectively. For 'happy 1', respondents were asked to what extent the characterisation of

[3]individuals identified with an overall positive attitude towards organic food, for the reasons listed in Figure 4.2.

[4]individuals identified with overall positive attitude towards the environment.

[5]individuals who state that they do not buy food for any reason.

'generally very happy' would describe them (dummy = 1 if 4 or 5, from 1 to 5). 'happy 2' is about how satisfied the respondent was with their life (dummy = 1 if satisfied and very satisfied, respectively 4 and 5, from 1 to 5 options).

In addition, within these categories, each specific question denotes behaviour that might be associated with the subject's choice. For example, an individual who agrees that they do not buy organic food because it is expensive (a 'con-organic' question) would be expected not to choose a card that includes 'organic' and has a high price tag. A deviation from this would characterise a hypothetical bias investigated in Section 4.3.2.

TABLE 4.2: *Buy Organic Characteristic: by socio-economic*

Variable	(1) NonOrg	(2) Organic	(3) dif	(4) St_Err	(5) t_value	(6) p_value	(7) Sample %
Gen-Y (1980-94)	0.210	0.241	0.032	0.015	2.10	0.035	21.2
Gen-BabyBoomer (1946-64)	0.432	0.398	-0.034	0.018	-1.85	0.061	43.0
Happy2 (satisfied)	0.671	0.696	0.024	0.018	1.40	0.168	67.3
Happy1 (very happy)	0.553	0.577	0.024	0.018	1.30	0.195	55.4
Married	0.666	0.688	0.022	0.018	1.25	0.205	66.7
Occupation-Farmer	0.002	0.004	0.002	0.002	1.20	0.228	0.2
Occupation-Sales	0.088	0.075	-0.013	0.011	-1.20	0.231	8.7
Occupation-Other	0.189	0.206	0.017	0.015	1.15	0.245	19.0
Small Children	0.005	0.009	0.003	0.003	1.15	0.258	0.6
Vegetarian	0.044	0.036	-0.009	0.007	-1.10	0.272	4.4
Retired	0.271	0.253	-0.017	0.017	-1.05	0.294	26.9
Occupation-Construction	0.016	0.011	-0.004	0.004	-1.00	0.316	1.6
Female	0.601	0.619	0.018	0.018	1.00	0.317	60.2
Healthy Family	0.492	0.510	0.018	0.018	1.00	0.321	49.3
Healthy	0.603	0.620	0.018	0.018	0.95	0.337	60.4
Gen-Z (1995-2012)	0.025	0.030	0.005	0.006	0.90	0.366	2.6
Occupation-Government	0.024	0.028	0.004	0.005	0.85	0.407	2.4
Fat Intolerant	0.032	0.027	-0.005	0.006	-0.80	0.425	3.2
Unemployed	0.126	0.135	0.008	0.013	0.65	0.512	12.7
Children-Teen	0.029	0.032	0.003	0.006	0.40	0.700	3.0
Special Diet	0.156	0.161	0.005	0.013	0.35	0.709	15.6
Occupation-Services	0.051	0.053	0.003	0.008	0.30	0.771	5.1
Occupation-Professional	0.206	0.202	-0.004	0.015	-0.30	0.780	20.6
Children-Junior	0.025	0.027	0.001	0.006	0.20	0.839	2.6
Gen-X (1965-79)	0.243	0.241	-0.002	0.016	-0.15	0.899	24.4
Gen-Silent (1925-45)	0.089	0.088	-0.001	0.011	-0.10	0.929	8.9

$Gen = Generation$

Table 4.2 shows some selected characteristics for analysis of individuals' choices for organic chicken, as the latent variable of interest, as opposed to their choices for conventional chicken (non-organic). Its purpose is to investigate whether each consumer characteristic is more or less represented within purchases of organic chicken (column 2) compared to non-organic (column 1). Significant t-test (column 5) indicates that one cannot reject the null that the difference between the subgroups is different from zero. From the main characteristics, such as socio-economic, happiness, and lifestyle, only two generations are significant when explaining consumers' choices for organic. This approach shows that 'millennials' (born between 1980 and 1994), which form 21% of the sample, are responsible for 24% of organic chicken purchases (compared to other generations), thus positively affecting the consumption of organic chicken. On the other hand, generation baby boomers (born between 1946 and 1964) buy relatively less organic chicken and form 43% of the sample as opposed to 39.8% of organic chicken buyers.

Although most consumer characteristics are not significant in explaining mean differences in the characteristics of those who buy and those who don't buy organic, one can note the direction of the deviation of choices for the 'organic' attribute from the choices for non-organic. Column 3 suggests a positive effect from individuals who stated that they are satisfied with their lives or very happy, married, farmer, with small children, female, with healthy family background, healthy, from generation Z, work for the government, unemployed, with teenage children, in a special diet, working in the service industry, and with junior children. These are primarily intuitive but are tested as explanatory variables in interaction with the 'organic' attribute in the regression models. Meanwhile, consumer characteristics which are suggested to have a negative effect on the choice of organic chicken, in addition to baby boomers, are individuals from generations X and silent (born between 1928 and 1945), vegetarians, retired, working in the construction and sales sector or professionals, and those who are fat intolerant. Again, these need further investigation, as shown in Section 4.5.

The data also indicates that individuals' behaviours associated with their perceptions of 'organic', their approach towards the environment, and their lifestyle are significant when explaining the mean differences between the subgroups of those who buy 'organic' and those who don't. Figure 4.2 summarises all choices for 'organic' based on socio-economic characteristics, behaviour and lifestyle of respondents, including only the statistically significant difference in the proportion of responses. 'Pro-organic' behaviours are associated with the highest proportion of respondents choosing 'organic' relative to the rest of the sample, ranging from 4.3% (those who perceive 'organic' as 'environmentally friendly') to 9.3%

The c

FIGURE 4.2: *Choice for 'organic': deviation from the sample average*

(those who perceive 'organic' as healthier). Only generation 'baby boomers' and those who don't buy 'organic' because they perceive it as expensive have a negative effect on the proportion of individuals choosing 'organic'. More detailed about descriptive behaviour statistics and further analyses are included in the Appendix C.

Consumer behaviour analysis

During the choice experiment, respondents were asked why they buy 'organic' to track the driving motivation for 'organic' consumption and identify who would be identified as 'pro-organic'. The data shows that 67.9% of respondents indicated that they buy 'organic' because it is 'environmentally friendly', the highest proportion, followed by those who buy because of animal welfare (59.6%) and those who bought 'organic' before and were satisfied with the product (56.4%). These respondents who indicated such a positive behaviour towards 'organic' were coherent when making their choices[6], therefore choosing organic chicken proportionally more. However, from the questions posed to respondents, the highest difference in favour of 'organic' was for those who stated that they buy 'organic' because it is healthier, lower price, fresher, non-genetically modified, and with better taste. These indicate that respondents answered more in line with what would be socially desirable, e.g. stated intention towards the positive externalities associated with 'organic', but their behaviour (choices) were more egotistical, probably trying to maximise their private benefit; thus, more related to their health and affordability.

The differences in choices for organic products based on the 'pro-organic' attitudes are illustrated in Figure 4.3, now stressing the proportion of total choices in the sample. For example, for those individuals who chose 'organic', 52% indicated that they buy 'organic' because it is healthier. This number drops to 41% within choices for conventional chicken. There is a more significant discrepancy in the proportion of individuals that buy 'organic' because it is fresher, showing a 10% difference between choices for organic and conventional chicken. The indication that only 33% of households that buy conventional chicken believe that 'organic' is fresher suggests a point of intervention in terms of information gap, or marketing opportunity to increase in market share, similar opportunities for health and taste characteristics. At the higher end, 'environmentally friendly' and 'animal welfare' characteristics of organic food are well established among respondents, with a high proportion of respondents who chose both 'organic' and conventional stating that they buy organic food because of these attributes.

Within 'con-organic', 'pro-environment', and 'healthy lifestyle' behavioural variables, Figure 4.4 shows that low proportions of the sample are against 'organic' because it is not advertised enough, and those who think that a donation to an environmental organisation is important. However, the two groups of people are proportionally larger among those who buy 'organic', respectively 39% and 36%, as opposed to 36% and 31% choices for conventional chicken. The most significant proportion of people agree that one should buy recycled products, that having a healthy life is important and favour environmental policies, all

[6] Worth stressing that the behavioural questions - previous shopping experience, general attitudes, stated tastes and emotions - were posed after the CE, thus avoiding compliance bias.

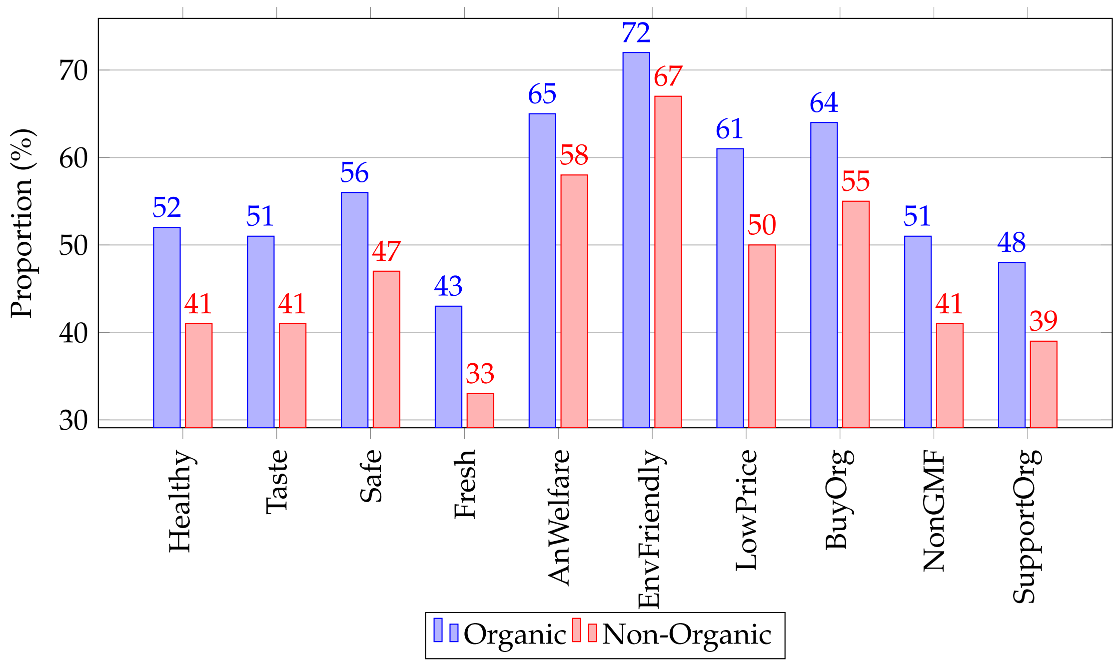

FIGURE 4.3: *Choice for organic relative to conventional: Pro-Organic Variables*

representing higher proportions within 'organic' choices than conventional. As discussed above, only respondents who don't buy 'organic' because it is expensive are represented in a lower proportion within the options for 'organic' compared to conventional (74% and 78%, respectively), thus acting consistently in the experiment.

TABLE 4.3: *Correlation check: multivariate regression - respondent characteristics and pro-organic behaviour*

	Age		Children		Married		Female		Income	
Pro-Org Reason	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.
Health	-4.376	-10.31	0.104	3.82	-0.043	-3.32	0.031	2.22	-38.227	-0.71
Taste	2.301	6.08	0.034	1.39	-0.089	-7.59	0.138	11.21	275.954	5.75
Safe	-2.277	-5.62	0.090	3.44	0.070	5.58	0.004	0.31	54.619	1.06
Fresh	-5.826	-14.94	0.170	6.76	0.062	5.13	-0.004	-0.35	262.040	5.29
An. Welfare	2.663	6.74	-0.043	-1.70	-0.028	-2.31	0.007	0.56	115.923	2.31
Env. Friendly	1.058	2.48	-0.177	-6.46	0.068	5.14	-0.046	-3.31	31.630	0.58
Local Production	0.693	1.86	-0.104	-4.33	0.058	5.00	-0.049	-4.09	80.565	1.70
Buy Org	-0.348	-0.90	0.133	5.33	-0.011	-0.91	0.041	3.31	-35.953	-0.73
Non GMF	-0.971	-2.50	-0.055	-2.20	0.064	5.36	0.074	5.90	32.883	0.67
Support Org	-2.201	-5.13	-0.001	-0.04	-0.037	-2.76	-0.020	-1.42	61.202	1.12
_cons	53.414	192.28	0.607	33.93	0.618	72.11	0.517	57.46	2085.840	59.14

To explore the characteristics of these respondents, Table 4.3 indicates the correlation between the main characteristics of individuals and the 'pro-organic' behaviour. One can observe that age negatively correlates with most characteristics, excluding taste, animal welfare, environmentally friendly and local production, which indicate more concerns about the environment and affordability. Table 4.3 shows the opposite for females and households

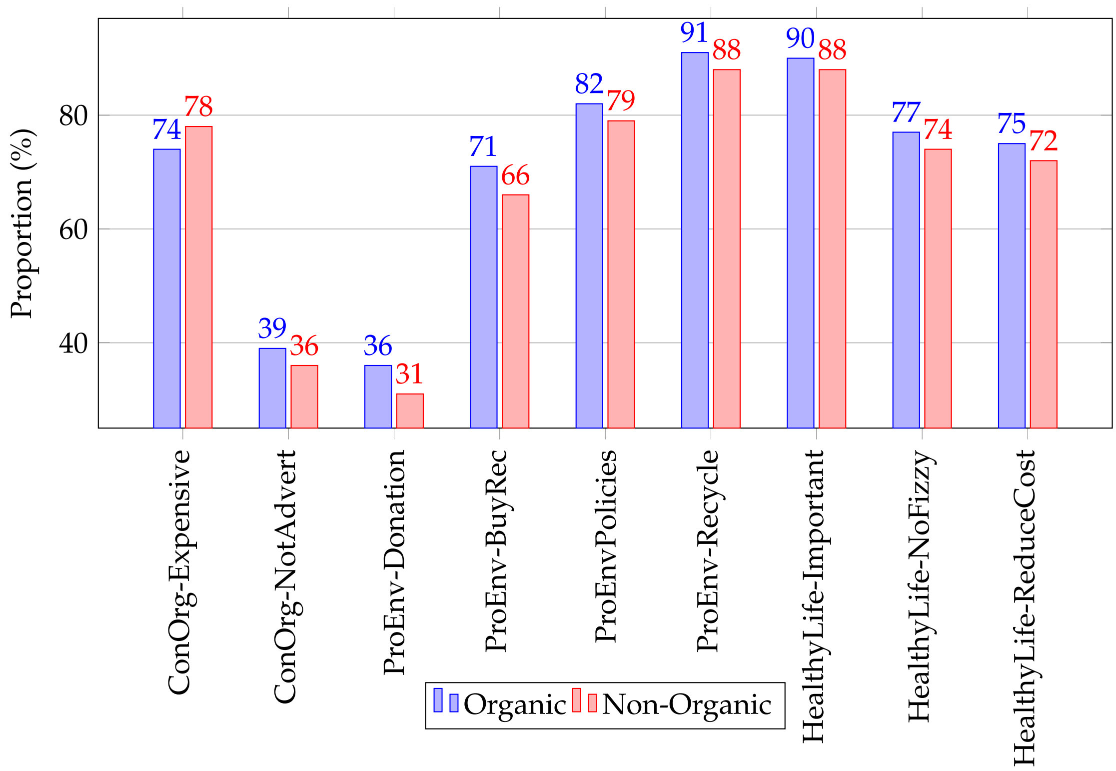

FIGURE 4.4: *The choice for organic relative to conventional: Other Significant Behavioural Variables*

with more children and higher income, i.e. they are more concerned about variables with potentially higher direct impact on their quality of life. 'Married' has a mixed effect on 'pro-organic' behaviour but was significant across all but one reason: 'taste' has the strongest negative correlation, while 'safe', 'environmentally friendly', 'local production' and 'non-GMF' are the most positive ones.

More generally, Table C.3 (Appendix) indicates that 'pro-organic' behaviour is positively correlated with income, female, married, and children, whilst negatively correlated with age. Respondents with children would generally be 'pro-organic', except for 'pro-animal welfare' (negative correlation) and 'pro-environmentally friendly' (not significant) motivations. In addition, Table C.5 (Appendix) shows that individuals who stated they are happy are less likely to be on any special diet, do not buy 'organic' because it is safe, and are less concerned about GMF. However, 'happy individuals' positively correlate with other 'pro-organic' behaviours. Respondents who have a healthy lifestyle, and those who are pro-environment, also showed 'pro-organic' behaviour. When posed with the option to choose 'organic' (Table 4.4), individuals identified as pro-organic picked the organic option more often for all pro-organic motivations. All differences are statistically significant.

TABLE 4.4: *Proportion of choices Organic vs Non-Organic: Pro-organic*

Why buy organic?	NonOrg	Organic	dif	St_Err	t_value	p_value	Sample %
Health	0.423	0.516	0.093	0.018	5.10	0.000	43.0
Taste	0.424	0.505	0.081	0.018	4.40	0.000	43.0
Safe	0.482	0.556	0.074	0.018	4.00	0.000	48.7
Fresh	0.339	0.424	0.086	0.018	4.85	0.000	34.5
Local Production	0.517	0.608	0.090	0.018	4.90	0.000	52.3
Buy Organic	0.559	0.640	0.080	0.018	4.40	0.000	56.4
Non GMF	0.422	0.505	0.083	0.018	4.55	0.000	42.8
Support Organic	0.403	0.475	0.072	0.018	4.00	0.000	40.8
Animal Welfare	0.592	0.652	0.060	0.018	3.30	0.001	59.6
Environmentally Friendly	0.676	0.719	0.042	0.018	2.45	0.015	67.9

Note: value = 0 if option 'not chosen' and value = 1 if 'chosen'.
Description: the proportion of choice for organic is higher for all pro-organic motivations.

Respondents were also asked why they do not buy 'organic', similar to 'pro-organic'; their responses were aggregated to identify the 'con-organic' behaviours, i.e. from individuals who have a negative perception of organic products. The experiment posed individuals with ten questions associated with anti-organic behaviour, as shown in Table 4.5. The proportions of individuals with 'con-organic' behaviour are relatively lower, with the highest percentages related to price and availability than organic product characteristics per se. Furthermore, most justifications for not buying 'organic' do not show a significant difference in the proportion of times respondents had chosen 'organic', as opposed to non-organic and no choice. The only significant differences were for those who stated that they don't buy 'organic' because it is expensive, 4% lower frequency of choices for 'organic', while those who don't buy 'organic' because it is not advertised enough choose relatively more (3%) when they were given the option to buy, which is intuitive. These suggest that their response might be associated with protest bids rather than their actual behaviour.

Similarly, Table 4.6 shows results for the proportion of individuals who chose 'organic' based on their approach to the environment, referred to as 'green behaviour'. Nonetheless, only four types of attitudes show significant differences in the proportion of individuals who choose 'organic', ranging from 2.5 to 4.2%. These are those who donate to environmental institutions, recycle, buy recycled items, and think environmental policies should be prioritised. Table C.5 (Appendix) also indicates that 'pro-environment' behaviour is positively correlated with all 'pro-organic' attitudes.

In the last behavioural description insight, Table 4.7 shows the difference in individuals' responses regarding their lifestyle. Only those who answered that a healthy lifestyle

TABLE 4.5: *Proportion of choices Organic vs Non-Organic: Con-Organic*

Why don't buy	NonOrg	Organic	dif	St_Err	t_value	p_value	Sample %
Expensive	0.774	0.739	-0.035	0.015	-2.30	0.022	77.2
Not Advertised	0.360	0.393	0.033	0.018	1.80	0.069	36.2
Low Variety	0.414	0.435	0.020	0.018	1.10	0.267	41.6
Not Available	0.259	0.275	0.017	0.016	1.00	0.305	25.9
Cannot Recognise	0.515	0.503	-0.013	0.018	-0.70	0.477	51.5
Do Not Trust	0.266	0.257	-0.009	0.017	-0.55	0.586	26.5
Not Attractive	0.185	0.192	0.006	0.015	0.40	0.673	18.6
Habit	0.389	0.383	-0.006	0.018	-0.35	0.733	38.8
Not Known	0.317	0.321	0.004	0.017	0.25	0.797	31.7
Short Expiring Date	0.348	0.348	-0.001	0.018	-0.05	0.967	34.9

Note: value = 0 if option 'not chosen' and value = 1 if 'chosen'.
Description: difference in the proportion of choices only significant in two motivations.

TABLE 4.6: *Proportion of choices Organic vs Non-Organic: Green-Behaviour*

One should:	NonOrg	Organic	dif	St_Err	t_value	p_value	Sample %
Donate the Env ONG's	0.320	0.362	0.042	0.018	2.40	0.015	32.3
Buy Recycled	0.666	0.709	0.042	0.018	2.40	0.016	66.9
Recycle	0.888	0.913	0.025	0.011	2.20	0.028	88.9
Prioritise Env Policies	0.790	0.823	0.033	0.015	2.15	0.032	79.2
Use Public Transport	0.512	0.533	0.022	0.018	1.20	0.238	51.3
Close Tap When Brushing	0.799	0.810	0.011	0.015	0.80	0.438	80.0
Use Own Bags	0.912	0.918	0.005	0.011	0.55	0.588	91.3
Switch Lights Off	0.928	0.931	0.003	0.009	0.25	0.802	92.9
Unplug Devices	0.723	0.727	0.004	0.017	0.25	0.818	72.3
Use Better Insulation	0.880	0.879	-0.001	0.012	-0.05	0.951	87.9

Note: value = 0 if option 'not chosen' and value = 1 if 'chosen'.
Description: the proportion of choice for organic is higher and significant for four green-behaviour.

is important, those who take such an approach to reduce healthcare costs, and those who don't drink fizzy drinks are suggested to show a significant difference in the proportion of their choices for 'organic', all with a positive effect. Except for no fizzy drink, the choice for 'organic' appears more correlated with their strategy (maybe intention) than with other 'healthy lifestyle' behaviours.

TABLE 4.7: *Proportion of choices Organic vs Non-Organic: Healthy Lifestyle*

Healthy Lifestyle	NonOrg	Organic	dif	St_Err	t_value	p_value	Sample %
Health is Important	0.882	0.904	0.022	0.012	1.90	0.059	88.3
HLS to Reduce Healthcare Cost	0.723	0.752	0.029	0.017	1.75	0.079	72.5
No Fizzy	0.743	0.770	0.027	0.016	1.70	0.094	74.5
Exercises are Important	0.860	0.880	0.019	0.013	1.55	0.123	86.1
Upset with Fast Food	0.426	0.454	0.028	0.018	1.55	0.125	42.8
Healthy Food is Important	0.902	0.918	0.016	0.011	1.50	0.138	90.3
No Fast Food	0.752	0.768	0.016	0.016	1.00	0.322	75.2
Low Fat/Sugar	0.637	0.647	0.010	0.018	0.55	0.571	63.8
Non Smoker	0.913	0.910	-0.003	0.011	-0.25	0.807	91.3
More Active (Less TV)	0.695	0.698	0.004	0.017	0.20	0.843	69.5

Note: value = 0 if option 'not chosen' and value = 1 if 'chosen'.
Description: the proportion of choice for organic is higher and significant for three green-behaviour.

