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United Kingdom Lamb consumer consumption behaviours and product preferences: A Latent Class Analysis of New Zealand lamb

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Research Report No. 380
August 2022

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and environmental issues.***

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Suggested citation for this report:

Tait, Peter, Caroline Saunders, Paul Dalziel, Paul Rutherford, Timothy Driver and Meike Guenther (2022). *United Kingdom lamb consumer consumption behaviours and product preferences: A Latent Class Analysis of New Zealand lamb*. AERU Research Report No. 380, prepared for Unlocking Export Prosperity Research Programme. Lincoln University: Agribusiness and Economics Research Unit.

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ISSN 1170-7682 (Print)
ISSN 2230-3197 (Online)
ISBN 978-1-99-103524-0 (Print)
ISBN 978-1-99-103525-7 (Online)



Acknowledgments

This research report has been prepared as part of the research programme *Unleashing Export Prosperity*, funded by the Ministry of Business, Innovation and Employment (LINX1701).

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Key Points

- The Agribusiness and Economics Research Unit (AERU) at Lincoln University with the support of research partners under the *Unlocking Export Prosperity from the Agri-food Values of Aotearoa New Zealand* research programme has estimated willingness-to-pay (WTP) values for selected credence attributes of lamb by United Kingdom consumers, with a focus on identifying preferences for attributes considered *distinctively New Zealand*.
- Preferences for many of the credence attributes considered here are not readily observable from market prices and so the non-market valuation method of Discrete Choice Experiments was used. This involved an online survey of UK residents in August 2021, using a research panel.
- As well as WTP values, this survey reports on:
 - Purchase frequency by lamb cut, and by country-of-origin
 - Prices paid by lamb cut type
 - Country-of-origin quality ranking
 - Lamb attribute importance
 - Use of digital media and smart technologies related to lamb
- Looking at how often consumers purchase different lamb cuts shows that mince, sausages, and chops have some of the highest weekly purchase frequencies. However, over a third of respondents have never purchased lamb sausages. The highest average price usually paid was for lamb leg at £9/kg and was purchased at least monthly by 73 per cent of respondents. Looking more closely at prices usually paid for lamb leg shows that 50 per cent of respondents usually pay between £6/kg and £11/kg, and about ten per cent of consumers pay £15/kg or more. The majority of expenditure on lamb products was through supermarkets (46 per cent) and butchers (19 per cent).
- Many respondents purchase New Zealand lamb, with two thirds purchasing NZ lamb at least occasionally, and NZ having the second highest country-of-origin purchase frequency overall, behind lamb raised in England. Just ten per cent of respondents had never purchased New Zealand raised lamb.
- Consumers were asked to rank the quality of lamb produced by eight country-of-origins in-market. New Zealand was ranked first by 27 per cent of consumers, while Spanish and French lamb were more often ranked last than other countries. Looking at the number of times each country is ranked in the top three revealed that 61 per cent of respondents ranked New Zealand within the top three, and practically the same as Welsh lamb (62 per cent), with just English lamb ranked higher (71 per cent).
- Consumers were asked to rate the importance of a set of lamb characteristics in their purchase decisions. Overall, it is important to consumers that lamb tastes good, is safe to eat, and exhibit natural farming practices, including the treatment of animals.
- Many consumers use mobile devices to search for information about beef products (47 per cent), and to make beef purchases (30 per cent). Respondents were asked which mobile apps they currently used for lamb related purposes, and which apps they were interested in using. While current use of mobile apps is relatively low, there is an indication of strong interest

across a variety of potential uses. Access to discounts/coupons, and dietary information are the most popular reason for respondents currently using mobile apps (15 per cent). 30 per cent of consumers purchase lamb products online. These consumers are spending, on average a quarter of their budget online, mainly because they like avoiding having to go into store, and being able to order products from overseas that are better, or not available domestically.