4.3.2 Hypothetical bias treatment

As a robustness check, this chapter explores the effect of hypothetical bias treatments (HBT) on WTP. For this data, Gschwandtner and Burton (2020) separated the sample into latent classes with similar characteristics to investigate the effect of HBT. The study found that HBT efficiently reduces WTP, and 'cheap talk' has a higher significance than 'honesty priming'. This chapter controls for heterogeneity across individuals, including interaction terms between their characteristics and the attributes, emphasising consumer attitudes driving WTP. Worthy mentioning, hypothetical bias can also underestimate, as shown by Murphy et al. (2005) in a lab experiment; thus, treatments can have a significant effect on estimates.

First, to analyse the effectiveness of the HBT applied in the choice experiment, one needs to test whether differences in parameters across HBT groups are driven by heterogeneity across the different HBT groups, testing whether the cases for the HBTs were randomly selected. Although this was certified to be the case, as questions were randomly allocated, the randomisation might not be balanced, so the model needs to verify and control this.

Table 4.8 shows the respective respondent characteristics and the differences between the mean value for the non-treated group (HBT0) and each treated group (HBT1 for 'cheap talk' and HBT2 for 'honesty priming'), clustered by individuals. The samples are suggested to be highly consistent, differing only in age for 'cheap talk', and unemployment in both treatments. As age has a negative effect on the choice probability of 'organic' (variable of interest), this would have a negative effect on estimates. Similarly, a lower percentage of unemployment in both treatments would also decrease quality estimates. Thus, these differences in sample characteristics had to be controlled in the regression (Table 4.10), as summary statistics might mislead interpretations about the effectiveness of the treatments. As it is argued in Section 4.5.1, results show the interaction terms (HBT and attributes), indicating that HBT2 (honesty priming) had an effect on price and HBT3 (both HBTs) on quality. As price is a central element of WTP estimations, these have to be taken into account and were controlled for in the model.

TABLE 4.8: *Individual characteristics by treatment (t-test adjusted for clustering by individual)*

	No Treatment		Treated					
	Obs	Mean	Obs	Mean	Diff	SE	T-value	P-value
Cheap talk								
Age	3048	47.95	3336	52.09	4.14	1.93	2.14	0.033
Female	3072	0.62	3360	0.58	-0.04	0.06	-0.64	0.522
Vegetarian	3072	0.05	3360	0.03	-0.03	0.02	-1.07	0.283
Married	3072	0.66	3360	0.67	0.02	0.06	0.26	0.794
Children	3072	0.66	3360	0.61	-0.04	0.12	-0.35	0.728
SmallChildren	3072	0.01	3360	0.00	-0.01	0.01	-1.05	0.297
Income	2760	2547.83	2808	2420.94	-126.89	260.43	-0.49	0.627
Unemployed	3072	0.20	3360	0.06	-0.13	0.04	-3.27	0.001
ProOrganic	3072	45.55	3360	43.14	-2.40	1.60	-1.50	0.134
ConOrganic	3072	40.87	3360	40.09	-0.77	1.28	-0.60	0.547
ProEnviron	3072	54.75	3360	54.03	-0.72	1.07	-0.68	0.500
Healthy	3072	0.61	3360	0.59	-0.02	0.06	-0.39	0.695
Honesty Priming								
Age	3048	47.95	2832	49.55	1.60	2.01	0.79	0.428
Female	3072	0.62	2832	0.64	0.03	0.06	0.43	0.664
Vegetarian	3072	0.05	2832	0.05	0.00	0.03	-0.13	0.894
Married	3072	0.66	2832	0.67	0.01	0.06	0.22	0.827
Children	3072	0.66	2832	0.69	0.03	0.14	0.22	0.826
SmallChildren	3072	0.01	2832	0.00	-0.01	0.01	-0.96	0.338
Income	2760	2547.83	2592	2409.72	-138.10	266.06	-0.52	0.604
Unemployed	3072	0.20	2832	0.11	-0.09	0.05	-1.85	0.065
ProOrganic	3072	45.55	2832	45.68	0.13	1.53	0.09	0.932
ConOrganic	3072	40.87	2832	40.81	-0.06	1.27	-0.05	0.961
ProEnviron	3072	54.75	2832	55.08	0.33	1.12	0.29	0.771
Healthy	3072	0.61	2832	0.64	0.03	0.06	0.42	0.673

4.4 Theoretical models

4.4.1 Choice experiment estimation models

Following McFadden et al. (1973) and Hoffman and Duncan (1988), when selecting the set of available attributes, the choice behaviour of an individual randomly drawn from the population aims to maximise their utility U, following a function which can be written as:

$$U_{ij} = V(X_i, Z_j) + \epsilon(X_i, Z_j) \tag{4.1}$$

Where: V_{ij} is the non-stochastic value (utility) of a given alternative j to an individual i, and it reflects the tastes of the individual with characteristics X_i, who faces J alternatives described by vectors of attributes Z_j. ϵ is the stochastic idiosyncrasies of the individual's tastes, which is unknown and treated as random. Thus, because of unobserved factors[7], one can only predict the probability that an individual i will choose an outcome with characteristic j over k if $U(i,j) > U(i,k)$, for $j \neq k$. In general, this can be shown as:

$$P_{ij} = Pr(V_{ij} > V_{ik}), for\ all\ k \neq j \tag{4.2}$$

Assuming that the individual will choose the alternative that will give them the highest utility (or at least are indifferent between alternatives), following their behaviour rule denoted by h_x, and the set of alternatives $B \subseteq Z$, the conditional probability $P(Z \mid X, B)$ that the individual will choose the alternative Z equals:

$$P_j \equiv P(Z \mid x, B) = \pi[h_\epsilon H \mid h_\epsilon(X, B) = X_j]$$

$$P_j = P\{[\epsilon(X, Z_k) - \epsilon(X, Z_j)] < [V(X, Z_k) - V(X, Z_j)]\}, for\ all\ k \neq j \tag{4.3}$$

Thus:

$$P_j = P\{[V(X, Z_j) + \epsilon(X, Z_j)] \geq [V(X, Z_k) + \epsilon(X, Z_k)]\} \tag{4.4}$$

The probability of selecting alternative j can be shown as:

[7]For this same reason, OLS estimation should be biased and inconsistent (Horrace and Oaxaca, 2006).

$$P_{ij} = \frac{exp(V_{i,j})}{\sum_{k=1}^{J} exp(V_{i,k})}, \ k \in J_i \tag{4.5}$$

Following the above theoretical background, modelling choice experiments depend on the assumptions about the unobserved $\epsilon_{X,Z}$.

Multinomial logit model:

To solve the choice probability above, McFadden et al. (1973) applied a multinomial logit (MNL) model in which individual choices of consumption are based on their observable characteristics, i.e. one nominal dependent variable given one or more independent variable (hence multinomial), such as income, and thus focuses on the analysis of individuals, and their characteristics as explanatory variables, therefore:

$$V_{ij} = f_1(X_i) \tag{4.6}$$

The model is based on the assumption that individuals' unobserved tastes and preferences are homogeneous, i.e. the probability of choosing an alternative with characteristic j over choosing characteristic k does not depend on the attributes of the other alternatives. Thus, the coefficient of the product attributes is assumed to be the same across all respondents. Therefore, MNL focuses on the respondents, and their characteristics are the explanatory variables. The choice probability in the MNL model is:

$$P_{ij} = \frac{exp(X_i\beta_j)}{\sum_{k=1}^{J} exp(X_i\beta_k)}, \ k \in J_i \tag{4.7}$$

In the MNL model, therefore, choice probabilities can only be affected by the different impacts individuals have on the other alternatives, i.e. the coefficient β_j for each explanatory variable shows the effect of individual characteristics on the probability of choosing each alternative.

Conditional logit model:

McFadden et al. (1973) also introduced the conditional logit (C-logit), which, in contrast to MNL, focuses on the set of alternatives available to individuals, thus conditional on the number of cases. Therefore, the explanatory variables are the characteristics of the other alternatives, and all observed factors or explanatory variables can be represented in Z_{ij} (Cushing et al., 2007). This has been more applied than MNL in models for discrete choice studies, as it relaxes the homogeneity assumption.

The choice probability in the conditional logit is shown as:

$$P_{ij} = \frac{exp(Z_{ij}\alpha)}{\sum_{k=1}^{J} exp(Z_{ik}\alpha)}, \ k \in J_i \tag{4.8}$$

Where α shows the effect of attributes on the probability of choosing each alternative.

The differences between MNL and C-logit are more evident when re-arranging equations 4.7 and 4.8 (dividing them by their respective numerator); thus, MNL can be re-written as:

$$P_{ij} = 1/\sum_{k=1}^{J} exp[X_i(\beta_k - \beta_j)], \ k \in J_i \tag{4.9}$$

And the C-logit model as:

$$P_{ij} = 1/\sum_{k=1}^{J} exp[(Z_{ik} - Z_{ij})\alpha], \ k \in J_i \tag{4.10}$$

In Equation 4.9, the probability depends on the difference between alternatives. In contrast, in the equation 4.10 it depends on the difference between the characteristics of the alternatives, i.e. the highest utility V_{ij} (given by the choice that the individual values the most) depends on the attributes Z_j, following an unspecified function form such as:

$$V_{ij} = f_2(Z_{ij}) \tag{4.11}$$

Therefore, the differences between MNL and C-logit reflect how the researcher aims to model individual behaviour based on the choice hypotheses. As Hoffman and Duncan (1988) argue, utility is primarily regarded as a function of an individual's level of consumption, which is equivalent to the exogenous level of income and the price set they face; thus, enforcing the equation 4.11. Moreover, while MNL models can offer relevant insight about individuals who made the choices, they are not adequately suited to test important hypotheses of why choices are made.

The main objective of this thesis is to investigate the contribution of product attributes to WTP, above all attributes associated with positive externalities. Also, more specifically, to Chapter 5, to provide estimates that are compatible with the hedonic price estimates from Chapter 3. Hedonic price models estimate parameters for product characteristics, similar to conditional logit. Thus this study focuses on estimates from the C-logit model.

Mixed logit:

Nonetheless, both MNL and C-logit models assume that the error terms are in equations 4.7 and 4.8 are independent across alternatives, i.e. choosing between options K and J does not depend on another alternative L. This assumption is often called independence of the irrelevant alternatives (IIA) and is associated with several limitations. Phanikumar and Maitra (2007) list these as mainly the consequent implication of strong assumptions of preference homogeneity (homogeneity of attributes across the sample, in the case of MNL), the proportional substitution between alternatives, and the assumption of independent errors over time, altogether unrealistic. Hoffman and Duncan (1988) show that IIA is likely to be an issue, especially when alternatives are similar, so unobserved factors affecting one alternative might affect the other. For this study, respondents made their choices for several rounds in which only a couple out of all possible choice cards were presented in each round. However, in a real shopping (one choice) situation, the availability of other options would affect their choice, and this would likely be affected by their preferences and needs at that time.

Therefore, more recently, mixed logit or random parameter logit (RPL) models have been used as an alternative solution to the IIA, as it allows for heterogeneity of preferences within the population, following the probability distribution (Van Loo et al., 2011). Mixed logit includes both the characteristics of individuals and the attributes available to them, i.e. the choice probability is a mixture of logits, and it allows for random taste variation across individuals; thus, the unspecified function form under mixed logit is written as:

$$V_{ij} = f_3(X_i, Z_{ij}) \tag{4.12}$$

Equation 4.12 includes characteristics of the alternatives, the product attributes Z, and the individuals X. Although in the C-logit model, the explanatory variables (Z) allow for variation across alternatives, its unitary impact is assumed to be constant, i.e. only one coefficient is estimated for each variable, and the difference across alternatives drives the effect of the variable on the choice. Therefore, variables with no variation across alternatives have no impact on the choice probability (Hoffman and Duncan, 1988). This also applies to the individual characteristics (X). Thus, if these variables are important, mixed logit is required. Mixed logit allows for more significant variability of preferences across individuals and how this takes place compared to MNL and C-logit. At the same time, it also can incorporate several observations from the same individual (Revelt and Train, 1998).

The choice probability that an individual i chooses an alternative j in a mixed logit model can be expressed as:

$$P_{ij} = \sum_{k=1}^{J} \frac{exp(X_i\beta_j + Z_{ij}\beta)}{exp(X_i\beta_k + Z_{ik}\alpha)} \tag{4.13}$$

This study uses conditional (McFadden's model) and mixed logit models. In the latter, relaxing the IIA assumption, each individual was assigned a case ID[8], and their respective case variables (individual characteristics) and alternatives (choice cards) were specified. Thus, results provide random coefficients, which allow the alternatives (attributes) to be correlated. As explained above, the conditional logit is alternative-specific. Thus, any case-specific variable included in the model must interact with each alternative. The results are shown in Section 4.5.

Chapter 3 uses consumer characteristics as instruments and shows that consumer characteristics are not homogeneous and affect the choice of individuals; thus, both conditional and mixed logit is applied. For the conditional logit, to relax the IIA assumption, this study uses interaction terms between product attributes and individual characteristics; this should consider the population's heterogeneity. Similar to Cushing (2008), a conditional logit model with interaction terms between attributes and individual characteristics would have a choice probability given as:

$$P_{ij} = \frac{exp[Z_{ij}\alpha + (Z_{ij} * X_i)\beta)]}{\sum_{k=1}^{J} exp[Z_{ik}\alpha + (Z_{ik} * X_i)\beta]} \tag{4.14}$$

[8]For McFadden's conditional logit, the case IDs were specified using the 'group' command option.

4.5 Results

As explained in Section 4.4.1, this chapter applies C-logit and mixed logit methods to estimate parameters driving the choice for organic chicken meat over its conventional counterpart. Table 4.9 shows the summary statistics of the attributes in the choice cards and the survey elements of each alternative. As explained in Section 4.2.1, the combination of attributes was randomly allocated by NGene. In the allocated choice cards, the 'organic' label was present on 17.2%, and 'low chemical usage' on 17.7% of the alternatives. These are relatively fewer than other attributes because these attributes overlap, i.e. 'organic' implies reduced chemical usage. Despite such a difference ('reduced' as opposed to 'free from'), consumers usually would not find a product with both labels simultaneously - in addition, 'organic' includes other attributes beyond reduced chemical usage. The price levels chosen were based on the UK market and ranged between £3 and £10 in the experiment (the average price of the products excluding SQ is £6.02).

4.5.1 Result: conditional logit

TABLE 4.9: *Summary statistics: choice cards (12,120 alternatives/observations)*

Variable	Description	Mean	sd	Min	Max
Organic	dummy for organic label	0.172	0.377	0	1
Chemical Usage	dummy = 1 if 'low' or = 0 if 'average'	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
Best Before	$= 1$ if ≥ 1 week or $= 0$ if < 1 week	0.334	0.472	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 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

The main variables related to the experiment design were the status quo (SQ) and the hypothetical bias treatment (HBT). SQ is option C in every choice card, present in one out of three of the alternatives. SQ entry implies that all the attribute dummies are equal to zero. Meanwhile, HBT0, HBT1, HBT2, and HBT3 indicate whether, for that observation, that choice card was presented to a respondent from a treated sample, being, respectively, 'no treatment', 'cheap talk' only, 'honesty priming' only, and both treatments. Addressing hypothetical bias is viewed as a central task in the SP approach. Thus, one needs to investigate the influence of these approaches on consumer choices.

One of the main objectives of this section is to elicit the marginal implicit price of socially desirable attributes usually associated with organic products. Therefore, this was considered when choosing the best model and analysing the assumptions made in Section 4.4.1. Nonetheless, this section reveals the results from both C-logit and mixed logit models, as they offer complimentary insights about the estimations.

The first set of results in Table 4.10 shows estimates from the C-logit. Although the assumptions underlying the OLS disqualify the method from efficiently estimating the regressors in the choice probability model, Column 1 shows such parameters for comparison. The coefficients from the OLS model are significantly smaller, which indicates that the model underestimates the marginal effect of the attributes, as also found in Chapter 3. In addition, the C-logit model in Column 2 includes only product characteristics (as given in Figure 4.1, Appendix), following a strict homogeneity assumption.

The main results for discussion are shown in Column 3, which incorporates variables of interaction between product attributes and characteristics of individuals and the survey, following Equation 4.14. This aims to relax the IIA assumption and allows for heterogeneity across respondents. Another interaction approach was to calculate the consumer characteristics variables as deviations (Dev) from the actual population at the survey time[9]. Lastly, interactions between the HBTs and the significant attributes were tested, but only quality with HBT3 and price with HBT2 were significant.

Most of the coefficients in Table 4.10 do not differ substantially between models C-logit 1 (attributes only) and C-logit 2 (with interaction terms). Thus, any potential bias driven by the IIA assumption appears minor. However, one can further benefit from relaxing such an assumption by having 'organic' now significant at explaining individuals' choices and preferences when controlling for age, income, and those who are 'pro-organic'. The heterogeneity provided by the interaction variables between the attributes and characteristics of survey subjects can also be valuable. A comprehensive range of interactions was tested, and only significant interactions were maintained in the C-logit extended model, following log-likelihood tests. The interpretation of these parameters explores the heterogeneity across the sample population. The attributes and individual characteristics are detailed in Section

[9]This aimed to minimise potential bias if the mean value was not representative of the UK population.

TABLE 4.10: *Regression Results: C-Logit Models*

VARIABLES	C-logit 1	C-logit 2
Organic (Org)	-0.018	0.473**
	(0.090)	(0.206)
Low Chemical Usage (CU)	-0.164*	-0.620***
	(0.092)	(0.196)
Env. Friendly (EF)	0.187***	0.094*
	(0.043)	(0.056)
Animal Welfare (AW)	0.322***	0.386***
	(0.072)	(0.104)
Best Before (BB)	0.033	-0.079
	(0.044)	(0.130)
Quality (Qua)	0.559***	0.388*
	(0.044)	(0.213)
Price (Pr)	-0.229***	-0.335***
	(0.020)	(0.049)
SQ	-2.100***	-1.700***
	(0.020)	(0.142)
Org-TrueAgeDev		-0.011**
		(0.005)
Org-ProOrgDev		0.021***
		(0.008)
Org-IncMidDev		0.000***
		(0.000)
EF-ProOrgDev		0.012***
		(0.003)
BB-ProEnvironmDev		-0.014**
		(0.007)
Qua-HealthDev		-0.127**
		(0.051)
Qua-Unemployed		0.247*
		(0.126)
Pr-Smallchild		0.331*
		(0.185)
SQ-Married		-0.639***
		(0.118)
SQ-Veget		0.919***
		(0.228)
SQ-HealthyLifeDev		0.025***
		(0.008)
SQ-IncomeDev		0.000***
		(0.000)
Qua-HBT3		-0.181*
		(0.097)
Pr-HBT2		0.043**
		(0.018)
Constant		
Observations	9,552	9,552
Log Likelihood	-3730.4459	-2713.7015
Pseudo R2	0.1595	0.2242
Wald F/Chi2 Joint Statistics	1109.84***	951.37***

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

C-logit 2 includes bevahioural interaction variables from Table C.11 (appendix)

4.3.1. Given that the 'organic' label, 'animal welfare' and 'quality' are the main attributes with a positive effect on the choice probability, one can analyse the coefficients of the interactions, including these attributes as the effect on the respective variables of individual characteristics on marginal utility.

The C-logit results show that having 'organic' as an attribute increases the probability of choosing the chicken breast by approximately 50%. This is significant and shows that consumers would value 'organic' in a similar proportion to 'quality', which is an attribute with an intuitive high impact on utility. One can then conclude that 'organic' has a negative effect on the marginal utility of older people. In contrast, it positively impacts individuals who are 'pro-organic' and have a higher income. Results also suggest that socially desirable attributes, i.e. 'environmentally friendliness', positively impact the choice probability. Still, the environmental impact is relatively less influential even for individuals with a 'pro-organic' behaviour. This indicates that consumer utilities are more impacted by attributes more directly associated with their well-being, such as health and taste, than altruistic attributes, despite valuing the latter.

Nonetheless, 'animal welfare' has a relatively sizeable marginal effect on consumer utility. An expiry date longer than one week (captured by 'Best Before') is suggested not to affect individuals' utility. The attribute is viewed negatively by 'pro-environment' individuals, except for those who believe that environmental policy should be prioritised and those individuals who stated that they feel upset after eating fast food (Table C.11, Appendix), and thus should be correlated with preferences towards fresh products.

Although the model does not include health as an attribute, the coefficient for chemical usage can be used as a proxy. However, respondents were found to be opposed to low chemical usage labels. This might be counter-intuitive, so one must investigate the interaction terms to find this source. From Table C.11 (see Appendix), one can see that the low chemical usage label increases the utility for those who buy 'organic' because they perceive it as safer (49% of the sample). Those with positive behaviour towards the environment ('unplug devices when not in use, 72% of the sample), and those who do not buy 'organic' because of its low variety (42% of the sample), while the significant disutility from the 'less chemical usage' label will be true for those with 'green behaviour' for using public transport (51% of the sample) and individuals who stated they are happy with their lives (67%

of the sample). This shows that consumers consider different levels of risk from chemical usage and also offers an opportunity to educate the population. Another reason might be that chemical usage in chicken production needed to be more specific in the survey, as consumers might be more familiar with an association of chicken meat with the use of, for example, hormones and antibiotics.

For the 'no buy' (status quo) option, vegetarians get higher utility from the SQ alternative, which is intuitive as it represents not buying any chicken meat choices, and there should be a negative effect on the household purchase. However, the fact that 'vegetarian' is not significant when interacting with health-related attributes, such as organic and chemical-free or the environment, captured by the 'environmentally friendly' label, might be surprising but understandable due to the nature of the product. Other studies, e.g. Piazza et al. (2015), Apostolidis and McLeay (2016), and Nocella et al. (2012) show that groups with higher vegetarian membership probability have significantly higher WTP for 'animal welfare', but this interaction was narrowly significant. However, this suggests that vegetarians abstain from meat mainly for moral reasons, with lower environmental motivation, usually stronger amongst 'meat reducers'. SQ was also positively correlated with income and 'healthy life' behaviours, thus showing that healthier individuals are more likely not to buy any chicken breast, regardless of labels. This, however, is not true for married respondents, who are 64% more likely to buy one of the alternatives available than all the other marital statuses.

Households with small children are relatively more sensitive to changes in price. This is essential information for policymaking aiming to address young children's nutrition and support measures to subsidise food with socially desirable attributes for these households. The quality attribute brings relatively higher utility for unemployed respondents while with a lower effect on healthy individuals, which might be surprising. In general, Bernués, Olaizola, and Corcoran (2003) also show socio-demographic heterogeneity of preference for the quality level of meat, but not specifically for employment and individuals' health. Considering that the UK unemployment rate in 2016 was relatively low (4.8%, ONS, 2021), driven mainly by rates among young people but also frictional unemployment, this is not necessarily related to low levels of household income; i.e. searching for better pay or working conditions in frictional unemployment can be consistent with preferences for quality.

Again, attribute interactions with HBTs were significant only for quality-HBT3 and price-HBT2. This shows that 'honesty priming' treatment slightly decreased the price sensitivity of individuals, while the combination of both treatments substantially decreased the perceived utility gained from the quality label. HBT adds robustness to the SP estimation and makes the SP and RP estimations more comparable and compatible in a joint estimation approach in Chapter 5 (a primary contribution of this thesis). In summary, coefficients from the HBTs show that hypothetical bias might not have a significant effect on estimates from CEs, but are statistically significant (especially for quality); thus, HBT needs to be incorporated in the SP studies. The implications of the results of the HBTs are further explained in Section 4.3.2.

As discussed above, OLS and C-logit2 models in Table 4.10 include the behavioural interaction terms. These are presented in Table C.11 and analysed in Section C.4 (Appendix). Collecting some level of information on respondents' approach to the environment is not rare. Still, these usually are limited and aimed to provide internal validation of the SP approach. Considering that CEs are less affected by hypothetical bias and that the survey applied different treatments, one can analyse the results of the interaction terms with more confidence. Most results are intuitive, and the argument favouring deeper behaviour analysis is vital even if individuals show intention behaviour gaps, so the motivations behind this can be investigated.

4.5.2 Results: mixed logit

For robustness, this chapter also applied a mixed logit model to the SP data, mainly driven by the criticism of the independence of irrelevant alternatives (IIA) assumptions, but also to test whether the C-logit model with interaction terms has indeed addressed these issues. One can observe that the coefficients in column 1 of Table 4.11 are very consistent with the C-logit results without the interaction terms (Table 4.10, thus suggesting that IIA may not be a major issue in this data, assuming that the mixed logit method addresses such an issue. However, beyond the inability to retrieve a significant estimation of the 'organic' label, in addition to low chemical usage, the analyses of the influence of individuals' characteristics on the choice probability shown in Table 4.11 are limited. This is because the attributes are allocated randomly to the choice cards, i.e. case variables do not explain any specific choice card or group of attributes. In other words, there are no fixed attributes in Alternative 1 for one to analyse the results of consumer characteristics on the choice probability from Column 2. For example, income would have a negative effect, while those who value local production positively impact choosing any combination of attributes posed as Alternative 1.

Nonetheless, Column 3 is more beneficial to characterise households who avoid buying, as these include the significance of behavioural variables when attributes are equal to zero, regardless of their combination. The coefficients of the main attributes are not statistically different from those in the C-logit model 1 (without interaction terms). Therefore, the results suggest that the independent and identically distributed (IID) assumption is not a significant issue in Model 2 and supports the C-logit results.

Nonetheless, concerning the SQ in Column 3, all used consumer characteristics are significant to explain their choice not to buy chicken, which is useful, for example, for marketing purposes, i.e. to increase market share. The positive coefficient for 'age' indicates that older consumers are more likely not to choose any available alternatives, though the negative age-squared suggests that this positive effect diminishes with higher age. Other variables positively correlated with 'no buy' choice are vegetarians, 'healthy life', 'pro-organic', and households with teenagers. Income also has a positive effect on SQ, but it is marginal. Families with teenagers might be viewed as counter-intuitive in this case, but is it narrowly significant. The negative coefficients for vegetarian and 'healthy life' are quite intuitive, as those individuals are expected to buy non-meat and healthier options, such as vegetables or fish.

'Organic supporters' (ProOrgSupportOrg) is positive correlated with SQ. The variable indicates that the individual was identified as 'pro-organic' (perceives the benefits of organic food) and would also support the 'organic' movement. Considering that 'organic' label was only available in 17% of the card choices, this is not surprising. If respondents have a strong position in favour of 'organic', they would only buy 'organic', i.e. would have a positive correlation with SQ (Column 3), meaning they would choose not to buy when 'organic' is not available, as a form of protest bid. For the same reason (low proportion of 'organic' options), non-organic has a negative effect on the no-buy choice, as most options are conventional. The other 'pro-organic' behaviour, i.e. because of attributes such as health, taste, 'animal welfare', and local production, might indicate that respondents would choose a card that would satisfy these requirements. This is possible because they are well-informed by the choice cards, which may not happen in a dynamic and hurried real shopping setting. Another interesting result is that married respondents are more likely to buy chicken; the same can be said about happy individuals.

To offset the problem of the randomisation of attributes described above, as a test, only the 'organic' attribute was rearranged in the data to have at least such characteristics consistently in one of the choice cards (Alternative 1). Thus, when individuals choose that option, one can argue that at least they did not object to selecting the product with 'organic' label; hence, correlation can be explored. This approach provided significant results for Alternative 1 and is consistent with previous results. Another advantage is that being 'environmentally friendly' is now significant.

Table 4.12 shows in Column (2) that individuals were less likely to choose Alternative 1 (organic) when they are older, vegetarian, and 'pro-organic because it is environmentally friendly' and has a 'healthy life - less TV'. Respondents are also less likely to choose 'organic' when compared to conventional 'because of its price'. Those who are 'against organic because of lack of advertisement' (from the variable ConOrgNotAdvert) have a positive effect on the probability of buying 'organic', which indicates that once that option is offered, they are likely to purchase it (the choice card can be considered the source of information in this case). Table 4.12 also shows that 'honesty priming' significantly reduced the probability that 'organic' would be chosen (HBT2), while 'cheap talk' was not significant. Thus, 'cheap talk' would affect WTP mainly via 'price'. The individuals' characteristics that positively affect the likelihood of selecting 'organic' are 'pro-organic because of their local production', also taste, safety, and non-GMF, in their respective size effects. Individuals who stated that a healthy life was essential had the most substantial impact on the choice probability in the model.

4.6 Chapter conclusion

This chapter investigated the individual socio-economic characteristics, behaviours and attitudes driving their WTP for environmental attributes and 'organic' labels. These were collected by a choice experiment (CE), which is a stated preference (SP) method, incorporating hypothetical bias treatments (cheap talk and honesty priming). The chapter used C-logit with interaction terms between attributes, consumer characteristics, and mixed logit

TABLE 4.11: *Regression Results: Mixed Logit*

VARIABLES	(1) All alternatives	(2) Alternative 1	(3) No Purchase
Organic	0.047		
	(0.088)		
Low Chemical Usage	-0.141		
	(0.089)		
Environmentally Friendly	0.193***		
	(0.040)		
Best Before	0.040		
	(0.041)		
Quality	0.568***		
	(0.041)		
Price	-0.238***		
	(0.020)		
Animal Welfare	0.332***		
	(0.071)		
Age		0.003	0.136***
		(0.016)	(0.029)
Age^2		-0.000	-0.001***
		(0.000)	(0.000)
Married		0.031	-0.489***
		(0.085)	(0.120)
Teen Children		-0.362	0.588*
		(0.246)	(0.314)
Income		-0.000**	0.000**
		(0.000)	(0.000)
Vegetarian		-0.283	0.810***
		(0.199)	(0.237)
Happy1		0.015	-0.133*
		(0.045)	(0.068)
Healthy Life		-0.001	0.018***
		(0.005)	(0.007)
ProOrgHealthy		-0.103	-0.296*
		(0.102)	(0.159)
ProOrgTaste		0.138	-0.335**
		(0.093)	(0.144)
ProOrgAnimalWelfare		-0.038	-0.735***
		(0.091)	(0.134)
ProOrgLocalProduction		0.259***	-0.368***
		(0.095)	(0.142)
ProOrgSupportOrg		-0.141	0.509***
		(0.106)	(0.166)
ConOrgExpensive		-0.026	-0.485***
		(0.100)	(0.146)
Constant		-0.064	-5.399***
		(0.463)	(0.786)
Observations	10,776	10,776	10,776
Log Likelihood: -2820.4139			
Wald Chi2: 545.25***			

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
SQ omitted due to collinearity

TABLE 4.12: *Regression Results: Mixed Logit 2 (organic alternative as 1)*

VARIABLES	(1) All alternatives	(2) Organic	(3) No Purchase
Environmentally Friendly	0.210**		
	(0.083)		
Best Before	0.061		
	(0.087)		
Quality	0.602***		
	(0.087)		
Price	-0.113**		
	(0.055)		
Animal Welfare	0.314*		
	(0.172)		
Age		-0.015**	-0.000
		(0.006)	(0.008)
Vegetarian		-1.076*	1.546***
		(0.565)	(0.471)
ProOrgTaste		0.593***	-0.186
		(0.194)	(0.256)
ProOrgSafe		0.498**	0.022
		(0.217)	(0.275)
ProOrgEnFr		-0.651***	-0.096
		(0.241)	(0.272)
ProOrgLocProd		0.854***	-0.216
		(0.203)	(0.252)
ProOrgNonGMF		0.355*	-0.164
		(0.201)	(0.279)
ConOrgExpensive		-0.669***	-0.413
		(0.195)	(0.266)
ConOrgNotAdvert		0.425**	0.374
		(0.186)	(0.244)
ConOrgHabit		-0.290	-0.583**
		(0.187)	(0.239)
HeaLifeImportant		0.781***	-0.003
		(0.294)	(0.329)
HeaLifeLessTV		-0.638***	0.140
		(0.195)	(0.249)
SchoolChildren		-0.120	-0.650**
		(0.217)	(0.321)
HBT1		-0.208	0.291
		(0.227)	(0.277)
HBT2		-0.604**	-0.511
		(0.237)	(0.335)
HBT3		-0.272	-0.117
		(0.238)	(0.305)
Constant		0.133	-0.770
		(0.490)	(0.607)
Observations	2,904	2,904	2,904

Standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1
Organic and low chemical usage omitted due to collinearity

models. These aimed to relax the strong assumption of independence of irrelevant alternatives (IIA) from mainstream multinomial logit models used in CEs. This chapter explores areas of individuals with pro-and 'con-organic' and 'pro-environment' attitudes, as well as a comparison of characteristics of those who buy and do not buy 'organic', including 'healthy lifestyle' and 'happiness'.

The data shows that consumers who stated that they buy organic because it is healthier, fresher, non-GMF and tastier, in addition to price, did choose more 'organic' when they had the option. From these, only non-GMF was insignificant in the effect of 'pro-organic' behaviour on the choice probabilities in Section 4.5, showing relatively more impact on consumer utility from 'organic', 'low chemical usage' and 'quality'. These are all attributes more related to self-interest, i.e. concerns about the direct effect on their health as opposed to factors such as animal welfare and the environment. However, their responses differed when choosing the alternatives. Results from the mixed logit show that HBT (honesty priming) significantly impacted the choice for 'organic'. In the same model, individuals who identified as 'pro-organic' because it is environmentally friendly were associated with a negative probability of choosing 'organic'. This might be counter-intuitive, but 'environmentally friendly' was one of the available attributes, so individuals would prefer this to 'organic'. The results show that the coefficient for this attribute was positive and significant in all models, showing that consumers may not assume that organic production is better for the environment.

Respondents identified as 'pro-environment' have a more diverse utility effect source but mixed results between the different environmental behaviours. Respondents who stated that they believe healthy food is essential showed the highest impact from quality, thus suggesting that quality should be a proxy for health and taste. Not considering 'price', 'quality' is the most significant attribute regarding the behavioural range of observation points, present in almost one-third of significant interaction terms. Assuming that healthy food is also perceived as of higher quality, including for young adults (Drewnowski et al., 1997), this reflects the potential welfare gain associated with the attribute. Thus, suppliers have more incentive to increase the provision of higher quality goods or narrow the potential information gap regarding the quality of healthy food.

A comparison of 'organic' labels with other attributes presented in the CE needs to consider the consumer motivation and perception of organic food. 'Pro-organic' individuals (because of the taste of organic food) gain relatively more utility from quality. The behavioural interaction terms demonstrate that 'organic' is a class of products which combines a series of attributes, including 'quality', 'environmentally friendliness', 'animal welfare' and 'low chemical usage'; thus, the higher utility can also be provided by these attributes directly. The data analysis (Section 4.3.1) maps the profile of organic chicken consumers, offering future intervention opportunities.

Survey respondents indicated that most of them buy 'organic' because of its environmental friendliness. The regression results suggest that such an attribute increases the choice probability by only 19%. This is significantly below the influence of 'quality' (56%) and 'animal welfare' (38.6%). However, for the average consumer, the organic label was insignificant in the C-logit without the interaction terms. This can be explained by individuals' answers, as they assume that 'organic' includes the socially desirable attributes present in the experiment when stating why they buy 'organic'. Thus, the label itself is not the driving force but what consumers perceive it represents, so they get higher utility from the direct attributes available. The interaction terms in the main model provide insights into the consumer characteristics driving WTP for the 'organic' label and show that individuals identified as 'pro-organic' (those who perceive the benefits of organic food) and age are the primary sources of heterogeneity, with substantial variations.

A caveat to this study is that, in the experiment, quality was not clearly defined, thus subject to the respondent's perception, which might differ from diet quality indices adopted by the World Health Organisation (WHO) or be related to more prestigious brands, or retailers' 'quality' labels. Therefore, the influence of such an attribute is potentially more appealing to the respondents. The results above also have implications for future experiments. When designing a CE for organic, researchers should focus more on the desirable features embedded in organic food rather than the label itself. Some other essential attributes were not available independent of the organic label, e.g. 'local production' and 'healthy', which would be more insightful if estimated independently. This would take advantage of the SP approach as many attributes are not usually available in real data, and are usually limited to the organic label. Knowing the value placed on the specific attributes offers more precise intervention points while addressing multicollinearity issues. In addition, it would have interesting to investigate the effect of other meats on chicken preferences, thus future survey designs might benefit from such an incorporation. For this data, although the interaction terms offered a solution to the IIA assumption and mixed logit is usually preferred over C-logit, results from the latter were highly consistent. Other estimation methods could have been considered, particularly the expectation maximisation (EM) machine learning algorithm method for latent variables, which would avoid strong assumptions such as IIR and accommodate the use of attributes and consumer characteristics simultaneously. Nonetheless, mixed logit offers a robust solution while providing valuable results from a wider range of individuals' characteristics. For a future CE, a solution would be to fix an 'organic' alternative (in addition to 'conventional' and 'no-purchase') and only randomise the attributes, including those mentioned above. This would expand the valuable insight from Table 4.12.

Chapter 5

Combined Stated and Revealed Preference Approach

5.1 Chapter introduction

Current valuation techniques are based on stated preference (SP) data (survey-based hypothetical purchases) or revealed preference (RP) data (real purchases). The issues with RP and SP techniques, explored in Chapters 3 and 4, have led some scholars to propose an alternative joint RP and SP technique, following the idea that these should be complements rather than substitutes, thus mitigating the problems encountered in SP and RP studies and estimating the most accurate WTP values. Different attempts at joint estimation have been developed since its introduction, most notably by Cameron (1992) and Adamowicz, Louviere, and Williams (1994). This chapter adapts recent developments in joint (RP and SP) estimations to a novel joint estimation of environmental attributes associated with organic chicken.

Chapter 3 uses exclusively revealed data to estimate the marginal utility of 'organic' and its associated attributes. However, as explained above, desirable attributes are not included, consistent with 'ex-ante' approaches. As Whitehead, Haab, and Huang (2012) argue, combining RP data with a CE offers significant advantages, including an alternative way to address multicollinearity[1] and prevent the endogeneity present in HP methods explored in Chapter 3. Although CE is arguably the most reliable SP method, it is not free from questions about hypothetical bias, despite the available treatments. Thus, combining the two

[1]Multicollinearity is minimised, given the broader range of attributes and greater freedom through their randomisation, while choice methods also avoid simultaneity caused when 'price' is set as a dependent variable, i.e. simultaneously defined by supply and demand equations.

techniques offers a better understanding of potential changes in the market. By incorporating the real shopping data used in Chapter 3, potential issues with hypothetical bias are addressed further.

However, combining the SP and RP data requires that their scales must be compatible. Other potential issues include inter-alternative error structures (derived from the likely correlation among alternatives) and unobserved and state-dependent heterogeneity. This chapter demonstrates how these issues can be overcome, so the results claimed to offer the best of both worlds (SP and RP) can be estimated robustly. For this, the scanner data was used to construct the set of alternatives individuals faced when they chose their purchases in a way consistent with the CE. Combining the two data is based on the utility maximisation assumption and the random utility treatment, i.e. assuming that the rule for both SP and RP choices for each individual follows the same probability rule in their discrete decisions. This chapter addresses common challenges faced by joint RP and SP estimations, i.e. sources of heterogeneity, scale differences, and inter-alternative error structures.

This study applies a conditional logit (C-logit) model to estimate consumers' WTP for key environmental attributes presented in the SP and RP data. To mitigate the strong assumption of independence of irrelevant alternatives, the C-logit estimation models include interaction terms between attributes and consumer characteristics as a source of heterogeneity within the population (similar to Chapter 4). However, scale differences and heterogeneity across the two samples might persist; thus, this chapter uses a heteroscedastic conditional logit model (CLHet) for the joint estimation. Again, CLHet models assume homogeneous preferences within each sample. To accommodate this, the main estimation model is also extended to include interaction terms, which is also a novel approach to CLHet.

Joining the two datasets is very attractive, and this chapter suggests an approach. Specifically for the data used in this study, parameter restriction was only accepted for the CLHet, not C-logit. Therefore, scale differences are suggested to form a significant issue which needs to be accommodated (something rarely done in the joint estimation literature). Although adding the interaction terms offered valuable insight, the assumption of independent and identically distributed (IID) error terms appears not to change the estimators.

Results show that individual preferences for key attributes across the two datasets are not significantly different between SP and RP. Thus, the results favour SP and joint estimations of characteristics not available in RP data such as the one used in Chapter 3, most notably environmental attributes. Compared with previous chapters, results in Section 5.5 are consistent with Chapter 4, and very close to estimates from Chapter 3. The joint WTP estimates are not statistically different from marginal implicit prices (MIP) in Chapter 3, except for values for 'offer' (respectively £-0.07 and £-0.19 lower bound) and 'quality' (respectively £1.60 and £2.23 lower bound)[2].

5.2 Theoretical background

The regression models in the previous chapters dealt with econometric issues associated with SP and RP studies when conducted independently. For the RP estimation in Chapter 3, to deal with endogeneity, the study used a generalised method of moments (GMM), which may not be feasible in all applications, as valid instruments are sometimes hard to find. In Chapter 4, in the SP estimation, the survey incorporated hypothetical bias treatments (honesty priming and cheap talk). Taking RP data as a baseline, adding SP data can provide extra observation points with better econometric efficiency (smaller and cheaper samples) and overcome multicollinearity and endogeneity (Whitehead et al., 2008), which are common in RP models. Another advantage of joint SP and RP estimations is that the combined data can reduce the probability of a hypothetical bias effect.

In Chapter 3, the hedonic price model had evidence of endogeneity and omitted variables. The SP data adds extra information in terms of new attributes and consumer characteristics. Combining RP and SP also allows the researcher to test the validity of SP results. This is referred to as convergent validity and will be analysed later in Section 5.5. Joining the two datasets also enriches the RP data in terms of product characteristics. In the case of this thesis, the SP data contains a series of product characteristics, such as 'environmentally friendly', 'animal welfare' and 'chemical usage' in various combinations that may not be readily available in the market.

5.2.1 Joint estimation methodology

Given the potential gains from combining RP and SP, this has become increasingly attractive and is recommended to be pursued whenever possible. However, this is not free from challenges, and there are certain conditions under which simplified joint estimation approaches

[2]Note that the RP samples are different so that in this chapter one can join with the SP data, e.g. this chapter only considers chicken breast, which has relatively higher MIP.

TABLE 5.1: *Combined RP and SP studies*

Combined Data	Stacked	Assumes IID
Comparison	NO	YES
Pooled	YES	YES
Panel	YES	NO
Mixed	NO	NO

can be carried out. As shown in Table 5.1, in addition to comparison studies that offer convergent validity, there are different types of combined RP and SP studies. The main joint approaches are pooled, panel and mixed data studies. The different approaches are based on the assumptions about the error terms in both data, e.g. whether they are identically and independently distributed (IID). Pooled and panel data studies are classified as stacked data, i.e. RP and SP data have similar variables, and the observations are added together. However, the joint data would violate the IID assumption, as the error terms across respondents are correlated, i.e. there should be a correlation in the choices by the same individual within the respective data as there are multiple rounds, although not across the SP and RP data as they come from different samples. Thus, such an implication must be considered in the regression models.

Comparison studies: Comparison studies do not stack the RP and SP data and assume IID errors. In these studies, RP (travel cost or hedonic price) and SP (mainly contingent valuation or choice experiment) methods are used to estimate willingness to pay independently. Ideally, comparison studies should require the RP and SP observations from the same sample of respondents, but the SP and RP models are estimated separately. Results are then compared and serve as a source of external validity, usually for the SP estimates. This approach is referred to as convergent validity. If results do not converge, the researcher will explore the bias driving both methods, and it should not be assumed that SP is incorrect, as RP has a different, but possible, source of bias. This is because SP can potentially suffer from hypothetical bias, but RP sometimes does not have enough variation and (or) might be influenced by endogeneity and multicollinearity. Therefore, joint estimations can mitigate these limitations. SP would contribute with enough variation, given that researchers can include randomised selection of attributes (some not available in the market), avoiding multicollinearity. Meanwhile, RP input would mitigate hypothetical bias from SP estimates, as its observations come from the real market. Examples of comparison between SP and RP studies include: Wardman (1988), which concludes that SP studies are accurate estimates of individuals' preferences in travel behaviour; Laughland et al. (1996), which identifies a low correlation between averting costs and contingent valuation of environmental improvements; and Scarpa et al. (2003), that concludes that choice experiments, compared to the hedonic method, pass external validity in their estimation of values of cattle traits.

Pooled data studies: The most attractive way to join RP and SP is to pool observations from the two datasets and stack them in the same sample. This usually restricts the coefficients to be equal across the SP and RP datasets. In this case, errors are assumed to be IID, implying that pooled data does not consider the correlation in behaviour by the same individual in their respective data source. However, it assumes that the coefficients across the RP and SP data are equal. Empirical studies using pooled data usually use ordinary least square, Poisson binomial or Tobit models for continuous choice, and multinomial logit (MNL) model for multiple discrete choices. All these models assume the errors are IID. Examples are: Adamowicz, Louviere, and Williams (1994) for using SP data in travel cost estimations; Layman, Boyce, and Criddle (1996), which combined estimation of recreation values derived from different fishery management conditions using travel cost (TC) and contingent valuation method (CVM); and Eiswerth et al. (2000), which is also pooled TC and CVM, though applied to the valuation of water recreation.

Mixed data studies: Mixed data do not stack RP and SP data; these are treated as different frameworks. However, these are jointly estimated (though not stacked) and allow for error correlation, thus relaxing the IID assumption. Applications of mixed data studies include: Cameron (1992), which combines TC and CVM data to value non-market resources and public goods; Huang, Haab, and Whitehead (1997), which uses comparative static analysis of SP and RP estimations, stressing that the difference in preference structures inhibits joint estimations; while Loomis (1997) uses data from TC and CVM inputs in a random effect probit to estimate the value of amenities of in-stream flow; and Brownstone, Bunch, and Train (2000) applies scaled multinomial and mixed logit models to joint SP and RP estimations, addressing the heterogeneity of preferences for automobiles, with best-improved fit from mixed logit models.