- The survey included a Discrete Choice Experiment to assess the willingness-to-pay by consumers for different attributes associated with lamb leg. Using a Latent Class Modelling approach, the consumers were segmented into 3 classes, each with different characteristics and preferences.
- The results demonstrate significant preference differences between consumer segments. The first segment is the largest of the three consumer groups. They have a broad set of considerations, but their preferences focus on environmental and animal health attributes. They have the highest WTP for these claims of the three segments. Consumers in this segment are more likely to be environmentally engaged, have higher usual spending on lamb, try to make purchases that minimise environmental harm, and be relatively younger.
- Consumers in the second segment also have significant preferences for environmental claims, but importantly that have the highest WTP for Māori farmed lamb of the three segments. Of the three segments, these consumers are more open to cultural experiences outside their own and have higher awareness of Māori culture. The third segment of consumers preferences focus on attributes which could be considered as representing natural farming systems, including no added hormones or antibiotics, pasture-raised, and GM-free feed. They value a 100% grass-fed claim the most, and highest of the three segments. These consumers are more likely to be relatively older, have higher NZ lamb purchase frequency, and to rank NZ lamb quality highly. The average respondent's willingness-to-pay across the three consumer segments is presented in the following table.

Lamb Attribute	Segment 1 Environmentally Engaged 49% of consumers	Segment 2 Cultural Consumers 32% of consumers	Segment 3 Natural Necessary 19% of consumers
No added antibiotics	17% (2%, 33%)	9% (6%, 13%)	12% (4%, 20%)
No added growth hormones	15% (-3%, 34%)		12% (3%, 22%)
Enhanced Animal Welfare	32% (1%, 64%)		11% (4%, 18%)
Māori farming system	13% (1%, 24%)	17% (11%, 23%)	
Organic farming system	15% (1%, 30%)	5% (2%, 9%)	
Water Quality Protection	9% (1%, 17%)	5% (0%, 9%)	
100% Pasture Raised	23% (0%, 46%)	4% (1%, 7%)	15% (9%, 21%)
Biodiversity Enhancement	29% (-2%, 59%)	22% (4%, 38%)	
Carbon Neutral	33% (-2%, 69%)	18% (3%, 33%)	
No GM Feed	9% (1%, 18%)		15% (7%, 23%)
100% Grass Fed	20% (-1%, 41%)		27% (18%, 37%)

Average WTP per kg lamb leg. 95% Confidence Intervals in brackets.

Chapter 1

Introduction

This study is part of a research programme entitled *Unlocking Export Prosperity from the Agri-food Values of Aotearoa New Zealand*. It is funded by the Ministry of Business, Innovation and Employment (MBIE) Endeavour Fund for science research programmes. Information on this research programme including reports of other surveys is available from the AERU website <https://www.aeru.co.nz/projects/uep>.

The research aims to provide new knowledge on how local enterprises can achieve higher returns by ensuring global consumers understand the distinctive qualities of the physical, credence, and cultural attributes of agri-food products that are “Made in New Zealand”.

Agricultural exports are an important contributor to the New Zealand (NZ) economy and the United Kingdom (UK) is established as an important lamb product destination. It is critically important for NZ exporters to understand export markets and the different cultures and preferences of those consumers to safeguard market access, and for realising potential premiums.

This report describes the application of a survey of UK lamb leg consumers that is designed to examine consumption behaviour and consumer Willingness-to-Pay (WTP) for credence attributes. While *search attributes* such as price or colour can be observed directly, *experience attributes* such as flavour or texture can be assessed when consumed, *credence attributes* such as environmental sustainability cannot be immediately seen or experienced at the point of sale. For products promoting credence attributes, the role of verification, including labelling, is of significant importance.

Our approach is to apply a Discrete Choice Experiment economic valuation method, analysed using a statistical approach called Latent Class Modelling that describes profiles for different consumer segments identified in the data and provides estimates of attribute WTP across these segments.



Chapter 2

Lamb Survey Method

To understand how consumers value NZ credence attributes this study used a structured self-administered online survey that included the Discrete Choice Experiment, conducted in the UK in July 2021. The survey was administered through Qualtrics™, a web-based survey system, and focused on lamb consumers with purchase frequency of at least monthly.

The survey was developed by the research team, drawing from a literature review on consumer trends for animal proteins, results from previous surveys examining consumer attitudes in overseas markets including the UK, and consultation with industry partners and stakeholders, especially those on the AERU advisory board.

Sampling involved recruiting participants from an online consumer panel database provided by an international market research company (dynata.com). Panel members are recruited by online marketing across a range of channels and panels are profiled to ensure adequate representativeness. Panels are frequently refreshed, with the participation history of members reviewed regularly. Respondents for each survey are compensated with a retail voucher for completing a survey.