Panel data studies: Panel data also stack RP and SP data, similarly to pool data, but assumes errors to be correlated. However, error terms in the SP and RP data come from different sources and are understandably inconsistent; thus, leading to heteroscedasticity (Whitehead, Haab, and Huang, 2012). Error correlation can be induced using methods such as heteroscedastic, fixed effects, random effects and autoregressive models, including random effect Tobit and random effect Poisson binomial models (Whitehead et al., 2008). Examples of panel data joint studies are: Hensher, Louviere, and Swait (1998), which make a case for SP data in market behaviour analyses to enrich RP insights, relaxing heteroscedasticity in a combined choice model; while Grijalva, Bohara, and Berrens (2003) estimate preferences of outdoor recreation using a joint TC and CVM pooled data; and Vass et al. (2018) apply heteroscedastic C-logit to value the interventions and services in a healthcare context. The latter allowed for scale differences between public samples and patients and also reported an improvement from a multinomial logit estimation. In a more recent study, Hindsley et al. (2022) uses a generalised multinomial logit model with inferred attribute non-attendance (ANA) to control for hypothetical bias derived from under-estimating SP cost coefficients, i.e. when ignoring the cost attribute. In addition to scale differences, Whitehead and Lew (2020) also explore underestimation of cost coefficients, which is particularly important when using an SP with cost attribute. This should be comparable to the RP studies that use travel cost methods, as the authors argue that SP travel costs do not explicitly differentiate costs associated with travel distance and time, in contrast with the former. I am not aware of any joint estimations applied to meat or organic chicken.

This thesis stacks the SP and RP data together (panel data study). It applies a heteroscedastic conditional logit model with interaction terms between attributes and individual characteristics to relax assumptions about both sources of heterogeneity (within and between SP and RP samples). Although ANA[3] is less likely to occur when 'price' is the cost attribute, hypothetical bias may still affect willingness to pay estimations; thus, they were treated in the SP data, as explored in Section 4.3.2. Further literature review and comparisons are found in Section 5.4.1.

[3] As in travel costs, explained above. These are relatively more consistent across the RP and SP data used in this thesis, i.e. price/Kg.

Common issues with joint estimations

Following Bhat and Castelar (2002), there are four main issues risen from joining RP and SP data: scale differences, inter-alternative error structure, unobserved heterogeneity effects, and state-dependence effects and their heterogeneity.

1. Inter-alternative error structure: Most joint estimations apply MNL models. As discussed in Section 4.4.1, the main problem with using MNL in random utility maximisation frameworks is that MNL assumes independence of irrelevant alternatives (IIA) restriction. Therefore, it is usually assumed within RP-SP studies that the error terms are IID across alternatives in the choice probability calculations of choosing an alternative from a set of alternatives. This is violated when the same individual (thus influenced by the same unobserved characteristics) offers multiple-choice observations, which is the case of the SP data used in this thesis.

2. Unobserved heterogeneity effects: These refer to differences in preferences across decision-makers that the researcher does not observe. For SP, for example, individuals' choices will likely be affected by their unobserved characteristics when presented with different alternatives. This is also true for RP data. Therefore unobserved characteristics would be correlated across choices of the same individual in the RP-SP sample. This also leads to a non-IID error structure, so IIA does not hold. However, most RP-SP studies do not accommodate this issue (Bhat and Castelar, 2002), which forms a potential problem especially when the SP and RP data are collected from the same population sample.

3. State-dependence and heterogeneity in state-dependence: State-dependence refer to the effect actual behaviour (state 1), captured through RP, might have on SP responses (state 2). These can be through 'habit persistence' or justification for the RP choices when responses for the RP and SP are from the same individuals. These combined studies may also suffer from 'compliance bias', i.e. respondents would attempt to be consistent across RP and SP responses. For example, subjects in Carlsson and Martinsson (2001)[4] might state donations in line with their actual donations in the experiment.

[4]Carlsson and Martinsson (2001) performed a combined approach in two stages: one hypothetical and one in which respondents could keep the money they received. The revealed preference was part of the experiment in which the same respondents (students) were asked to donate a portion of the money the interviewers gave to their environmental attributes of choice. The study also performed a convergent validity analysis.

4. Scale difference: This has been identified and addressed in some RP-SP studies. Theoretically, it is not feasible to identify which data error has the most significant variance. Still, it is unrealistic that the unobserved effects incorporated in the error terms in the RP and SP data will be the same. For the RP, error terms would include, for example but not restricted to, individual decision-making factors, unmeasured attributes and measurement error in variables. Meanwhile, SP errors would incorporate unobserved individual factors, omission of relevant variables and the influence of the experiment design.

Bhat and Castelar (2002) argue that joint RP-SP studies rarely simultaneously accommodate these four issues. However, this should take place as there might be interactions between them. Failing to do so is problematic as analysing a given point in isolation may lead to misleading conclusions about the accommodation of the problem, the scale effect and the required measures to deal with them. The conclusion about individuals' preferences is also compromised. This study tries to accommodate all these issues simultaneously, as explained in the following section.

5.3 Data

This section presents the SP and RP datasets used in this chapter. The SP data is explored in Chapter 4, and the RP data is a sample from the same household panel used in Chapter 3, both collected in 2016. Scanned purchases from the RP panel, from which 9,948 contributed to 58,170 used observations. Although the SP and the RP datasets have different respondents, both samples consist of representative British grocery shoppers.

5.3.1 RP dataset

The RP sample used in this chapter is a data cut from the RP data used in Chapter 3, which contains 336,970 chicken purchases from 26,658 households. For this chapter, only purchases of chicken breast are included, so the RP data is consistent with the type of product presented to respondents in the choice experiment, and the two datasets can be pooled together. As a result, the number of households included in this chapter is reduced to 9,948, contributing to 58,170 observations.

Table 5.2 shows the socio-economic characteristics of the households from the RP sample. For representativeness, these should be checked against the characteristics of the household

TABLE 5.2: *Summary statistics: households*

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

9948 Observations

member responsible for house shopping rather than the average indicators of the UK population. The average age of the household member responsible for the grocery shop in the sample is 48.3 years old, 78% of whom are female. These are not significantly different from the figures in Table 4.1, i.e. average age of the respondents is around 50, and most shoppers are women, which is expected in a sample of supermarket shoppers. In contrast, there is a significant difference in the proportion of married couples between the RP (29.2%) and SP data (66.7%), both figures deviating from the national average in 2016 (50.9% in England and Wales (ONS, 2021), and 47% in Scotland (ScottishGovernment, 2016)), which would be close to the average of the two samples; thus, the joint data would be more representative in this regard.

Households are, on average, formed by three people (2.9) and have one child (0.7) - similar to the SP data. Different family structures amongst households are fairly distributed. Still, the highest proportion of households is 'pre-family' (housewife below 45 years old, with no children) and 'empty-nest' (45-65 years old with no children in the household), forming 19% and 18% of the sample, respectively. The smallest number (11%) are 'middle-family' (families with the youngest child between 5 and 9 years old) and 'older-family' (families with the youngest child above ten years old).

Concerning employment and income, central indicators of WTP, the RP sample has an average gross income within category 4 (£30,000 to £39,999 per annum), which was above the national average income in 2016 (£26,300). The proportion of unemployed people in the sample was 2% (below half the 4.8% rate for the UK in 2016). For employment, 43% of respondents were full-time and 23% of part-time workers (1% below and 7% above the national rates). Section 5.5.1 investigates the variables' effects on the WTP and whether these discrepancies between SP and RP should be mitigated.

5.4 Regression models

5.4.1 Joint estimation models

This chapter's main joint estimation model is a heteroscedastic conditional logit (CLHet) model. This section justifies the use of the model and why SP and RP can and should be combined. As explained in Section 5.2.1 pooling RP and SP data is tempting but can be challenging. Carson et al. (1996) show a positive correlation between contingent valuation (most popular SP method) and RP methods, indicating that RP and SP methods are based on shared preferences. Thus, joint estimations would be valid. Phaneuf, Taylor, and Braden (2013) also show that, although RP and SP methods differ in their estimation approaches, i.e. in SP methods, the magnitude estimates are estimated from the utility function. For this thesis, RP uses the price function, the baseline marginal WTP $\frac{\delta P}{\delta q}$ derived from SP approaches is equal to the marginal implicit price of attributes in RP. Also, both RP and SP are based on the random utility theory following equation 4.1.

Although most RP-SP estimations use MNL models, closely related to this study, Brooks and Lusk (2010) estimated a pooled log-likelihood function joining scanned milk purchase data and responses from a choice experiment to estimate WTP for selected milk attributes. The study included organic, cloned animal, and rBST[5]. This chapter applies CLHet models, but it is helpful to review the MNL and C-logit models in the context of a joint estimation to understand their advantages.

Starting with MNL and following Whitehead et al. (2008), the MNL model can be re-written as:

[5]recombinant bovine growth somatotropin (rBGT) is a bovine hormone, which is a modification of bovine natural somatotropin, which has raised concerns amongst the population of possible links with cancer.

$$P_{ij} = \frac{exp(\mu\beta' X_{ij})}{\sum_{k=1}^{J} exp(\mu\beta' X_{ik})} \tag{5.1}$$

Assuming random errors are IID Gumbel errors, similar to Section 4.4.1, P_{ij} is the probability that an individual i would choose an alternative j. μ is the scale factor, usually assumed to be one, β is the vector of parameters, and X_{ij} is a vector of variables specific and individual characteristics. As the theoretical choice framework for the RP and SP methods are the same, MNL can be used to estimate both RP and SP, and the joint data (Whitehead et al., 2008). The choice probability in the SP model would then be:

$$P_{ij} = \frac{exp(\mu_S \beta'_S X_{ij})}{\sum_{k=1}^{J} exp(\mu_S \beta'_S X_{ik})} \tag{5.2}$$

If elements in X_{ij} are identical, the choice probability in the RP model would be:

$$P_{ij} = \frac{exp(\mu_R \beta'_R X_{ij})}{\sum_{k=1}^{J} exp(\mu_R \beta'_R X_{ik})} \tag{5.3}$$

For the C-logit models, equations 5.2 and 5.3 can be re-written respectively as:

$$P_{ij} = \frac{exp(\mu_S \alpha'_S Z_{ij})}{\sum_{k=1}^{J} exp(\mu_S \alpha'_S Z_{ik})} \tag{5.4}$$

$$P_{ij} = \frac{exp(\mu_R \alpha'_R Z_{ij})}{\sum_{k=1}^{J} exp(\mu_R \alpha'_R Z_{ik})} \tag{5.5}$$

Where α_R and α_S, and β_R and β_S are the vectors of parameters, and μ_R and μ_S are the scale parameter of the RP and SP data, respectively.

However, if RP and SP are stacked for a joint estimation, the error terms are likely to have unequal variance and; thus, unequal scale parameters. For example, if $\mu_R = 1$, SP data would have higher variance, and $0 < \mu_S < 1$, thus $\beta_R > \beta_S$ (Whitehead et al., 2008). This can be accommodated with a heteroscedastic model.

As an alternative solution to scale differences, Resano-Ezcaray, Sanjuán-López, and Albisu-Aguado (2010) applied nested logit (NL) to a joint scanned RP data and SP data collected from a choice experiment to evaluate quality certificates of Spanish dry-cured ham. These papers use real market data and do not recall data from simulations, similar to the present thesis. NL model groups the RP and SP data in different 'nests' and allows for relaxation of

IIA imposed by MNL. Further details in Section D (Appendix). However, as an extension of MNL, NL assumes constant variance within each nest, which is a limitation.

Heteroscedastic conditional logit and scale parameter

Considering the nature of this study, especially the estimation of individual preferences from the CE, the heteroscedastic conditional logit (CLHet) model is suitable for the joint estimation. The model relaxes the IID assumption across samples (issue 2), allows for scale differences (issue 4), and the use of interaction terms also allows for variance within the SP and RP samples (issue 1). In addition, the fact that the SP and RP data collected from different samples relaxes issue 2 and prevents potential problems with state-dependency (issue 3) and compliance bias.

This study uses techniques to relax IIA and heterogeneity effects (issues 1 and 2 from Section 5.2.1) with conditional logit with alternative specific variables and interaction terms between alternative and case variables. The SP study in Chapter 4 also applies mixed logit, which relaxes the IIA assumption. Still, the randomised order of alternatives present in the choice experiment design implies that a significant number of observations from the SP data is lost[6] in the mixed logit model. Therefore, the main discussions about SP results are based on C-logit.

Joining the stated and revealed data usually also raises issues with stated dependence (issue 3) and scale differences (issue 4) between the two datasets, as discussed in Section 5.2.1. For this study, the former does not pose a problem, given that the subjects from the two datasets are not the same. Traditionally, in joint estimations, the researcher surveys individuals to collect their choices from a set of hypothetical alternatives, then collect their actual choices, or vice-versa[7]. Therefore, scale difference is the main issue addressed by the CLHet model.

Scale parameters can differ significantly between RP and SP data as the parameters of tastes and preferences of individuals influencing the choice for a specific attribute should be influenced by different factors in the RP and SP samples. In a CE, respondents are implicitly encouraged to consider the utility effect of their choices more cautiously. As an illustration, the error term ϵ in equation 4.1 is associated with the alternative to be selected in the rational

[6] As explained in Section 4.5.2.

[7] For example, the survey includes questions about the costs of a current or past trip to a site in travel cost methods or individuals' shopping behaviour; thus, giving margins for state-dependence or compliance bias.

choice of individual i. From equation 4.3, adapted from Vass et al. (2018), one can analyse the probability of unobserved heterogeneity between alternatives $\epsilon_{i,k} - \epsilon_{i,j}$ is less than the observed $V_{i,k} - V_{i,j}$. In the Gumbel distribution, variance is defined as $\frac{\pi^2}{6\mu}$. Thus, the scale parameter μ is inversely related to the variance of the error term, i.e. $\sigma^2_{\epsilon_{i,j}} = \frac{\pi^2}{6\mu}$. Multiplying through the choice probabilities in equation 4.5 by μ gives:

$$P_{ij} = \frac{exp(\mu V_{i,j})}{\sum_{k=1}^{J} exp(\mu V_{i,k})}, \; k \in J_i \tag{5.6}$$

Therefore, the scale parameters and preferences cannot be separately identified. Thus, each observable variable affects the scale parameter, reported as $\mu\beta$ (scaled preference parameters). As μ increases, variance decreases and estimates β are shown larger. However, these estimated coefficients have no interpretation, considering that utility has no scale and may differ between samples or survey models (Vass et al., 2018). Therefore, $\mu\beta$ prevents us from establishing the source of differences in preferences as the level of utility from choosing one alternative or variance of the error term.

The CLHet allows μ_i to be a function of individuals' characteristics X, i.e. λ_i is parameterised as $exp(X_{i\gamma})$, where γ is a vector of parameters which incorporates the effect of individuals on the scale parameter (Hole et al., 2006). Therefore, equations 5.4 and 5.5 can be expressed as an alternative (heteroscedastic) conditional logit model, which allows for unequal variance across individuals, re-written as:

$$P_{ij} = \frac{exp(\mu_i \beta Z_{ij})}{\sum_{k=1}^{J} exp(\mu_i \beta Z_{ik})} \tag{5.7}$$

In the CLHet, the $exp(Z_{i\gamma})$ treats μ_i as positive for all individuals, and collapses to C-logit when $\gamma = 0$. In addition, following DeShazo and Fermo (2002), $\mu\beta$ is estimated by the log-likelihood function:

$$LL = \sum_{i=1}^{I} \sum_{j=1}^{J} y_{ij} lnPij \tag{5.8}$$

Where $y_{ij} = 1$ if alternative j is chosen by individual i $y_{ij} = 0$ if not.

Likelihood ratio, Wald or Lagrange multiplier tests for parameter restrictions and homoscedasticity (Greene, 2003). Results and discussion for this study are shown in Section 5.5.1

5.5 Results

5.5.1 Joint estimation

Considering the theoretical framework discussed in Section 5.2, for the RP observations to be consistent with the choice respondents faced in the CE, a set of alternatives needed to be constructed from the RP data. First, only purchases of chicken breast were kept. A purchase (i.e. choice made) was selected by tracking the household in a given week from a supermarket in a given postcode. Only single purchases in a week were considered. As there were numerous observations available, only visits when there were two options for chicken breast available in the shop were included. Although this tried to be more consistent with the experiment and facilitates the construction of the alternatives, it is not required to limit the number of options to two. Like the CE, each product and its attributes were randomly assigned as either alternative 1 or 2 for each week and shop. The third option was again no buy (status quo), a choice in which all attribute dummies receive zero value and only household characteristics are kept.

Furthermore, to be consistent with the choice cards from the CE, households who chose not to buy (alternative 3) were tracked from the data, as they bought a different product in the respective shop in the same week. The alternatives (choice card equivalent) used were available in the shop, but they chose neither. The SQ outcome has to be incorporated into the alternative construction as it captures the preferences of individuals in the population that do not consume the product. Thus, potential estimates of total welfare are more accurate with the variable, and failure to do so would overestimate WTP results.

Table 5.3 shows the summary statistics from the stated preference (SP), revealed preference (RP) and combined (RPSP) data. In CEs, the number of alternatives is smaller but also forms a representative sample and was designed to capture enough variation of attributes across alternatives. Adding the interaction terms between attributes Z and individual characteristics X into Equation 5.7, the model is calculated as:

$$P_{ij} = \frac{exp\{\mu_i[\alpha Z_{ij} + \beta(Z_{ij} * X_i)]\}}{\sum_{k=1}^{J} exp\{\mu_i[\alpha Z_{ik} + \beta(Z_{ik} * X_i)]\}} \tag{5.9}$$

TABLE 5.3: *Summary Statistics (attributes and consumer characteristics)*

	SP			RP			RPSP		
Variable	Mean	SD	D=1	Mean	SD	D=1	Mean	Max	D=1
Price	4.01	3.50		6.45	1.58		6.04	10	
Volume	0.27	0.19		0.59	0.26		0.55	1.0	
Organic (D)	0.17	0.38	2082	0.00	0.02	31	0.03	1	2113
FreedomFood (D)	0.31	0.46	3815	0.00	0.04	113	0.05	1	3928
Quality (D)	0.35	0.48	4270	0.01	0.08	423	0.06	1	4693
LowChemical (D)	0.18	0.38	2150				0.03	1	2150
EnvFriendly (D)	0.33	0.47	4022				0.06	1	4022
Healthy (D)				0.00	0.01	12	0.00	1	12
Offer (D)				0.46	0.50	27527	0.38	1	27527
Age	50.45	15.62		47.43	13.37		47.93	95	
Income	3.33	1.96		4.38	1.95		4.20	8	
Unemployed	0.13	0.33	1536	0.02	0.14	1164	0.04	1	2700
Married	0.67	0.47	8088	0.30	0.46	17969	0.36	1	26057
Children	0.61	0.98		0.78	0.99		0.75	7	
PreFamily	0.07	0.26	888	0.12	0.32	7201	0.11	1	8089
YoungFamily	0.01	0.08	72	0.19	0.40	11705	0.16	1	11777
Observations		12,120			60,143			72,263	

SD: standard deviation; D: dummy; D=1: number of 'dummy=1' entries.
Mean values for the dummy variables represent the % from total entries.

Again, Equation 5.9 takes the scale factor μ into consideration. However, it now calculates the choice probability that an individual i with characteristics X would choose alternative j with attribute Z across the J alternatives. The following paragraphs show the tests for scale differences and the effectiveness of the CLHet.

Including socio-economic characteristics, the SP and RP datasets provide data with 66,994 observations (each alternative counts as an observation). To join the two samples, the SP and RP need to be consistent. In other words, the joint model needs to accept the joint data's parameter restrictions, which can be tested with a log-likelihood ratio (LLR) test, as explained in Sections D.1 and 5.4.1. Only the CLHet model passed the LLR test once data inconsistencies and scale differences were addressed. In contrast, C-logit models failed the test in both attempts, showing that scale differences are an issue that needs to be addressed. Modelling a joint RP and SP data using C-logit, and testing for parameter equality, provided a p-value = 0.000. Thus, one can reject the null hypothesis that the coefficients in the SP and RP models are the same without accommodating scale differences.

After investigating the source of inconsistencies, the main variables were 'status quo' (SQ), 'price', and 'volume'. The mismatch in price was because the RP data includes values of up to £26 per kilogram, while in the SP, the highest price was £10. The 'volume' also differs between the datasets, as the CE gave options of 400 grams chicken breast packs only. Thus, the model truncated 'price' at £10 per kilogram and included 'volume' as an explanatory variable limited to up to 1 kilogram. Chapter 3 shows that 'volume' significantly affects 'price' and the MIP of most attributes; thus, the variable is a pivotal source of heterogeneity for which needs to be controlled. Keeping only 400 g package for the RP data did not offer enough values and variation of attributes.

The SQ option in the samples has also been found to be a significant source of scale inconsistency, potentially driven by different unobserved factors influencing consumers to not choose a product from the alternatives given. One possible example is that when faced with the alternatives in a survey, the respondent feels more inclined to make a choice, not only driven by the hypothetical characteristic of the experiment (they do not have to pay for their choice) but also because the attributes are more clearly available than in a real shopping situation. In a real shopping scenario, respondents should be less encouraged to buy from a choice set with which they are not totally happy or familiar, so they can choose a different shop (or a different set of alternatives), which is not the case in the experiment as they can (and do) 'purchase' a product in every round. For this reason, SQ in the SP and RP data was treated as two different attributes, SQSP and SQRP, respectively.

Independent analyses of the SP and RP results would fall into the joint estimation comparison category of external validity described in Section 5.2.1. Whitehead et al. (2008) argue that even if the convergence validity test fails, joining both data would mitigate the bias in both SP and RP estimations; thus, that type of joint estimation is still encouraged. However, passing the LLR test should be a condition to proceed with a joint estimation using a single model. The remaining attributes have no suggestion of inconsistency across the samples as detailed below.

After accounting for 'price', 'volume', and SQ inconsistencies, new LLR tests continue to give p-values of 0.000 for the RPSP-Clogit model. However, the LLR test for the CLHet model is now 0.1718; thus, one cannot reject the null that the coefficients in Columns 1 and 2 are the same once the difference in scale between the SP and RP datasets is accommodated. In other words, the LLR test indicates that the SP and RP parameters are equivalent; hence, the two datasets can be meaningfully combined only in the CLHet model.

Table 5.4 shows regression results from the SP, RP, and joint RPSP conditional logit models (Columns 1 to 3, respectively) and results from the joint RPSP heteroscedastic conditional logit (CLHet) in Column 4.