2.1 Using Discrete Choice Experiments to examine consumer preferences

Discrete Choice Experiments are a survey-based valuation approach that have been widely used to value consumer preferences for food product attributes. They are particularly useful for examining the role of new attributes, and attributes that are not easily observable in market prices, such as the attributes explored in the current report. The ability of this method to identify which individual attributes are more important in consumer choices, and to estimate consumers WTP for these, has seen this approach to valuation become increasingly favoured by researchers.

Designing a Discrete Choice Experiment survey involves deciding which product attributes are of interest, combining these into different product offerings, and asking consumers to pick which offering they prefer from a range of alternatives. In this study, alternative lamb leg products are described by production practices and price (Table 2-1). Attribute selection was primarily informed by previous surveys, including scoping surveys that used a combination of open text and structured questions to identify which attributes UK consumers considered distinctive of NZ lamb.

Table 2-1 Lamb attribute descriptions used in the Discrete Choice Experiment

Lamb attributes		Attribute descriptions
Lamb attributes	Organic	The lamb may be labelled showing if production is Organic. Pasture is managed without using artificial fertilisers and pesticides. No added hormones, antibiotics or animal by-product supplementation including in or on the food they eat.
	Environmental Sustainability	The lamb may be labelled showing if production employs a management system that is either Carbon Neutral, Enhances Biodiversity, or Protects Water Quality.
	Enhanced Animal Welfare	The lamb may be labelled showing if production employs a management system that is above minimum welfare standards.
	Animal Housing	The lamb may be labelled as being pasture raised where they are allowed to range free.
	Animal Feed	The lamb may be labelled as being 100% grass-fed or fed with GM-free feed. Grass-fed lamb is lower in calories, contains more healthy omega-3 fats, vitamins A and E, beta-carotene and antioxidants.
	Māori Production	The lamb may be labelled as being produced on Māori farms. Māori, New Zealand's indigenous people, produce 30% of NZ lamb. Like other indigenous people, they see themselves as belonging to the land. Māori seek to maintain and protect the health of their land for the welfare of current and future generations, and so to produce food that supports the health and wellbeing of their customers.
	Production Additives	The lamb may be labelled as being raised without added hormones or antibiotics.
	Price	The lamb is labelled with the price per kg.



Changes in lamb leg attributes are described using the levels in (Table 2-2). Price levels were determined by market prices, and from what scoping survey respondents said that they usually paid.

Table 2-2 Lamb attribute levels used in the Discrete Choice Experiment

Lamb attributes	Attribute levels			
Animal Housing	No Label	100% pasture raised		
Enhanced Animal Welfare	No label	Certified		
Farming System	Conventional	Organic	Māori	
Animal Feed	No label	100% Grass-fed	No GM feed	
Production Additives	No label	No added hormones	No added antibiotics	
Environmental Sustainability	No Label	Carbon Neutral	Biodiversity Enhancement	Water Quality Protection
Price £/kg lamb leg	£7	£12	£13	£19

An example of alternative product offerings presented to respondents is shown in Figure 2-1. Each set of offerings comprises three options, of which respondents chose their preferred one. Two options present alternative lamb leg product, while the third is a ‘none of these’ option. Each respondent answered ten choice sets. Product choices are statistically analysed using Latent Class Models to identify consumer preferences for each product attribute and to estimate consumers’ WTP for each attribute. A more detailed description of the theoretical foundation and statistical procedure of Discrete Choice Experiments can be found in Appendix A: Statistical Method.

Set 1 of 10 Given the information that is provided, **which of the following New Zealand grown lamb leg products do you prefer?**

Mark your choice using the buttons below, and please bear in mind the price that is associated with your choice and how that would fit into your budget. [More Info](#)

	Lamb Leg A	Lamb Leg B	
Farming System	Māori	Organic	
Environmental Sustainable	Carbon Neutral	Biodiversity Enhancement	
Enhanced Animal Welfare	Enhanced Animal Welfare		
Production Additives		No added antibiotics	
Animal Housing		Pasture Raised	
Animal Feed		No GM feed	
Price £/kg	£7/kg	£19/kg	
Selection:	<input type="radio"/>	<input type="radio"/>	<input type="radio"/> I would choose a different lamb leg product

Figure 2-1 Example of a Discrete Choice Experiment question shown to respondents

Chapter 3 Survey Results

3.1 Sample demographic description

- The sample comprised a wide range of demographics, which is important to ensure that the sampling process has broadly canvassed the relevant population (Figure 3-1).
- It is important to note that we are not attempting to represent the overall UK population, but rather those that purchase lamb leg at least monthly.