TABLE 5.4: *Regression results from SP, RP and Joint CLogit, and CLHet models*

VARIABLES	(1) SP_CLogit	(2) RP_CLogit	(3) RPSP_CLogit	(4) RPSP_CLHet
Price	-0.210***	-0.549***	-0.489***	-0.214***
	(0.017)	(0.008)	(0.007)	(0.014)
Organic	-0.022	1.150**	0.701***	0.030
	(0.080)	(0.501)	(0.070)	(0.070)
AnimalWelfare	0.275***	0.796***	0.933***	0.289***
	(0.064)	(0.260)	(0.051)	(0.053)
Quality	0.546***	1.461***	0.661***	0.554***
	(0.039)	(0.137)	(0.038)	(0.034)
LessChemicals	-0.240***		0.434***	-0.226***
	(0.081)		(0.075)	(0.076)
EnvFriendly	0.221***		0.260***	0.220***
	(0.038)		(0.039)	(0.038)
Volume		-1.435***	-1.417***	-0.561***
		(0.042)	(0.041)	(0.042)
Healthy		-0.436	-0.464	-0.171
		(0.836)	(0.821)	(0.327)
Offer		-0.148***	-0.152***	-0.059***
		(0.023)	(0.023)	(0.010)
SQRP		-3.044***	-2.888***	-1.189***
		(0.043)	(0.039)	(0.081)
SQSP	-2.013***		-3.184***	-2.013***
	(0.093)		(0.071)	(0.080)
Scale Parameter (RP)				0.940***
				(0.068)
LLR	-3730.733	-14099.871	-17993.745	-17833.105
LLR Test			326.28***	5.00
			(0.000)	(0.172)
Observations	12,120	60,143	72,263	72,263
Number of groups			24,875	24,875

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

In terms of potential hypothetical bias, one can see from Column 4 in Table 5.6 that WTP estimates from the joint model are lower than the SP estimates (Column 1), except for 'animal welfare', which has a lower value in the SP but with a higher standard deviation. Comparing the two joint models (CLogit and CLHet), the scale term (last row) of 0.940 is significant, confirming the scale differences between the SP and RP data. The sample characteristics likely drive these, and, as discussed in Section 4.4.1 of Chapter 4, this chapter includes interaction terms to account for within-sample heterogeneity but also helps control these variations. In other words, the estimates can be driven by preferences for the attributes and the variance of the unobserved element of utility (Vass et al., 2018). The heteroscedastic conditional logit model would address this issue. The post regression log-likelihood test shows an improvement in the model (+160), associated with a p-value = 0.000; thus, there is a statistically significant improvement. Therefore, the results from the CLHet (Column 4) are the most reliable, even though 'organic' is not statistically significant in the model for now.

The scale parameter (RP as baseline) is positive, which indicates that the RP data has a statistically significant greater scale parameter. CLHEt parameters λ_n as $exp(X_{n\lambda})$, where X_n is a vector of individual characteristics, are detailed in Section 5.2.1. Therefore, the scale parameter is the exponential term (for the RP), i.e. 2.56 is the scale of difference of the RP data compared to the SP. The scale parameter also shows decreased error variance in the RP data, most likely because the RP is more than five times larger than the SP. Unobserved factors and survey design are also more likely to influence coefficient estimates from the SP data.

The attributes' coefficients, which again indicate the change in the probability that the individual would choose an alternative, can differ substantially between the two joint models, notably 'price', 'organic', 'animal welfare', and 'volume'. These results indicate that not taking the scale difference would lead to misleading results.

Another issue discussed in Section 5.4.1, is the second source of heterogeneity within samples. The CLHet model assumes that individuals within the samples have the same preferences. The inclusion of interaction terms mitigates this. Therefore, Table 5.5 presents results with interaction terms. This shows the results from the four models with interaction terms. Starting with the scale parameter, although this is now lower, they are not statistically different. This is the same for the attributes, suggesting that the IID assumption does not

TABLE 5.5: *Joint Regression (individuals' interaction terms)*

VARIABLES	(1) SP_CLogit	(2) RP_CLogit	(3) RPSP_CLogit	(4) RPSP_CLHet
Price	-0.243***	-0.554***	-0.481***	-0.234***
	(0.023)	(0.018)	(0.013)	(0.017)
Volume		-0.760***	-0.747***	-0.318***
		(0.029)	(0.029)	(0.026)
Organic	0.963***	0.995	1.762***	1.009***
	(0.234)	(1.831)	(0.236)	(0.219)
AnimalWelfare	0.295***	0.958***	0.898***	0.318***
	(0.069)	(0.263)	(0.055)	(0.057)
Quality	0.408***	0.385	0.389***	0.330***
	(0.086)	(0.395)	(0.084)	(0.072)
LessChemicals	-0.209**		0.401***	-0.206**
	(0.088)		(0.081)	(0.082)
EnvFriendly	0.183***		0.214***	0.180***
	(0.041)		(0.042)	(0.040)
Healthy		-0.376	-0.400	-0.157
		(0.837)	(0.820)	(0.350)
Offer		-0.220***	-0.222***	-0.092***
		(0.023)	(0.023)	(0.012)
SQRP		-2.809***	-2.688***	-1.173***
		(0.041)	(0.039)	(0.085)
SQSP	-2.112***		-3.162***	-2.096***
	(0.100)		(0.077)	(0.088)
AgeOrganic	-0.020***	0.004	-0.023***	-0.020***
	(0.004)	(0.041)	(0.005)	(0.004)
UnemployedQuality	0.387***		0.376***	0.399***
	(0.119)		(0.122)	(0.117)
IncomeQuality	0.030	0.226***	0.070***	0.056***
	(0.021)	(0.075)	(0.020)	(0.016)
IncomePrice	0.007*	0.008**	0.003	0.004***
	(0.004)	(0.004)	(0.003)	(0.001)
Scale Parameter (RP)				0.873***
				(0.072)
LLR	-3235.137	-14195.506	-17552.434	-17434.680
LLR Test			243.58***	8.07
			(0.000)	(0.233)
Observations	10,632	56,362	66,994	66,994
Number of groups			22,470	22,470

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

form a significant issue in the model. For the attributes with interaction ('price', 'organic', and 'quality'), the interpretation of the coefficients differs substantially, as now the effect of these attributes on the choice probability needs to take into consideration all variables containing them.

In general, for a linear model, the marginal effect of Z on choice probability P_i would be $P_i^{'} = \alpha Z + \beta X * Z$. Thus, for 'organic' (organic = 1), it would be $P_i^{'} = 1.009 - 0.020 * Age_i$. Similarly, for 'price' $P_i^{'} = -0.234 + 0.004 * Income_i$, and for 'quality' $P_i^{'} = 0.330 + 0.399 * Unemployed_i + 0.056 * Income_i$. Using the values from Table 5.3, the average values for 'organic', 'price' and 'quality' would be 0.066, -0.217, and 0.580, respectively. Again, these are not statistically different from the results in Table 5.4.

Nonetheless, the interaction terms offer valuable insight into the heterogeneity within the sample. All variables of consumer characteristics were tested, but these were either irrelevant or incompatible (did not pass the LLR test of restricted parameters[8]).

As different companies collected the CE and scanner data from different samples, most individual characteristics and criteria were different, thus limiting the scope. However, age, employment, and income were relevant in explaining consumer choices and consistent across the SP and RP samples. More insight is available in Chapter 4. 'Age', again, is central in defining relatively lower marginal utility from 'organic', while 'income' is positively correlated with 'quality' and 'price', as one might expect.

The joint estimation also shows an increase in marginal utility from 'quality' attributes for unemployed people, which might be counter-intuitive, but consistent with the analysis in Section 4.5.1 from Chapter 4. One may argue that given that unemployment in the UK in 2016 was primarily frictional, valuing 'quality' is not too contrasting with people who are mainly looking for better pay and (or) working conditions. In summary, the coefficient of the interaction variable tells us how much the influence of the attribute on the choice probability will change when the consumer characteristic changes. The marginal effect of 'age' on 'organic', and 'income' on 'quality' and 'price' are, respectively, -0.020, 0.056 and 0.004. These show that an increase of one year in age would decrease the probability of choosing 'organic' by 2% when available. In contrast, one unit higher income increases the probability of selecting quality by 5.6% and by 0.4% when 'price' increases by one unit.

[8]As the primary variable of interest, for the robustness check, all interaction terms with 'organic' were included in the CLHet. The LLR test generated a chi-squared of 1.363 and a p-value of 0.506. Thus, adding further interaction terms for 'organic' does not improve the model.

For dummy interactions, the analysis is more straightforward. In the results, unemployed individuals would increase the quality coefficient by 0.399.

Altogether, these factors affect WTP estimations. First, one can also check whether the WTP values for the attributes across the two samples are the same. WTP values are estimated as the ratio between the attribute and price coefficients (available as explanatory variables in the models). WTP estimates are not affected by the difference in variance across SP and RP samples, i.e. the heteroscedastic errors as explained in Section 5.4.1. If normalising $\lambda_{SP} = \lambda_{RP} = 1$ is not true, i.e. heteroscedastic, the scale heterogeneity is eliminated in the WTP estimation:

$$\frac{\lambda\beta_{attribute}}{\lambda\beta_{price}} = \frac{\beta_{attribute}}{\beta_{price}}$$

Willingness to pay, shown in Table 5.6, is estimated as:

$$WTP = -\frac{(Attribute \quad Coefficient)}{(Price \quad Coefficient)} \tag{5.10}$$

TABLE 5.6: *WTP Comparison (£)*

Attributes	(1) SP	(2) RP	(3) RPSP	(4) RPSP (CLHet)
Volume		-2.61 (0.16)	-2.90 (0.18)	-2.62 (0.16)
Organic	-0.10 (0.75)^i	2.09 (1.79)	1.43 (0.27)	0.14 (0.63)^i
AnimalWelfare	1.31 (0.48)	1.45 (0.93)	1.91 (0.19)	1.35 (0.41)
Quality	2.60 (0.53)	2.66 (0.48)	1.35 (0.16)	2.58 (0.35)
Chemicals	-1.14 (0.87)		0.89 (0.30)	-1.06 (0.76)
EnvFriendly	1.05 (0.38)		0.53 (0.16)	1.03 (0.36)
Healthy		-0.79 (2.99)^i	-0.95 (3.29)^i	-0.80 (2.99)^i
Offer		-0.27 (0.08)	-0.31 (0.09)	-0.27 (0.08)

Standard deviations in parentheses
i: Statistically insignificant
2016 values

In terms of the average WTP, the effect on marginal utilities is more clearly shown in Table 5.6, as those are estimates for the whole sample. As a source of robustness check, Table D.1 (Appendix) shows the results of the CLHet using the SP data as scale parameter baseline instead of the RP. In Column 1, the coefficients of regressors are larger but at proportional rates. Thus, WTP estimates (Column 2) remain unchanged when compared to the main results in Table 5.6. In contrast, Table 5.7 estimates need to consider the interaction terms, i.e. analyse the categories captured in the interaction terms.

Table 5.6 shows that 'organic' is not significant in the SP data, which is not astounding, as in the SP data some attributes are usually associated with 'organic' ('environmental friendliness', 'animal welfare' and 'chemical usage') were independent in the experiment. Therefore, individuals do not necessarily value the organic label per se, but what it represents in terms of the attributes about which individuals are concerned. However, the WTP estimation from the RP data is £2.09 (33% premium), reaching £3.88 (upper limit, including standard deviation).

Nonetheless, estimates from Table 5.7 control for the heterogeneity of preferences more closely. Therefore, a more diligent approach would interpret the WTP in line with the marginal utilities being measured in the extended models with the interactions, i.e. consider WTP for the rest of the sample and exclude the groups controlled in the interaction terms. For 'organic', this means that the WTP of £4.31 would decrease by approximately 2% (about 8.5 pence) per year of age (considering the marginal effect of age on price). Therefore, an 18-year-old person would be willing to pay £2.87 for the 'organic' attribute.

Similarly, for 'quality', the joint estimation indicated a WTP of £2.58 for the most valued attribute (Table 5.6). In terms of consumer characteristics, the WTP for 'quality' increases with the level of income and unemployment. At the same time, income positively correlates with 'price' (contributing to increased WTP for 'quality'). Thus, an increase in one income level increases the WTP for 'quality' by £0.27. This gives an average WTP for 'quality' of £2.67 (44% premium), consistent with estimates without interaction terms. For 'animal welfare', 'less chemical usage', 'environmentally friendly', and 'healthy', the WTP are not statistically different in the models with and without interaction terms (Tables 5.6 and 5.7). The WTP for 'healthy' is insignificant in the data and has the highest variation. The attribute was not available in the CE, and very few products from the revealed sample had the 'healthy' label; thus, for future studies, one would need more information for a better analysis, most likely by including it as an attribute in a CE, as the attribute is not commonly available from real data. For 'animal welfare', consumers are willing to pay a premium of £1.35 (22%).

In comparison, they also receive higher utility from environmentally friendly products and are willing to pay on average £1.03 (17%) for such an attribute. The CLHet model estimates a negative effect from the 'low chemical usage' label. However, counter-intuitive and different from results from the joint C-logit, this is consistent with the SP results (the RP data does not have the attribute), reinforcing the notion that scale heterogeneity has to be addressed, as there is unlikely to be any other reason why the joint estimation would deviate from the SP in this case.

Therefore, the results suggest that IID is not a significant source of bias in the joint estimation of this thesis, given that including the interaction terms did not statistically change the coefficients of the attributes. However, scale differences can significantly impact WTP; thus, if not addressed, the SP and RP offer better results if estimated separately.

TABLE 5.7: *WTP Comparison - with interaction terms*[1] *(£)*

Attributes	(1) SP	(2) RP	(3) RPSP	(4) RPSP (CLHet)
Volume		-1.37 (0.13)	-1.55 (0.14)	-1.36 (0.13)
Organic	3.96 (1.91)	1.80 (6.49)	3.66 (0.97)	4.31 (1.83)
AnimalWelfare	1.21 (0.48)	1.73 (0.94)	1.87 (0.22)	1.36 (0.40)
Quality	1.68 (0.69)	0.70 (1.39)	0.81 (0.33)	1.41 (0.61)
LessChemicals	-0.86 (0.79)		0.83 (0.32)	-0.88 (0.75)
EnvFriendly	0.75 (0.35)		0.44 (0.17)	0.77 (0.35)
Healthy		-0.68 (2.96)^i	-0.83 (3.34)^i	-0.67 (2.93)^i
Offer		-0.40 (0.09)	-0.46 (0.10)	-0.39 (0.08)

Standard deviations in parentheses
i: Statistically insignificant
1. Results are WTP (2016 values) for the attributes, based on estimations from Table 5.5

5.6 Chapter conclusion

This chapter estimated consumer preferences for environmental attributes associated with chicken meat using stated, revealed, and joint (stated + revealed) preference methods. The stated preference (SP) data was collected with the help of a choice experiment (CE), and the revealed preference (RP) data came from scanner shopping data, both from representative samples of British consumers.

Joint estimations are increasingly popular, but the problems associated with such studies cannot be ignored. These include inter-alternative error structures, unobserved heterogeneity effects, state-dependence and heterogeneity state-dependence, and scale difference. This chapter demonstrated that heteroscedastic C-logit (CLHet) offers a viable way to offset these issues simultaneously. The main models included a series of interaction terms, providing a wide range of information about consumer characteristics and behaviours when selecting the product and their attributes while addressing the strong assumption of independent and identically distributed error terms.

For this thesis, joining the two datasets brought several benefits. This allowed the model to accommodate the non-buy (SQ) alternative, which is not usually taken into consideration in RP studies. This is also the case for the estimation of individual WTP for attributes such as 'environmental friendliness' and 'low chemical usage', which are often not easily available in a revealed dataset. Moreover, joining the two datasets helps to deal with issues of multicollinearity and heteroscedasticity typical for RP data. For this RP data, more expensive products are usually labelled with more prestigious attributes such as 'organic', 'animal welfare' and 'quality'; thus, forming a possible source of multicollinearity. Finally, RP grounds SP data in actual choices and makes the results less prone to different types of biases typical for SP, such as hypothetical, anchoring and compliance biases.

The joint estimation arguably offers the 'truest' WTP, as it is likely to accommodate the issues associated with both SP and RP methods when applied independently, above all hypothetical bias, multicollinearity and endogeneity. Results show that WTP for 'organic' would decrease by 1% and 2% per year of age in the stated and joint preference approaches, respectively, and would be 2% higher for the 'pro-organic' group (available in the SP data). These reveal market and intervention opportunities; for example, sellers can target younger generations. Policymaking can be in line with information on the benefits of organic food. Also, better marketing in terms of the attributes incorporated into the 'organic' label, given that results indicate that consumers might not necessarily understand these. Indeed, the CE shows that consumers value the attributes that should be embedded in the 'organic' label, but with no significant overall effect. For related attributes, when available independently, individuals are willing to pay £1.36 for 'animal welfare' and £0.77 for an 'environmentally friendly' label. The latter has a relatively low WTP, and less chemical usage has a negative effect on WTP, indicating that meat consumers are more concerned about the welfare of the animal; thus, WTP for a more 'humane' treatment of the chicken in the production process. At the same time, consumers are willing to pay an average of £2.64 (44% premium) for better quality, indicating that their welfare is intuitively even more valued.

For future joint RP and SP studies, results show that the common problems arising from pooling the two samples can be mitigated with the application of a heteroscedastic conditional logit model and the inclusion of interaction terms between attributes and consumer characteristics. For the latter, results suggest that the IID assumption does not significantly change estimates. For this study, the parameter restriction was only accepted in the CLHet model and failed in the C-logit model. Therefore, failure to accommodate for scale differences can severely impact the estimates of coefficients of the choice probability, as the SP and RP have different parameters; thus, biasing WTP and welfare calculations.

Closely related to this paper, for combining scanner data and a choice experiment, Brooks and Lusk (2010) concludes that a joint SP and RP offers robust results. However, although the study accommodates scale differences, the parameters could not converge when using an MNL model. The study focuses on the evaluation of organic and cloned milk, thus different from the subject of this thesis, but does not offer insight on the reasons driving WTP and (consistent with MNL models) heterogeneity of preferences. Hindsley et al. (2022) also use an MNL model in a joint RP (travel cost) and SP (choice experiment) estimation of WTP for recreation, and identify a significant effect from scale parameter. The study shows that this was driven by hypothetical biases on cost estimates, thus justifying the treatment using attribute non-attendance (ANA) model[9].

Although this chapter can contribute to the literature at application and methodological levels, some socially desirable attributes could not be estimated, as the RP and SP data emphasised the 'organic' label. These include 'local production', but especially 'health'. As discussed in Chapter 3, the latter is a significant driver of 'organic' consumption, and this thesis provided qualitative insight about the attribute, though a significant WTP estimate would be more desirable[10]. At the methodological level, joining RP and data has proven to be fruitful; however, trimming the data so that the parameters are compatible can be too restrictive and valuable data might be lost, especially when using small RP datasets, which can be costly.

[9] ANA models could have been incorporated in the survey, i.e. questioning which attributes subjects ignored. However, the CE used in this thesis had its own HBTs, and the issue did not form a source of scale differences in this paper.

[10] The attribute was not present in the CE, and did not have sufficient observations in the RP data.

Chapter 6

Conclusion

This thesis estimates the WTP for environmental attributes associated with organic food, particularly chicken meat, and confirms the potential welfare gain from promoting and producing food that contains these attributes, e.g. 'organic', 'environmental friendliness', and 'animal welfare'.

In Chapter 2, a meta-analysis provides an overview of the WTP for organic attributes found in the literature. It offers valuable information about heterogeneity amongst studies of WTP premium for organic food, as it benefited from input from a worldwide distributed sample. However, the studies under analysis offered limited reliable information about some key attributes of organic food and thus the real motivators of organic food consumption. Most product types were not statistically significant (beyond price factors); indeed, they do not share many attributes that could be explored across the sample. Such attributes are, for example, perceived health contribution, local production, and environmental friendliness, in addition to quality, taste, and appearance. However, the meta-analysis evidenced the need for future studies to focus on these attributes, which would offer more intervention points. These include areas of health and the environment, social marketing and corporate social responsibility strategies, and market expansion (or penetration) strategy at the production and retail levels. The results indicated that consumers across countries and products are willing to pay an average premium of 60% for organic food. The meta-analysis also shows that SP approaches offer higher estimation values than RP ones; thus, stressing the need for hypothetical bias treatment in SP studies. The function selection also evidenced the need to include socio-economic characteristics on WTP.

Chapter 3 applies an HP model, as the most popular revealed preference (RP) approach, using a GMM method, and shows that family structures can be used successfully to treat endogenous attributes driving price. It also demonstrates that if endogeneity of attributes is not addressed in estimates or not adequately accommodated, results are likely to be biased. Endogeneity may lead to under-estimation in the case of OLS and overestimation when applying the 2SLS model. However, the econometric limitations of HP models pose significant challenges to researchers in addressing them successfully, particularly the difficulties in finding suitable instruments. If there are several variables of interest, it can be unfeasible that all potentially endogenous variables can be controlled. In addition, the price equilibrium condition under non-market valuation techniques sometimes does not fully consider the dynamics defining consumers' WTP. In this sense, a combined revealed and SP model can link static valuation studies to more dynamic consumer preference surveys and experiments. The latter can also contribute by offering data points, i.e. entries for attributes not available in revealed datasets, such as those used in Chapter 5. For 'organic', another limitation of RP is that the attribute is a label representing a combination of attributes not necessarily branded. Therefore, when consumers buy the product, they might place different values on some characteristics that might be assumed to be embedded in that label, such as chemical usage, environmental friendliness, animal welfare, and potentially, local production, as explored in this thesis. Therefore, the WTP for 'organic' in the RP could be higher than in an experiment, where all attributes are available independently for consumers to choose from, which is the case in this thesis.

Nonetheless, the analysis above offers justification in favour of stated preference (SP) approaches, as these labels are not usually available from revealed data. In other words, the WTP estimates from the RP approach might offer the value consumers place for the combination of attributes more feasibly elicited from the survey. In this sense, Chapter 4 uses a CE as a state-of-the-art SP method, treating hypothetical bias and addressing this primary concern. With more freedom about the attributes to be included in the valuation method, the results from Chapter 4 offer insightful information about the value attributes not available from the revealed data. A mixed logit and a C-logit model with interaction terms provided helpful information about the characteristics of consumers, and their motivators in line with their attitude and behaviour towards socially desirable attributes; thus, mapping the individual characteristics relevant to policymaking and marketing opportunities. A limitation of the SP approach, despite HBT, remains its reliability due to its hypothetical nature conducted in the CE. Therefore, combining these with the RP approach was a source of external validity. This thesis demonstrates that, if compatible, SP and RP offer more valuable and reliable results if combined in a joint estimation.

The joint estimation arguably offers the 'truest' WTP, as it is likely to accommodate the issues associated with both SP and RP methods when applied independently, above all hypothetical bias, multicollinearity and endogeneity. In Chapter 5, the RP and WTP for the organic attribute are first compared to SP estimates. Using the same choice model, thus exploring the freedom it gives the researcher to investigate the effect of other variables not present in revealed datasets, some describing use and non-use values. Examples of the need for an SP approach in this thesis included investigating the effect of 'environmentally friendly' on WTP and eliciting a significant coefficient for any other anthropocentric aspects of organic food not available in the RP data. Including real purchase information into the stated preference data, for instance, appears to have efficiently reduced the hypothetical bias in cases where there has been overstatement in the SP responses. This is particularly true for the choice of 'organic' and 'quality' attributes, which are more sensitive to budget constraints, giving more credibility to results obtained in the joint estimation approach. The chapter also demonstrates that heteroscedastic conditional logit (CLHet), with and without interaction variables between consumer characteristics and product attributes, can mitigate the issues posed by joint SP and RP estimation yet not commonly addressed. Above all, scale differences (parameter restrictions) and heterogeneity effects, thus relaxing the strong assumption of an independent and identically distributed (IID) error structure.

Appendix A

Appendix for Chapter 2

TABLE A.1: *Regression Results: Restricted Model*

lnPWTP	Coef.	St.Err	t-value	p-value	Sig.
Stated	0.094	0.318	0.29	0.768	
CV	0.183	0.42	0.44	0.664	
HBT	-0.486	0.461	-1.05	0.295	
InfoGiven	-2.018	1.188	-1.7	0.093	*
Online	0.304	0.486	0.63	0.533	
PubPrior2008	-0.397	0.182	-2.19	0.032	**
Post2012	0.095	0.28	0.34	0.735	
Beverage	-1.526	0.328	-4.64	0	***
Fruit	0.374	0.436	0.86	0.394	
Leaf	1.438	0.402	3.57	0.001	***
Meat	-0.126	0.274	-0.46	0.648	
Eggs	2.107	0.328	6.43	0	***
Seasoning	0.63	0.672	0.94	0.352	
Ornamental	3.761	1.267	2.97	0.004	***
Africa	1.542	0.312	4.95	0	***
Asia	0.848	0.375	2.26	0.026	**
NAmerica	0.111	0.468	0.24	0.813	
WEurope	1.178	0.346	3.4	0.001	***
UK	0	0.357	0	0.999	
_cons	-1.762	0.352	-5.01	0	***
R-squared	0.68	Number of obs		102	
Akaike crit. (AIC)	181.098	Bayesian crit. (BIC)		230.97	

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

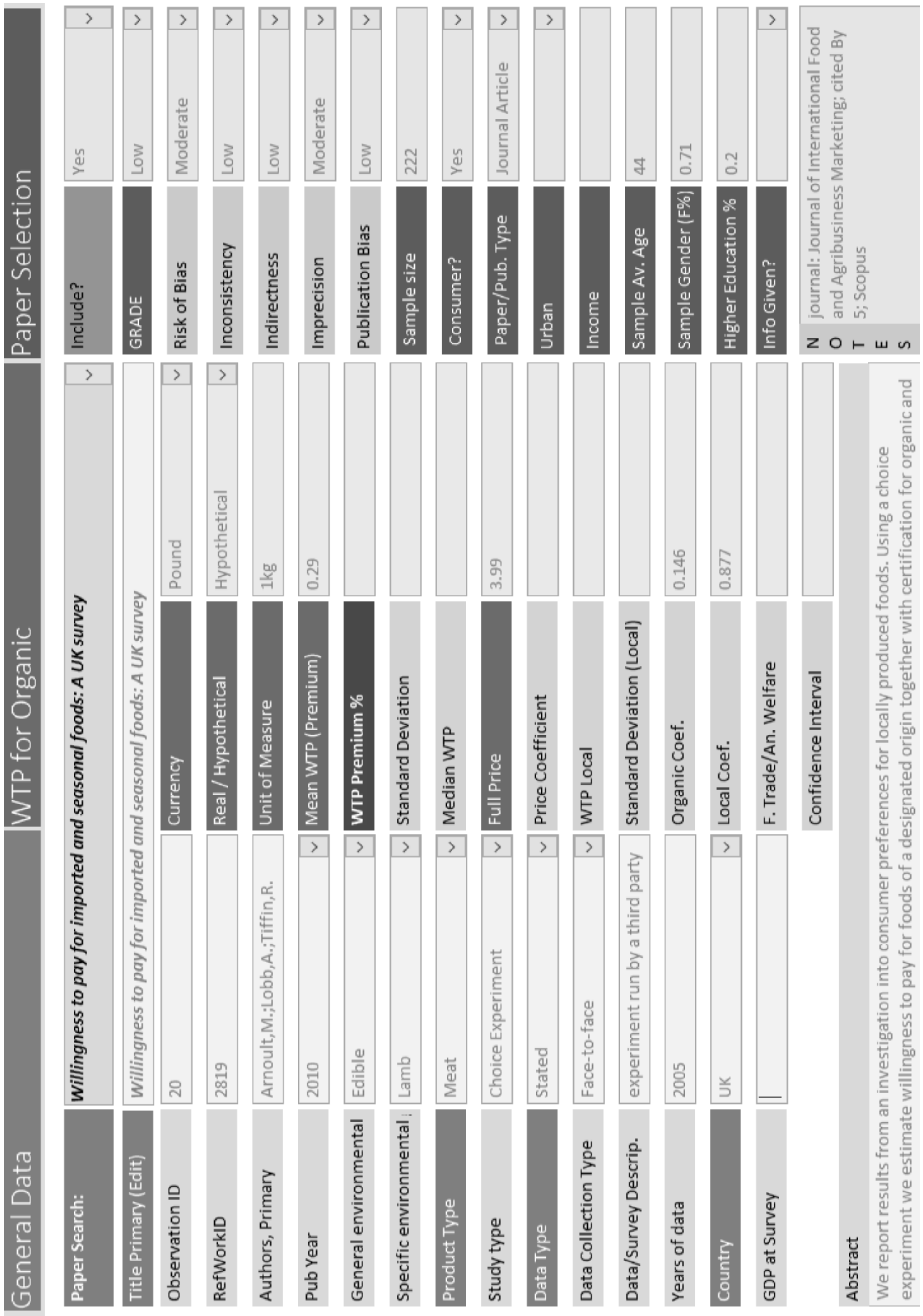

FIGURE A.1: *Data collection: Microsoft Access form*

TABLE A.2: *Correlation test*

	Namerica	GDPi	Asia	HEdu	P2012	CV	Stated	Info	Online
Namerica	1.00								
GDPi	0.69	1.00							
	(0.00)								
Asia	-0.26	-0.49	1.00						
	(0.01)	*(0.00)*							
HighEdu	0.40	0.25	0.10	1.00					
	(0.00)	*(0.07)*	*(0.47)*						
Post2012	-0.10	-0.11	0.21	-0.04	1.00				
	(0.28)	*(0.26)*	*(0.03)*	*(0.76)*					
CV	-0.38	-0.41	0.08	-0.21	-0.03	1.00			
	(0.00)	*(0.00)*	*(0.41)*	*(0.13)*	*(0.80)*				
Stated	-0.07	0.00	0.14	0.22	0.15	0.31	1.00		
	(0.47)	*(0.97)*	*(0.16)*	*(0.11)*	*(0.12)*	*(0.00)*			
InfoGiven	0.25	0.26	-0.09	0.01	0.15	-0.19	0.09	1.00	
	(0.01)	*(0.01)*	*(0.38)*	*(0.93)*	*(0.13)*	*(0.04)*	*(0.34)*		
Online	0.14	0.23	-0.11	0.06	0.18	-0.10	0.12	-0.07	1.00
	(0.16)	*(0.02)*	*(0.27)*	*(0.66)*	*(0.06)*	*(0.29)*	*(0.23)*	*(0.45)*	

Values in brackets are p-values

TABLE A.3: *Linear Regression: Restricted*

VARIABLES	(1) PWTP Restricted Model
Stated	0.281**
	(0.126)
CV	-0.115
	(0.120)
InfoGiven	-1.945
	(1.347)
Online	-0.163
	(0.232)
PubPrior2008	-0.228
	(0.164)
Post2012	0.013
	(0.197)
Beverage	-0.688***
	(0.125)
Fruit	0.079
	(0.140)
Leaf	2.092
	(1.448)
Eggs	0.635
	(0.499)
Seasoning	0.306
	(0.516)
Ornamental	3.109**
	(1.523)
Africa	1.186**
	(0.514)
Asia	0.879***
	(0.273)
NAmerica	-0.088
	(0.190)
WEurope	0.444*
	(0.226)
UK	-0.464***
	(0.046)
HighEdu	
Constant	0.180
	(0.217)
Observations	105
R-squared	0.503

*Robust se in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

TABLE A.4: *Linear Regression: Extended (including 'education')*

VARIABLES	(1) PWTP Extended Model
Stated	0.458***
	(0.123)
CV	0.018
	(0.091)
InfoGiven	0.192
	(0.142)
Online	-0.543***
	(0.128)
PubPrior2008	-0.052
	(0.147)
Post2012	0.407***
	(0.105)
Beverage	0.894
	(0.534)
Fruit	0.242**
	(0.109)
Leaf	0.580***
	(0.080)
Seasoning	2.023***
	(0.535)
Ornamental	0.410
	(0.716)
Asia	1.145***
	(0.124)
NAmerica	0.592***
	(0.150)
WEurope	-0.671
	(0.535)
UK	0.364
	(0.555)
HighEdu	-1.667***
	(0.373)
Constant	0.273*
	(0.145)
Observations	53
R-squared	0.871

*Robust se in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Appendix B

Appendix for Chapter 3

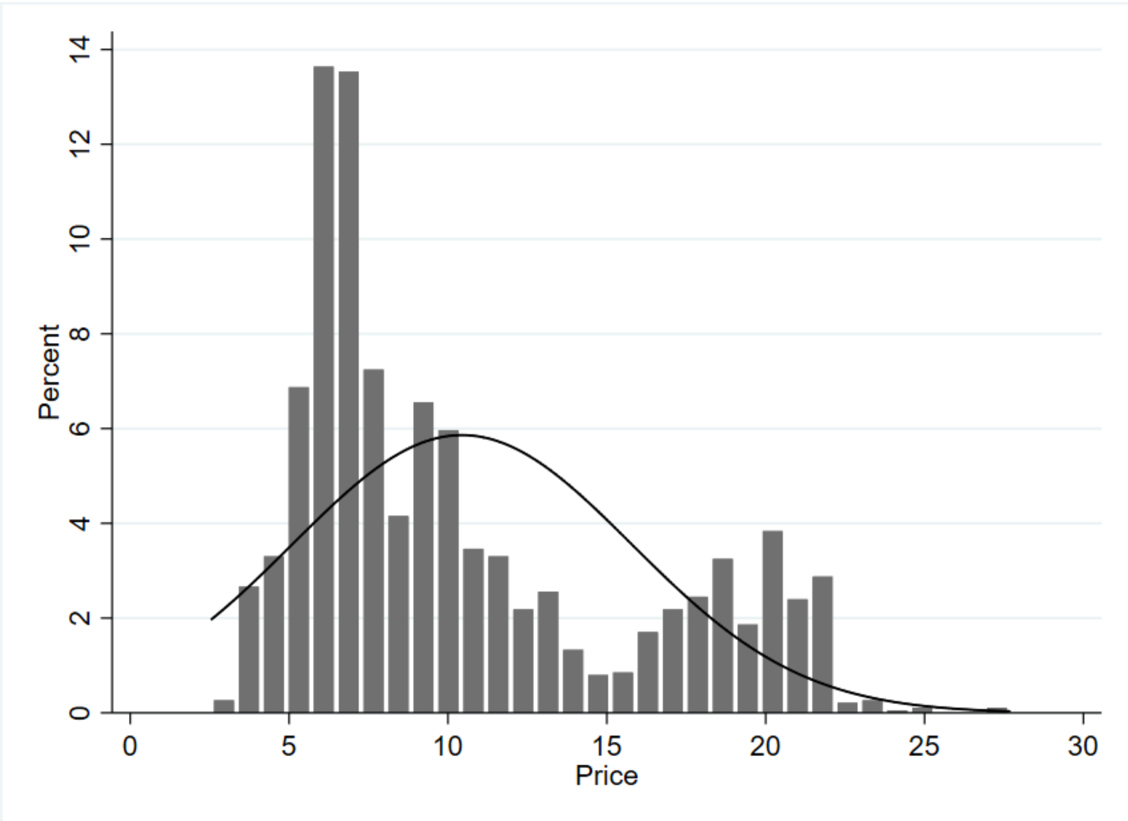

FIGURE B.1: *Price Distribution: all retailers*

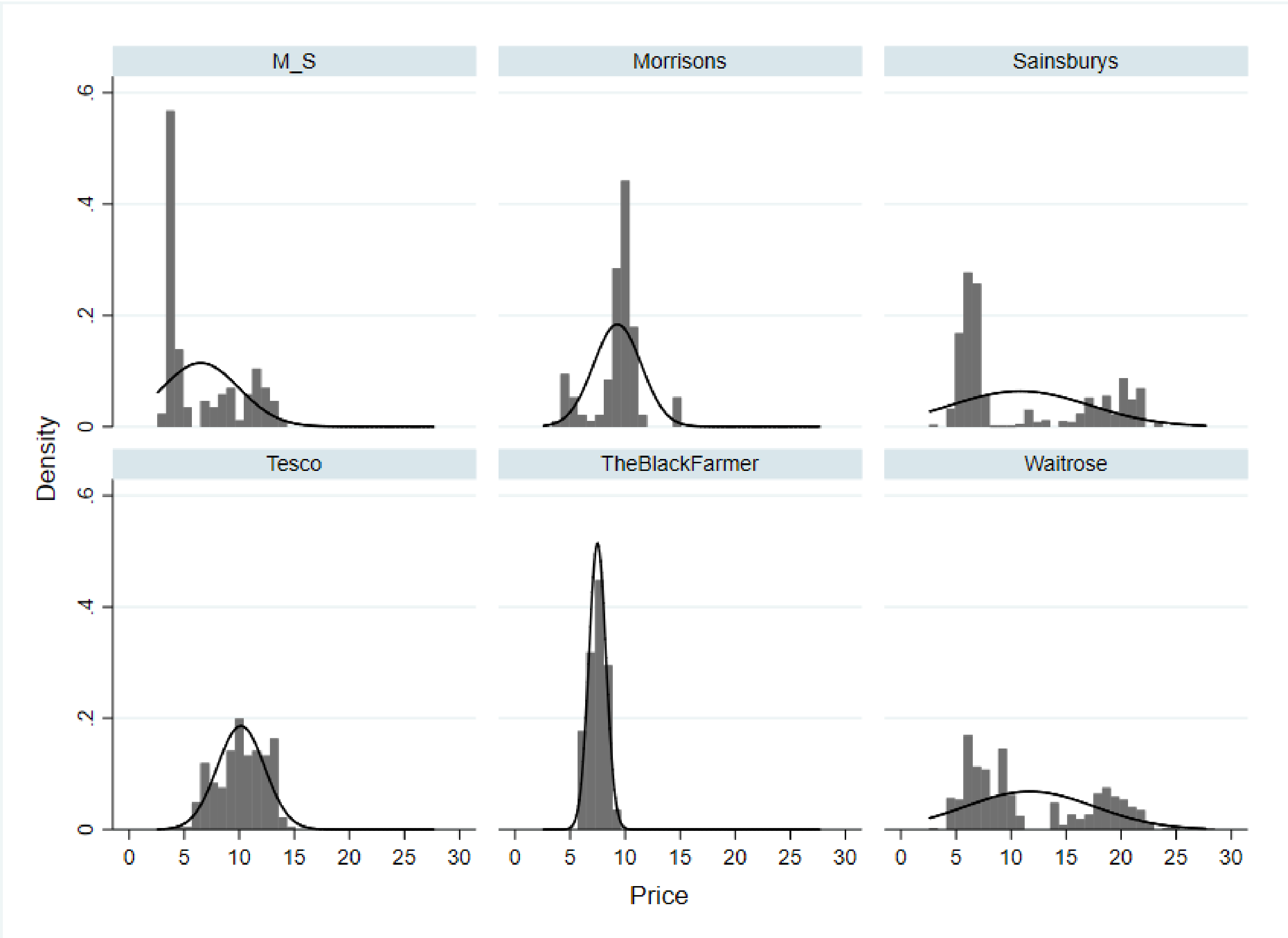

FIGURE B.2: *Price Distribution by Retailer*

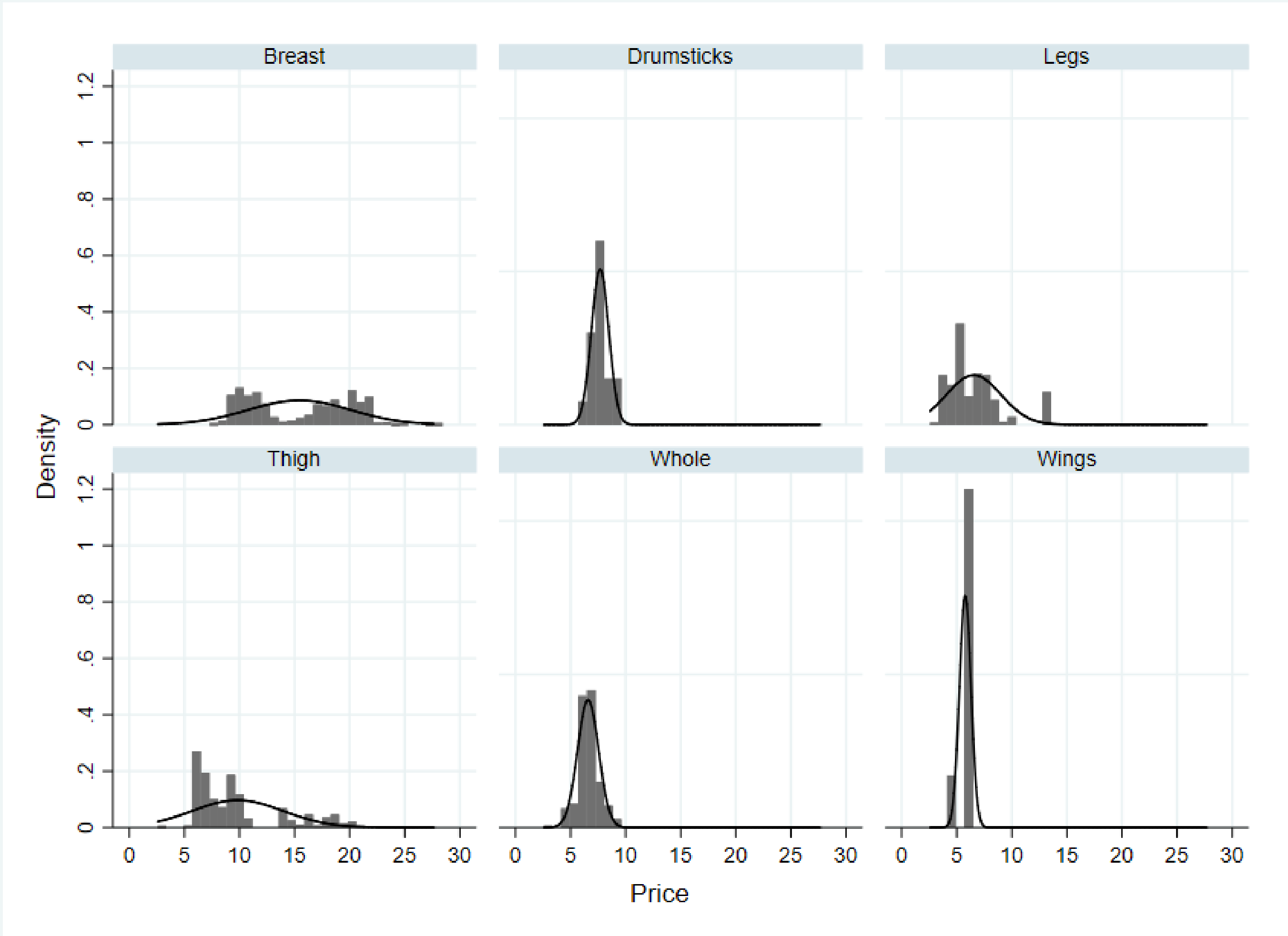

FIGURE B.3: *Price distribution by parts*

TABLE B.1: *First stage regression of socio-economic characteristics*

VARIABLES	(1) Probit	(2) OLS	(3) OLS (Family Structure)	(4) OLS (Main Model)
Income	0.062***	0.001***		
	(0.005)	(0.000)		
Female	0.024	0.000		
	(0.022)	(0.000)		
Age	-0.015***	-0.000***		
	(0.002)	(0.000)		
BMI	-0.027***	-0.000***		
	(0.002)	(0.000)		
PreFamily	0.159***	0.002***	0.001**	0.001**
	(0.042)	(0.001)	(0.000)	(0.000)
YoungFamily	0.204***	0.003***	0.002***	
	(0.037)	(0.001)	(0.000)	
MiddleFamily	0.294***	0.005***	0.003***	0.003***
	(0.038)	(0.001)	(0.000)	(0.000)
OlderFamily	-0.024	-0.000	-0.002***	
	(0.045)	(0.000)	(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***	0.005***	0.005***
	(0.077)	(0.001)	(0.000)	(0.000)
Observations	238,860	238,860	336,942	336,942
R-squared		0.002	0.000	0.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE B.2: *Correlation socio-economic variables with Price*

Variables	LnPrice
Income	0.123
Age	-0.099
Female	0.009
BMI	-0.047
Retired	-0.053
Children	0.020
PreFamily	0.059
YoungFamily	0.042
MiddleFamily	-0.000
OlderFamily	0.005

All $p < 0.01$

TABLE B.3: *Correlation BMI with Retailers*

Variables	Cor BMI	Avrg Price	Avrg BMI
Asda	0.034	4.79	27.50
Aldi	-0.019	3.80	26.74
Lidl	-0.002	3.91	26.96
Iceland	0.009	3.87	27.40
Coop	-0.001	5.72	26.92
Costco	0.006	4.92	27.45
Morrisons	0.026	4.91	27.43
M&S	-0.005	5.56	26.79
Ocado	-0.017	6.33	25.59
Sainsburys	-0.015	5.46	26.76
Tesco	-0.008	4.90	26.91
TheBlackFarmer	-0.023	7.49	20.20
Waitrose	-0.036	7.40	25.65

TABLE B.4: *Regression of socio-economic characteristics on Price*

LnPrice	Coef.	St.Err	t-value	p-value	Sig.
Income	0.007	0.000	31.59	0.000	***
Age	-0.001	0.000	-9.85	0.000	***
Female	0.001	0.001	1.32	0.188	
BMI	0.000	0.000	-1.27	0.203	
Retired	0.002	0.002	1.28	0.200	
Children	-0.002	0.001	-2.74	0.006	***
PreFamily	-0.015	0.002	-7.45	0.000	***
YoungFamily	-0.001	0.002	-0.47	0.636	
MiddleFamily	0.003	0.002	1.40	0.161	
OlderFamily	0.002	0.002	0.85	0.394	
Constant	1.207	0.018	67.23	0.000	***

R-Squared = 0.856

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

All variables from the baseline model were included

TABLE B.5: *Sample purchases distribution and total expenditure by region*

Region	Purchas.	Expenditure	Exp (%)	Mean	Median	sd
North	86,387	369,000.00	25.76	4.27	3.69	3.06
South	83,336	354,000.00	24.71	4.24	3.79	2.48
Midlands	58,134	243,000.00	16.96	4.19	3.70	2.78
East	38,403	165,000.00	11.52	4.30	3.78	2.77
London	29,958	129,000.00	9.00	4.32	3.67	3.50
Scotland	25,111	108,000.00	7.54	4.30	3.75	2.67
Wales	15,641	64,641.45	4.51	4.13	3.64	2.74
Total	336,970	1,432,641.45	100.00	4.25	3.75	2.85

TABLE B.6: *Sample Distribution: Retail by region*

Retail	East	London	Midlands	North	Scotland	South	Wales
Tesco	12,491	7,037	12,021	14,987	5,018	23,400	3,952
Aldi	5,074	1,735	12,095	17,006	3,772	8,044	2,558
Asda	3,884	3,219	6,545	15,641	4,134	9,194	2,262
Sainsburys	4,874	5,872	6,544	7,124	1,729	12,928	899
Morrisons	3,530	1,871	7,329	11,770	3,421	6,877	1,535
Lidl	2,707	3,149	4,467	6,133	3,483	10,489	2,536
Waitrose	1,060	1,292	1,017	914	115	3,256	173
M&S	410	589	695	1,923	913	1,370	226
Iceland	602	1,015	788	1,508	412	1,158	406
Coop	676	218	951	1,055	545	1,251	187
Costco	230	251	199	420	190	426	56
Ocado	232	210	328	278	4	521	16
TheBlackFarmer	0	99	3	1	0	5	0
Others	2,633	3,401	5,152	7,627	1,375	4,417	835
Total (336,970)	38,403	29,958	58,134	86,387	25,111	83,336	15,641

TABLE B.7: *Sample Distribution by Chicken Part*

SubProduct	Observations (purchases)	Share (%)	Mean (£/Kg)	Median (£/Kg)	sd
Breast	164,490	48.81	6.67	6.15	1.77
Whole	105,761	31.39	2.62	2.42	1.07
Thigh	36,378	10.80	3.74	3.00	1.85
Legs	13,310	3.95	2.69	2.43	1.11
Drumsticks	11,126	3.30	2.35	2.25	0.54
Wings	5,185	1.54	2.23	2.32	0.58
Others	649	0.19	2.82	2.49	1.22
Half	71	0.02	4.75	4.90	1.15
Total	336,970	100.00	4.71	5.20	2.47

TABLE B.8: *Price of organic chicken by retailers*

Retailer	N	mean	sum	p50	sd	p1	p10	p99
Sainsburys	759	10.82	8213.68	6.72	6.27	4.77	5.30	22.11
Waitrose	474	11.69	5541.50	9.32	5.85	4.72	5.75	23.87
Tesco	288	10.15	2923.19	10.00	2.15	5.81	6.94	13.60
Morrisons	121	9.30	1125.25	9.75	2.17	4.33	5.42	15.06
M S	110	6.49	713.79	4.28	3.49	2.99	3.65	13.22
TheBlackFarmer	108	7.49	808.70	7.65	0.78	6.06	6.45	9.13
Ocado	15	16.74	251.08	16.65	1.38	14.19	15.81	20.83
Asda	2	11.44	22.87	11.44	0.59	11.02	11.02	11.85
TOTAL	1877	10.44	19,600.06	8.55	5.34	3.67	5.30	21.97

TABLE B.9: *Price comparison: organic vs conventional chicken parts*

	All Chicken Purchases			Organic Chicken		
SubProduct	Observations (purchases)	Share (%)	Mean (£/Kg)	N (£/Kg)	Mean (%)	Share
Breast	164,490	48.81	6.67	689.00	15.44	36.71
Whole	105,761	31.39	2.62	409.00	6.60	21.79
Thigh	36,378	10.80	3.74	353.00	9.83	18.81
Legs	13,310	3.95	2.69	394.00	6.55	20.99
Drumsticks	11,126	3.30	2.35	17.00	7.69	0.91
Wings	5,185	1.54	2.23	15.00	5.78	0.80
Others	649	0.19	2.82	-	-	-
Half	71	0.02	4.75	-	-	-
Total	336,970	100.00	4.71	1877	10.44	100.00

TABLE B.10: *Regression Results (Non-FE)*

LnPrice		GMM	MIP(£/Kg)
Organic	1.353***	(0.104)	6.36
Freedom_Food	0.392***	(0.009)	1.84
Size1	0.200***	(0.011)	0.94
Size2	0.177***	(0.011)	0.83
Size3	0.102***	(0.011)	0.48
Size4	-0.014	(0.011)	-0.07
Breast	0.507***	(0.009)	2.38
Drumsticks	-0.241***	(0.009)	-1.13
Half	0.227***	(0.027)	1.07
Legs	-0.195***	(0.011)	-0.92
Thigh	0.074***	(0.009)	0.35
Wings	-0.327***	(0.010)	-1.54
Whole	-0.032***	(0.009)	-0.15
Offer	-0.020***	(0.004)	-0.09
Branded	0.028***	(0.005)	0.13
BudgetLabel	-0.102***	(0.009)	-0.48
Quality	0.338***	(0.010)	1.59
Halal	0.164***	(0.011)	0.77
Healthy	-0.021	(0.029)	-0.10
Asda	0.013***	(0.003)	0.06
Aldi	-0.013	(0.009)	-0.06
Lidl	-0.006	(0.009)	-0.03
Iceland	-0.105***	(0.005)	-0.49
Coop	0.089***	(0.003)	0.42
Costco	0.135***	(0.004)	0.63
Morrisons	0.048***	(0.005)	0.23
M&S	-0.130***	(0.016)	-0.61
Ocado	0.062***	(0.007)	0.29
Sainsburys	0.003	(0.009)	0.01
Tesco	0.001	(0.004)	0.00
TheBlackFarmer	-0.580***	(0.097)	-2.73
Waitrose	0.107***	(0.021)	0.50
Scotland	-0.011***	(0.003)	-0.05
Wales	-0.008***	(0.002)	-0.04
North	-0.003**	(0.001)	-0.01
Midlands	-0.004***	(0.001)	-0.02
London	-0.025***	(0.004)	-0.12
East	-0.004***	(0.001)	-0.02
Constant	-0.047***	(0.014)	-0.22
Observations		336,940	

Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
All models include monthly dummies

TABLE B.11: *GMM regression results: regions*

VARIABLES	Scotland	North	London	South	Midlands	East	Wales
Instrument	P-Family	M-Family	M-Family	Y-Family	Adults	Y-Family	No IV
IV F-statistic	90	138	106	22	90	32	
Organic	0.353***	1.537***	0.990***	1.376***	-0.158	1.526***	0.406***
	-0.105	-0.166	-0.09	-0.176	-0.249	-0.229	(0.060)
Freedom_Food	0.273***	0.357***	0.433***	0.374***	0.381***	0.420***	0.347***
	-0.014	-0.013	-0.014	-0.013	-0.012	-0.025	(0.026)
Offer	-0.041***	-0.028***	-0.011*	-0.022***	-0.052***	-0.012	-0.054***
	-0.004	-0.004	-0.006	-0.006	-0.002	-0.009	(0.003)
Branded	-0.011	-0.018*	0.105***	0.017	0.019	-0.012	-0.068***
	-0.012	-0.011	-0.009	-0.013	-0.014	-0.017	(0.019)
BudgetLabel	-0.194***	-0.068***	-0.070***	-0.105***	-0.154***	-0.073***	-0.174***
	-0.03	-0.016	-0.02	-0.02	-0.015	-0.028	(0.027)
Quality	0.276***	0.354***	0.346***	0.324***	0.263***	0.377***	0.306***
	-0.011	-0.022	-0.016	-0.013	-0.009	-0.021	(0.015)
Halal		0.247***	0.102***	0.184***	0.094***	0.393***	0.406***
		-0.034	-0.014	-0.022	-0.023	-0.144	(0.020)
Healthy		-0.081	0.078*		-0.016		-1.173***
		-0.072	-0.042		-0.043		(0.023)
Asda	0.036***	0.019***	0.006	0.012***	0.041***	0.003	0.006
	-0.005	-0.003	-0.005	-0.005	-0.003	-0.007	(0.008)
Aldi	0.077**	-0.039**	-0.094***	-0.004	0.051***	-0.045	0.046
	-0.03	-0.017	-0.021	-0.021	-0.015	-0.029	(0.029)
Lidl	0.093***	-0.030*	-0.085***	0.001	0.061***	-0.019	0.049*
	-0.03	-0.017	-0.021	-0.021	-0.015	-0.029	(0.029)
Iceland	-0.025**	-0.094***	-0.174***	-0.103***	-0.056***	-0.089***	-0.136***
	-0.01	-0.007	-0.01	-0.008	-0.007	-0.012	(0.014)
Coop	0.110***	0.099***	0.070***	0.088***	0.114***	0.096***	0.068***
	-0.007	-0.005	-0.011	-0.006	-0.005	-0.01	(0.012)
Morrisons	0.070***	0.046***	0.029***	0.059***	0.101***	0.060***	0.066***
	-0.006	-0.007	-0.008	-0.009	-0.004	-0.009	(0.009)
M&S	-0.040***	-0.170***	-0.115***	-0.089***	-0.028*	-0.185***	-0.129***
	-0.015	-0.035	-0.024	-0.022	-0.016	-0.044	(0.026)
Sainsburys	0.065***	0.030***	-0.012	0.009	0.066***	-0.016	0.016*
	-0.009	-0.007	-0.011	-0.013	-0.005	-0.027	(0.009)
Tesco	0.018***	0.012***	-0.030***	0.004	0.039***	0.008	0.003
	-0.007	-0.004	-0.007	-0.006	-0.003	-0.009	(0.008)
Waitrose	0.252***	0.078*	0.048	0.138***	0.244***	0.160***	0.202***
	-0.016	-0.042	-0.032	-0.03	-0.009	-0.029	(0.015)
Constant	-0.235***	-0.041	-0.022	-0.029	-0.037	-0.114***	-0.147***
	-0.051	-0.027	-0.028	-0.04	-0.028	-0.039	(0.039)
Observations	25,109	86,380	29,952	83,328	58,130	38,400	15,641
R-squared							

*Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*
All models include chicken parts, package sizes and month dummies

TABLE B.12: *GMM regression results: parts*

VARIABLES	Breast	Drumsticks	Legs	Thighs	Wings	Whole
Instrument	O-Family	O-Family	Y-Family	O-Family	O-Family	O-Family
IV F-Statistics	38	11	21	35	12	15
Organic	1.602***	0.035	1.260***	2.766***	1.580***	2.978***
	(0.032)	(2.107)	(0.070)	(0.112)	(0.467)	(0.062)
Freedom_Food	0.349***		0.398***	0.265***		0.818***
	(0.005)		(0.024)	(0.032)		(0.019)
Offer	0.006***	-0.039***	-0.090***	0.254***	-0.113***	0.007
	(0.001)	(0.013)	(0.010)	(0.017)	(0.021)	(0.008)
Branded	0.059***	0.122***	0.397***	-0.245***	0.213	-0.040***
	(0.003)	(0.021)	(0.017)	(0.020)	(0.014)	(0.014)
BudgetLabel	0.098*	-0.406***	-0.212***	-0.217***	-0.229***	0.065***
	(0.053)	(0.007)	(0.021)	(0.009)	(0.010)	(0.011)
Quality	0.259***	-0.111***	0.341***	0.391***	0.429***	0.557***
	(0.010)	(0.011)	(0.011)	(0.015)	(0.095)	(0.014)
Halal	0.047***	0.038	0.113***	0.348***	0.198***	0.092**
	(0.008)	(0.032)	(0.034)	(0.028)	(0.044)	(0.037)
Healthy	0.125***					
	(0.028)					
Scotland	-0.022***	-0.027***	0.006	0.002	0.023	-0.020
	(0.003)	(0.005)	(0.008)	(0.013)	(0.017)	(0.012)
Wales	-0.001	-0.025***	-0.011	0.014	0.022	-0.004
	(0.002)	(0.006)	(0.011)	(0.014)	(0.019)	(0.007)
North	0.003**	-0.010***	-0.030***	0.013	0.010	-0.023***
	(0.001)	(0.004)	(0.007)	(0.012)	(0.015)	(0.006)
Midlands	0.000	-0.007	-0.032***	-0.042**	0.002	-0.013*
	(0.002)	(0.004)	(0.008)	(0.019)	(0.013)	(0.007)
London	-0.030***	-0.003	-0.047***	-0.086***	-0.002	-0.097***
	(0.004)	(0.007)	(0.010)	(0.020)	(0.016)	(0.016)
East	-0.003	-0.003	-0.052***	0.024*	0.012	-0.018*
	(0.002)	(0.005)	(0.011)	(0.013)	(0.017)	(0.010)
Observations	164,462	11,126	13,310	36,377	5,185	105,760
R-squared						

*Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*
all regressions include main retailers, package size and month dummies

TABLE B.13: Retailers Heterogeneity (GLM method)

VARIABLES	(1) Asda	(2) Ocado	(3) Waitrose	(4) Sainsburys	(5) Tesco	(6) Morrisons	(7) M&S
Organic	0.274***	0.571***	0.210***	0.370***	0.382***	0.160***	0.123***
	(0.052)	(0.029)	(0.005)	(0.003)	(0.006)	(0.008)	(0.015)
Freedom_Food	0.146***			0.328***		0.196***	
	(0.006)			(0.002)		(0.038)	
Size1	0.330***	0.584***	0.260**	0.227***	-0.325***	0.203***	0.561**
	(0.025)	(0.025)	(0.125)	(0.041)	(0.021)	(0.023)	(0.219)
Size2	0.208***	0.511***	0.251**	0.139***	-0.338***	0.111***	0.366*
	(0.025)	(0.024)	(0.125)	(0.041)	(0.021)	(0.023)	(0.219)
Size3	0.130***	0.385***	0.163	0.098**	-0.443***	0.075***	0.368*
	(0.025)	(0.022)	(0.125)	(0.041)	(0.021)	(0.023)	(0.219)
Size4	0.015		0.002	-0.033	-0.573***	0.050**	0.260
	(0.025)		(0.126)	(0.042)	(0.020)	(0.023)	(0.219)
Offer	-0.038***	-0.075***	-0.156***	-0.016***	0.041***	-0.055***	-0.162***
	(0.001)	(0.006)	(0.003)	(0.001)	(0.001)	(0.002)	(0.005)
BudgetLabel	0.012				-0.052***	-0.215***	
	(0.042)				(0.011)	(0.010)	
Quality	0.219***		-0.093***	0.780***	0.369***	0.306***	-0.078***
	(0.006)		(0.017)	(0.038)	(0.003)	(0.007)	(0.011)
Halal	0.086***				0.181***		
	(0.007)				(0.012)		
Scotland	0.008***	0.038	-0.002	0.012***	-0.002	-0.002	0.013**
	(0.002)	(0.043)	(0.011)	(0.002)	(0.002)	(0.002)	(0.006)
Wales	-0.003	-0.002	-0.034***	-0.015***	-0.004	-0.004	-0.036***
	(0.003)	(0.028)	(0.011)	(0.004)	(0.002)	(0.004)	(0.013)
North	-0.004**	-0.021***	-0.010**	0.005***	0.003*	-0.005***	-0.003
	(0.002)	(0.008)	(0.005)	(0.001)	(0.001)	(0.002)	(0.005)
Midlands	-0.001	0.010	-0.013***	-0.003**	0.002	0.004**	-0.010
	(0.002)	(0.007)	(0.005)	(0.002)	(0.002)	(0.002)	(0.007)
London	-0.007***	-0.025***	-0.014***	0.002	-0.012***	-0.013***	-0.006
	(0.003)	(0.009)	(0.004)	(0.002)	(0.002)	(0.003)	(0.007)
East	-0.009***	-0.012	-0.002	-0.001	0.000	-0.003	-0.015*
	(0.002)	(0.009)	(0.004)	(0.002)	(0.002)	(0.003)	(0.009)
Constant	-0.133***	-0.041***	0.285**	0.015	0.439***	-0.066***	0.019
	(0.027)	(0.016)	(0.126)	(0.042)	(0.020)	(0.023)	(0.219)
Observations	44,879	1,588	7,827	39,970	78,904	36,333	6,108

Standard errors in parentheses
The model includes month and parts variables
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix C

Appendix for Chapter 4

C.1 Figures

C.2 Figures

FIGURE C.1: *Questions about your opinion on Organic Products:* reasons for buying or not buying organic products

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	neutral (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
They are healthier (1)	❍	❍	❍	❍	❍	❍	❍
They taste better (2)	❍	❍	❍	❍	❍	❍	❍
They are fresher (3)	❍	❍	❍	❍	❍	❍	❍
They are safer (4)	❍	❍	❍	❍	❍	❍	❍
They involve higher animal welfare (5)	❍	❍	❍	❍	❍	❍	❍
They are produced in a more environmentally friendly way (6)	❍	❍	❍	❍	❍	❍	❍
To support local producers (7)	❍	❍	❍	❍	❍	❍	❍
I have bought organic products before and I was satisfied with them (8)	❍	❍	❍	❍	❍	❍	❍
I fear that conventional products may be genetically manipulated and may be less safe than organic products (9)	❍	❍	❍	❍	❍	❍	❍
I want to support the Organic Movement (10)	❍	❍	❍	❍	❍	❍	❍

C.3 Correlation tables

TABLE C.1: *Multivariate regression: pro-organic behaviour (Y) and household characteristics (X)*

Y:	Healthy		Taste		Safe		Fresh		An. Welfare		Env. Frindl.		Local Production		Buy Org		Non GMF		Pro Org	
	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.	Coef.	t-val.
Female	0.061	6.17	0.149	15.05	0.045	4.56	0.038	4.00	0.052	5.17	0.031	3.32	0.016	1.63	0.072	7.20	0.093	9.41	0.042	4.28
Married	0.042	4.00	-0.035	-3.34	0.102	9.65	0.068	6.75	0.047	4.46	0.091	9.04	0.095	8.81	0.041	3.90	0.096	9.10	0.057	5.47
Age	-0.007	-20.62	-0.002	-6.40	-0.006	-19.10	-0.007	-21.34	-0.002	-5.57	-0.003	-9.76	-0.004	-12.73	-0.004	-11.26	-0.005	-15.51	-0.006	-18.41
Children	-0.005	-0.98	0.006	1.16	-0.009	-1.79	0.003	0.55	-0.022	-4.24	-0.040	-8.11	-0.032	-6.07	0.004	0.79	-0.028	-5.46	-0.021	-4.03
Income	0.000	6.94	0.000	13.63	0.000	6.36	0.000	9.62	0.000	9.00	0.000	7.44	0.000	7.30	0.000	6.58	0.000	6.73	0.000	7.89
_cons	0.668	31.59	0.393	18.47	0.674	31.56	0.558	27.57	0.583	27.23	0.732	36.15	0.631	29.16	0.649	30.38	0.536	25.28	0.601	28.58

Residual 10,626; overal significance: p=0.000

TABLE C.2: *Correlation check: probit - choice for Organic and consumer behaviour*

	Pro-Organic		Con-Organic		Pro-Environment		Lifestyle	
	Coef.	t-value	Coef.	t-value	Coef.	t-value	Coef.	t-value
Var1	Healthy		**Expensive**		Unplug Devices		Health Important	
	0.078	1.51	-0.090**	-2.06	-0.034	-0.78	0.111	1.34
Var2	Taste		Don't Trust		Switch Lights Off		Health Food is Important	
	0.035	0.74	-0.012	-0.27	-0.011	-0.13	-0.024	-0.25
Var3	Safe		Not Available		Close Tap Brushing		Excercises are Important	
	0.005	0.10	0.019	0.40	0.004	0.07	0.037	0.48
Var4	Fresh		Cannot Recognise		Donate to Env ONG's		More Active (less TV)	
	0.065	1.38	-0.035	-0.84	0.058	1.41	-0.050	-1.07
Var5	Animal Welfare		Low Variety		Buy Recycled		No Fast Food	
	0.039	0.79	0.044	1.00	0.061	1.38	0.015	0.29
Var6	Env. Friendly		Not Attractive		Use Own Bags		Low Fat Sugar	
	-0.083	-1.53	0.019	0.34	-0.061	-0.80	-0.031	-0.72
Var7	**Local Production**		Short Expiring		Prioritise Env Policies		Upset with Fast Food	
	0.097**	2.10	-0.015	-0.33	0.084	1.53	0.044	1.11
Var8	Buy Organic		Not Advertised		Use Public Transport		No Fizzy	
	0.030	0.61	0.063	1.48	-0.004	-0.09	0.057	1.15
Var9	Non GMF		Habit		Use Better Insulation		Non Smoker	
	0.067	1.39	-0.018	-0.40	-0.092	-1.43	-0.113	-1.56
Var10	Support Organic		Not Known		**Recycle**		Reduce Healthcare Cost	
	-0.037	-0.69	0.006	0.14	0.133*	1.83	0.066	1.36
_cons	-1.650***	-46.15	-1.469***	-38.10	-1.596***	-19.51	-1.591***	-21.27

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Significant variables in bold

TABLE C.3: *Correlation: socio-economic and pro-organic behaviour (1)*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Age	1.000								
	(0.000)								
(2) GenderFem	-0.239	1.000							
	(0.000)								
(3) Married	0.095	-0.007	1.000						
	(0.000)	(0.412)							
(4) Child	-0.319	0.188	0.181	1.000					
	(0.000)	(0.000)	(0.000)						
(5) Children	-0.271	0.167	0.185	0.846	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)					
(6) HIncomeMid	-0.127	-0.023	0.199	0.141	0.155	1.000			
	(0.000)	(0.016)	(0.000)	(0.000)	(0.000)				
(7) ProOrgHealth	-0.19	0.101	0.019	0.109	0.069	0.099	1.000		
	(0.000)	(0.000)	(0.041)	(0.000)	(0.000)	(0.000)			
(8) ProOrgTaste	-0.088	0.150	0.002	0.084	0.085	0.133	0.515	1.000	
	(0.000)	(0.000)	(0.859)	(0.000)	(0.000)	(0.000)	(0.000)		
(9) ProOrgSafe	-0.175	0.088	0.091	0.123	0.093	0.102	0.587	0.435	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
(10) ProOrgFresh	-0.233	0.104	0.061	0.151	0.133	0.136	0.465	0.532	0.461
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(11) ProOrgAnWe	-0.069	0.048	0.053	-0.023	-0.007	0.095	0.413	0.323	0.471
	(0.000)	(0.000)	(0.000)	(0.012)	(0.421)	(0.000)	(0.000)	(0.000)	(0.000)
(12) ProOrgEnFr	-0.099	0.048	0.082	0.013	0.015	0.088	0.477	0.365	0.492
	(0.000)	(0.000)	(0.000)	(0.165)	(0.100)	(0.000)	(0.000)	(0.000)	(0.000)
(13) ProOrgLocProd	-0.114	0.033	0.057	0.037	0.032	0.093	0.461	0.365	0.384
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(14) ProOrgBuyOrg	-0.130	0.085	0.049	0.092	0.094	0.084	0.529	0.448	0.473
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(15) ProOrgNonGMF	-0.166	0.122	0.067	0.121	0.079	0.093	0.487	0.406	0.511
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(16) ProOrgSupportOrg	-0.178	0.082	0.039	0.076	0.072	0.105	0.557	0.427	0.529
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Standard errors in parenthesis

TABLE C.4: *Correlation: socio-economic and pro-organic behaviour (2)*

Variables	(10)	(11)	(12)	(13)	(14)	(15)
(1) Age						
(2) GenderFem						
(3) Married						
(4) Child						
(5) Children						
(6) HIncomeMid						
(7) ProOrgHealth						
(8) ProOrgTaste						
(9) ProOrgSafe						
(10) ProOrgFresh	1.000					
(11) ProOrgAnWe	0.342	1.000				
	(0.000)					
(12) ProOrgEnFr	0.32	0.611	1.000			
	(0.000)	(0.000)				
(13) ProOrgLocProd	0.409	0.393	0.448	1.000		
	(0.000)	(0.000)	(0.000)			
(14) ProOrgBuyOrg	0.402	0.441	0.457	0.504	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)		
(15) ProOrgNonGMF	0.401	0.369	0.405	0.401	0.461	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
(16) ProOrgSupportOrg	0.441	0.437	0.467	0.535	0.510	0.602
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Standard errors in parenthesis

TABLE C.5: *Correlation: lifestyle and pro-organic behaviour (1)*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Happy1	1.000								
	(0.000)								
(2) Happy2	0.736	1.000							
	(0.000)								
(3) HealthyLife	0.052	0.063	1.000						
	(0.000)	(0.000)							
(4) ProEnvironm	0.057	0.053	0.587	1.000					
	(0.000)	(0.000)	(0.000)						
(5) ConOrganic	-0.035	0.011	-0.122	-0.167	1.000				
	(0.000)	(0.216)	(0.000)	(0.000)					
(6) SpecialDiet	-0.106	-0.039	0.094	0.038	-0.007	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.473)				
(7) ProOrgHealth	0.029	0.011	0.244	0.194	-0.166	0.045	1.000		
	(0.001)	(0.245)	(0.000)	(0.000)	(0.000)	(0.000)			
(8) ProOrgTaste	0.033	0.006	0.218	0.142	-0.235	0.045	0.515	1.000	
	(0.000)	(0.484)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(9) ProOrgSafe	-0.015	-0.046	0.317	0.253	-0.133	0.082	0.587	0.435	1.000
	(0.089)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
(10) ProOrgFresh	0.047	0.038	0.188	0.161	-0.132	0.089	0.465	0.532	0.461
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(11) ProOrgAnWe	0.007	-0.031	0.287	0.285	-0.093	0.021	0.413	0.323	0.471
	(0.453)	(0.001)	(0.000)	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)	(0.000)
(12) ProOrgEnFr	0.012	0.032	0.288	0.322	-0.127	0.016	0.477	0.365	0.492
	(0.18)	(0.000)	(0.000)	(0.000)	(0.000)	(0.084)	(0.000)	(0.000)	(0.000)
(13) ProOrgLocProd	0.097	0.063	0.264	0.291	-0.103	0.073	0.461	0.365	0.384
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(14) ProOrgBuyOrg	0.069	0.047	0.205	0.225	-0.211	0.016	0.529	0.448	0.473
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.087)	(0.000)	(0.000)	(0.000)
(15) ProOrgNonGMF	-0.005	-0.012	0.272	0.228	-0.145	0.09	0.487	0.406	0.511
	(0.600)	(0.182)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(16) ProOrgSupportOrg	0.006	0.022	0.33	0.338	-0.219	0.108	0.557	0.427	0.529
	(0.478)	(0.016)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Standard errors in parenthesis

TABLE C.6: *Correlation: lifestyle and pro-organic behaviour (2)*

Variables	(10)	(11)	(12)	(13)	(14)	(15)
(1) Happy1						
(2) Happy2						
(3) HealthyLife						
(4) ProEnvironm						
(5) ConOrganic						
(6) SpecialDiet						
(7) ProOrgHealth						
(8) ProOrgTaste						
(9) ProOrgSafe						
(10) ProOrgFresh	1.000					
(11) ProOrgAnWe	0.342	1.000				
	(0.000)					
(12) ProOrgEnFr	0.32	0.61	1.000			
	(0.000)	(0.000)				
(13) ProOrgLocProd	0.409	0.393	0.448	1.000		
	(0.000)	(0.000)	(0.000)			
(14) ProOrgBuyOrg	0.402	0.441	0.457	0.504	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)		
(15) ProOrgNonGMF	0.401	0.369	0.405	0.401	0.461	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
(16) ProOrgSupportOrg	0.441	0.437	0.467	0.535	0.510	0.602
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Standard errors in parenthesis;

TABLE C.7: *Correlation: socio-economic and lifestyle (1)*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Age	1.000						
	(0.000)						
(2) GenderFem	-0.239	1.000					
	(0.000)						
(3) Married	0.095	-0.007	1.000				
	(0.000)	(0.412)					
(4) Child	-0.319	0.188	0.181	1.000			
	(0.000)	(0.000)	(0.000)				
(5) Children	-0.271	0.167	0.185	0.846	1.000		
	(0.000)	(0.016)	(0.000)	(0.000)			
(6) HIncomeMid	-0.127	-0.023	0.199	0.141	0.155	1.000	
	(0.239)	(0.002)	(0.36)	(0.000)	(0.000)		
(7) AnyIntolerance	0.011	-0.028	-0.008	-0.023	-0.042	0.112	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
(8) ProOrganic	-0.166	0.160	0.060	0.100	0.086	0.078	0.078
	(0.147)	(0.000)	(0.000)	(0.000)	(0.000)	(0.473)	(0.000)
(9) ConOrganic	0.013	-0.073	0.061	0.053	0.080	-0.093	-0.007
	(0.000)	(0.000)	(0.091)	(0.000)	(0.013)	(0.000)	(0.000)
(10) ProEnvironm	0.055	0.067	-0.015	-0.048	-0.092	-0.024	0.038
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(11) Happy1	0.153	-0.060	0.180	-0.004	0.033	0.120	-0.106
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
(12) Happy2	0.113	-0.039	0.202	0.037	0.062	0.170	-0.039
	(0.239)	(0.002)	(0.36)	(0.000)	(0.000)	(0.000)	(0.000)
(13) SpecialDiet	0.011	-0.028	-0.008	-0.023	-0.042	0.112	1.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)

Standard errors in parenthesis

TABLE C.8: *Correlation: socio-economic and lifestyle (2)*

Variables	(8)	(9)	(10)	(11)	(12)
(1) Age					
(2) GenderFem					
(3) Married					
(4) Child					
(5) Children					
(6) HIncomeMid					
(7) AnyIntolerance					
(8) ProOrganic	1.000				
(9) ConOrganic	-0.224	1.000			
	(0.000)				
(10) ProEnvironm	0.344	-0.167	1.000		
	(0.000)	(0.000)			
(11) Happy1	0.048	-0.035	0.057	1.000	
	(0.216)	(0.000)	(0.000)		
(12) Happy2	0.030	0.011	0.053	0.736	1.000
	(0.473)	(0.000)	(0.000)	(0.000)	
(13) SpecialDiet	0.078	-0.007	0.038	-0.106	-0.039
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Standard errors in parenthesis

TABLE C.9: *Correlation organic choice - lifestyle*

Variables	Choice Organic	Pro Organic	Con Organic	Pro Env	Happy 1	Happy 2	Special Diet
ChoiOrg	1.000						
	(0.000)						
ProOrganic	0.050	1.000					
	(0.000)						
ConOrganic	-0.013	-0.224	1.000				
	(0.158)	(0.000)					
ProEnvironm	0.016	0.344	-0.167	1.000			
	(0.075)	(0.000)	(0.000)				
Happy1	0.016	0.048	-0.035	0.057	1.000		
	(0.082)	(0.000)	(0.000)	(0.000)			
Happy2	0.01	0.03	0.011	0.053	0.736	1.000	
	(0.274)	(0.001)	(0.216)	(0.000)	(0.000)		
SpecialDiet	0.003	0.078	-0.007	0.038	-0.106	-0.039	1.000
	(0.709)	(0.000)	(0.473)	(0.000)	(0.000)	(0.000)	
HealthyLife	0.014	0.328	-0.122	0.587	0.052	0.063	0.094
	(0.116)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Standard errors in parenthesis

C.4 SP regressions: behavioural variables

Table C.11 shows results from the interaction terms included in the regression model from Table 4.10.

Results from the coefficients of the significant interactions between the reason for being pro-organic and the attributes of their choices. For the respondents that stated positive attitude in support of organic food, only those who answered that they buy organic because of its potential local production characteristic have shown a significant increase in marginal utility from the organic label. Those that stated that they buy organic because it is safe, have demonstrated a higher utility from low chemical usage. An apparent contradiction is the negative effect of quality for those who are pro-organic because it is fresh. Price has also positive effect on these individuals, but it is marginal. More intuitive, however, is that individuals who are pro-organic because of its taste receive relatively higher utility from quality, thus the attribute might serve a proxy for taste, which usually is difficult to measure.

Pro-environmental respondents have the largest variety of significant interactions, with the highest number of significant variables associated with the environment. However, individuals that claimed to be pro-environment because they use public transport in fact have negative effect from organic label, animal welfare, best before (longer expiry date), and low

TABLE C.10: *Correlation Regression*

ChoiOrg	Coef.	St.Err	t-value	p-value	Sig.
price	0.117	0.006	18.94	0.000	***
IncomeMid	0.000	0.000	-0.02	0.982	
GenSilent	-0.107	0.158	-0.68	0.500	
GenBBoomer	-0.109	0.135	-0.81	0.419	
GenX	-0.146	0.135	-1.08	0.281	
GenY	-0.091	0.136	-0.68	0.500	
GenderFem	0.001	0.048	0.02	0.985	
Married	0.027	0.051	0.54	0.592	
JuniorChildren	-0.010	0.128	-0.08	0.940	
TeenChildren	0.055	0.125	0.43	0.663	
OcupProf	-0.098	0.127	-0.77	0.440	
OcupService	-0.046	0.151	-0.31	0.759	
OcupSales	-0.161	0.142	-1.14	0.254	
OcupConstr	-0.285	0.219	-1.30	0.192	
OcupGov	0.015	0.174	0.09	0.931	
OcupRetired	-0.085	0.135	-0.63	0.532	
Unemployed	0.000	0.139	0.00	0.998	
OcupOther	-0.057	0.132	-0.43	0.666	
SpecialDiet	0.057	0.071	0.81	0.418	
FatInt	-0.085	0.136	-0.62	0.533	
Vegetarian	-0.158	0.121	-1.31	0.191	
Satisfied	0.031	0.062	0.51	0.613	
VeryHappy	0.022	0.055	0.41	0.684	
SmallChildren	0.194	0.308	0.63	0.529	
HealthyFamily	0.022	0.049	0.45	0.652	
Healthy	0.030	0.055	0.55	0.585	
ProOrgHealth	0.095	0.063	1.52	0.129	
ProOrgTaste	0.006	0.056	0.10	0.920	
ProOrgSafe	0.036	0.060	0.60	0.549	
ProOrgFresh	0.085	0.056	1.51	0.130	
ProOrgAnWe	0.045	0.059	0.75	0.451	
ProOrgEnFr	-0.115	0.066	-1.75	0.080	*
ProOrgLocProd	0.095	0.055	1.74	0.081	*
ProOrgBuyOrg	-0.012	0.058	-0.22	0.829	
ProOrgNonGMF	0.108	0.056	1.93	0.053	*
ProOrgSupportOrg	-0.061	0.066	-0.94	0.350	

Table continuation on next page.

Table continuation

ChoiOrg	Coef.	St.Err	t-value	p-value	Sig.
ConOrgExpensive	-0.027	0.059	-0.47	0.641	
ConOrgNoTrust	0.007	0.054	0.13	0.894	
ConOrgNotAvail	0.018	0.060	0.30	0.761	
ConOrgNotRecon	-0.053	0.049	-1.08	0.279	
ConOrgNotVar	0.033	0.052	0.62	0.533	
ConOrgNotAttract	0.030	0.067	0.46	0.649	
ConOrgNotLong	-0.001	0.054	-0.02	0.981	
ConOrgNotAdvert	-0.029	0.053	-0.54	0.588	
ConOrgHabit	0.002	0.054	0.03	0.974	
ConOrgNotKnown	0.016	0.055	0.29	0.774	
ProEnvUnplug	-0.045	0.053	-0.85	0.394	
ProEnvSwiOff	0.045	0.108	0.41	0.678	
ProEnvTapOff	0.015	0.063	0.24	0.806	
ProEnvDonation	-0.052	0.054	-0.95	0.340	
ProEnvBuyRec	0.043	0.054	0.80	0.425	
ProEnvOwnBag	-0.083	0.095	-0.87	0.383	
ProEnvPolPrior	0.061	0.069	0.88	0.380	
ProEnvPubTransp	0.018	0.048	0.37	0.709	
ProEnvInsulation	-0.090	0.077	-1.17	0.241	
ProEnvRecycle	0.110	0.087	1.26	0.209	
HeaLifeImportant	0.109	0.095	1.15	0.251	
HeaFoodImportant	0.111	0.126	0.87	0.382	
HeaLifeExercise	-0.066	0.096	-0.69	0.493	
HeaLifeLessTV	-0.071	0.057	-1.25	0.212	
HeaLifeNoFastF	-0.065	0.059	-1.09	0.277	
HeaLifeLowFatSug	-0.038	0.052	-0.73	0.466	
HeaLifeUpsetFF	0.011	0.050	0.21	0.831	
HeaLifeNoFizzy	0.092	0.060	1.54	0.123	
HeaLifeNoSmoking	-0.133	0.087	-1.53	0.127	
HealthcareCost	0.016	0.060	0.26	0.793	
_cons	-2.116	0.209	-10.14	0.000	***
Mean dependent var	0.065	SD dependent var		0.246	
Pseudo r-SQuared	0.09	Number of obs		10824	
Chi-SQuare	467.41	Prob > chi2		0	
Akaike crit. (AIC)	4864.8	Bayesian crit. (BIC)		5353.2	

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

TABLE C.11: *Regression Results: C-logit 2 (behavioural interactions)*

	Reason	Interaction	Coef.	Sig.	St.Err	t-value	p-value
Pro-organic	ProOrgTaste	Quality	0.227	**	0.099	2.30	0.021
	ProOrgSafe	Less Chemicals	0.318	*	0.167	1.90	0.057
	ProOrgLocProd	Organic	0.399	**	0.186	2.14	0.032
	ProOrgHealth	Price	0.053	***	0.019	2.83	0.005
	ProOrgFresh	Quality	-0.237	**	0.107	-2.22	0.026
	ProOrgFresh	Price	0.077	***	0.020	3.85	0.000
Pro-environment	ProEnvUnplug	Less Chemicals	0.382	**	0.193	1.98	0.048
	ProEnvUnplug	Price	-0.057	***	0.021	-2.68	0.007
	ProEnvSwiOff	Quality	-0.741	***	0.219	-3.39	0.001
	ProEnvSwiOff	Price	0.097	**	0.040	2.41	0.016
	ProEnvRecycle	Price	0.066	**	0.027	2.41	0.016
	ProEnvPubTransp	Organic	-0.326	*	0.189	-1.72	0.085
	ProEnvPubTransp	Less Chemicals	-0.457	**	0.193	-2.37	0.018
	ProEnvPubTransp	AW	-0.321	**	0.148	-2.16	0.030
	ProEnvPubTransp	BB	-0.257	**	0.105	-2.44	0.015
	ProEnvPubTransp	Price	0.098	***	0.029	3.44	0.001
	ProEnvPolPrior	BB	0.436	***	0.133	3.28	0.001
	ProEnvPolPrior	Price	-0.086	***	0.023	-3.71	0.000
	ProEnvOwnBag	Quality	0.432	**	0.168	2.58	0.010
	ProEnvInsulation	Quality	0.351	**	0.144	2.43	0.015
	ProEnvDonation	AW	0.244	**	0.122	2.01	0.045
Healthy life	HeaLifeUpsetFF	BB	0.165	*	0.094	1.76	0.078
	HeaLifeNoSmoking	Price	-0.140	***	0.035	-4.03	0.000
	HeaLifeLowFatSug	Organic	-0.297	*	0.176	-1.69	0.091
	HeaLifeLowFatSug	BB	-0.279	***	0.100	-2.80	0.005
	HeaLifeLowFatSug	Price	0.056	***	0.020	2.71	0.007
	HeaLifeExercise	Quality	-0.536	**	0.209	-2.57	0.010
	HeaLifeExercise	Price	0.119	***	0.040	2.99	0.003
	HeaFoodImportant	Quality	0.815	***	0.239	3.41	0.001
	HeaFoodImportant	Price	-0.073	*	0.044	-1.66	0.096
Con-organic	ConOrgNotVar	Less Chemicals	0.449	***	0.160	2.81	0.005
	ConOrgNotVar	Quality	-0.181	*	0.093	-1.95	0.051
	ConOrgNoTrust	Quality	-0.381	***	0.095	-4.02	0.000
	ConOrgNotRecon	Quality	0.212	**	0.090	2.36	0.018
	ConOrgHabit	EF	0.250	***	0.085	2.94	0.003
Happy	VeryHappy	Price	0.072	***	0.021	3.48	0.000
	VeryHappy	AW	-0.250	*	0.134	-1.86	0.063
	Satisfied	Less Chemicals	-0.320	*	0.174	-1.84	0.065

chemical usage. Price again has a positive effect on three types of behaviour, but has negative effect on individuals who unplug their devices when not using them (protect the environment and save money), and those who believe that the environment should have policy priority. The former also place lower value on quality, which in contrast is more valuable for those who support insulation and those who use own bags when shopping. Another intuitive result is that people who donate have increased marginal utility from animal welfare attribute. Animal protection accounted for 25% of all donations in 2016 in the UK (UK-Fundraising, 2017), demonstrating this a central cause for our society.

For interactions of "healthy life' those who prefer low fat/sugar food, organic is not valued, nor longer expiry date. Also, respondents who stated that they do exercises do not value quality and have positive effect from price. The results from these two groups are counter-intuitive, however individuals that think that healthy food is important have the highest utility from quality, which one might expect. Lastly, those who are upset when eating fast food value longer expiry data. Other health related attributes are not significant within 'healthy life' behaviour. The hypothetical bias treatment might have an effect on this, but further analyses are made in section 4.3.2.

People who are against organic because they do not trust the label, or because organic lack variety, have less utility from quality attribute. The latter is also more averse to chemical usage, which indicates that might not be aware that organic is associated with lower chemical usage, which indicate that there might be an issue with information gap. Similarly, individuals who are con-organic because of habit have shown positive impact from environmentally friendliness attribute. Lastly, those who do not recognise organic have a positive effect from quality, altogether in this group to support the opportunities for more information or better labelling, especially for socially desirable attributes.

The last behavioural insight involves happiness and life satisfaction. Respondents who stated that they are satisfied with their lives lately have a negative impact from low chemical usage. Meanwhile, those who stated to be very happy do not value animal welfare as much, and are less sensitive to price, being more likely to buy more expensive products.

The number of significant interactions by product label are shown in table C.12.

Therefore, price is the most significant factor affecting respondents across the various behavioural insights (11 times). Quality is the second most frequent interaction (10), at least 2.5 times chemical usage and best before. This is relevant because the attribute coefficients

TABLE C.12: *Significant interaction terms*

Attribute	Interactions
organic	3
chemicalusage	4
environmentallyfriendly	1
animalwelare	2
bestbefore	4
quality	10
price	11
Total	35

show the average marginal effect on the rest of the population, but this information is complementary to the potential proportion of the population affected by the variable. As an example, organic food is suggested to provide higher marginal utility (or implicit price), but only a small proportion of the population afford to buy it. Similarly, most individuals would be expected to have their utility affected by the quality of the product.

Appendix D

Appendix for Chapter 5

D.1 Nested Logit

Following Hensher, Rose, and Greene (2005), Espino, Dios Ortúzar, and Román (2007) and Train (2009), in the MNL model, μ_R and μ_S are inseparable from the attributes parameters and not possible to be identified. However, NL allows for possible differences in scale. The probability of choosing alternative i in nest SP is given by:

$$P_{in} = \frac{exp(V_{in}/\lambda^S)[\sum_{j \in SP} exp(V_{jn}/\lambda^S)]^{\lambda^S - 1}}{\sum_{d \in SP,RP}[\sum_{j \in d} exp(V_{jn}/\lambda^d))]^{\lambda^d}} \tag{D.1}$$

Where λ is the scale parameter and λ^d is the inclusive value, i.e. degree of independence in unobserved utility from alternatives within nest $d(d = SP, RP)$. As illustration, if $\lambda^d = 1$ for all d, then NL would be equal to MNL. The inclusive values are the inverse of the respective nest scale parameters, i.e. $\lambda^S = 1/\mu_S$ and $\lambda^R = 1/\mu_R$. The NL model estimates the inclusive values, thus providing values for the scale parameter (μ_S/μ_R) and the variance of the non-observed component (σ_R^2/σ_S^2).

A similar approach to deal with inconsistencies between RP and SP data is to use latent class (LC) estimations. Jeon and Herriges (2017) segmented the data into two groups, the first group (class C) they had RP and SP observations that were consistent, and the second group (class IC) had inconsistent responses. The class membership, however, is unknown to the researcher.

The overall likelihood function is given as:

$$\mathcal{L}(\theta) = s\mathcal{L}_i^C(\theta^C) + (1-s)\mathcal{L}_i^{IC}(\theta^{IC}) \tag{D.2}$$

Where $s \in [0, 1]$ is the probability of an observation being in the consistent class and $\theta \equiv (\theta^C, \theta^{IC}, s)$ is the set of parameters. After identifying the factors influencing the inconsistency, these can be accommodated.

Alternatively, Brooks and Lusk (2010) allowed for differences in error variance across the RP and SP data sets, and controlled for scale differences. In their model, the SP scale μ_S was set to 1, and the RP scale μ_R was estimated from the error variance relative to the SP data. The pooled log-likelihood maximisation function is given by $LLF^{pooled} = LLF^{RP} + LLF^{SP}$, conditional on the parameters of price and the attributes of interest are equivalent across the two samples, i.e. $\beta_R = \beta_S$.

TABLE D.1: *Joint Estimation Results - CLHet (Scale Parameter = SP)*

	CLHet		CLHet-Interactions	
VARIABLES	Coef	WTP	Coef	WTP
Price	-0.548***		-0.560***	
	(0.008)		(0.017)	
Volume	-1.436***	-2.62***	-0.761***	-1.36***
	(0.042)	(0.16)	(0.029)	(0.13)
Organic	0.078	0.14	2.417***	4.31***
	(0.177)	(0.63)	(0.521)	(1.83)
AnimalWelfare	0.739***	1.35***	0.761***	1.36***
	(0.115)	(0.41)	(0.115)	(0.40)
Quality	1.417***	2.58***	0.790***	1.41***
	(0.101)	(0.35)	(0.178)	(0.61)
LowChemicalUsage	-0.579***	-1.06***	-0.493**	-0.88**
	(0.214)	(0.76)	(0.213)	(0.75)
EnvFriendly	0.564***	1.03***	0.432***	0.77***
	(0.102)	(0.36)	(0.100)	(0.35)
Healthy	-0.438	-0.80	-0.376	-0.67
	(0.836)	(2.99)	(0.837)	(2.93)
Offer	-0.150***	-0.27***	-0.221***	-0.39***
	(0.023)	(0.08)	(0.023)	(0.08)
sqSP	-5.151***		-5.019***	
	(0.271)		(0.278)	
sqRP	-3.043***		-2.808***	
	(0.043)		(0.041)	
AgeOrganic			-0.048***	
			(0.010)	
UnemployedQuality			0.955***	
			(0.291)	
IncomeQuality			0.133***	
			(0.038)	
IncomePrice			0.010***	
			(0.003)	
SP	-0.940***		-0.873***	
	(0.068)		(0.072)	
Observations	72,263		66,996	

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

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