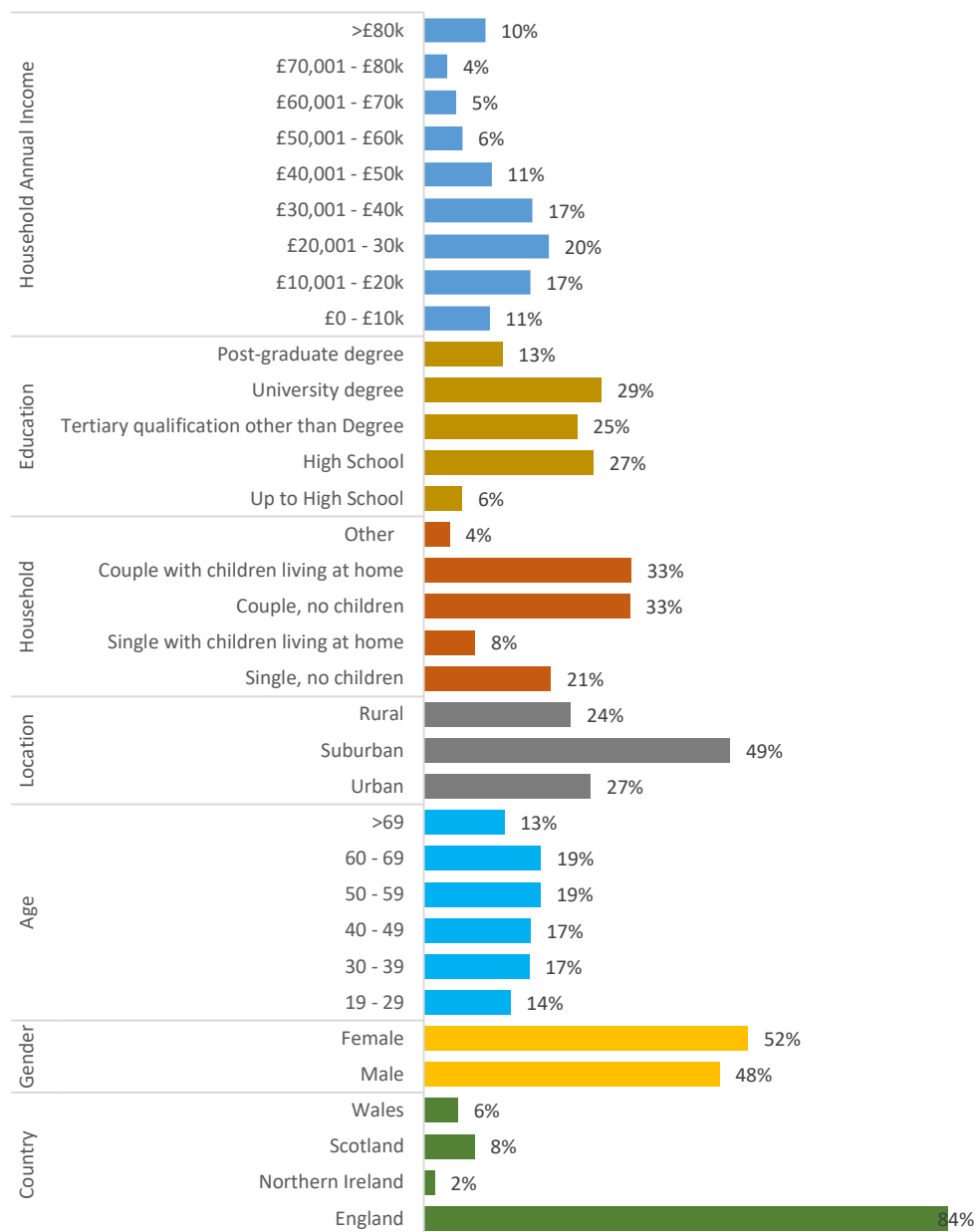


Figure 3-1 Sample demographics

3.2 Purchase and Consumption Behaviours

3.2.1 Purchase frequency by lamb cut

- Looking at how often consumers purchase different lamb cuts shows that mince, sausages, and chops have some of the highest weekly purchase frequencies. However, over a third of respondents have never purchased lamb sausages (Figure 3-2).

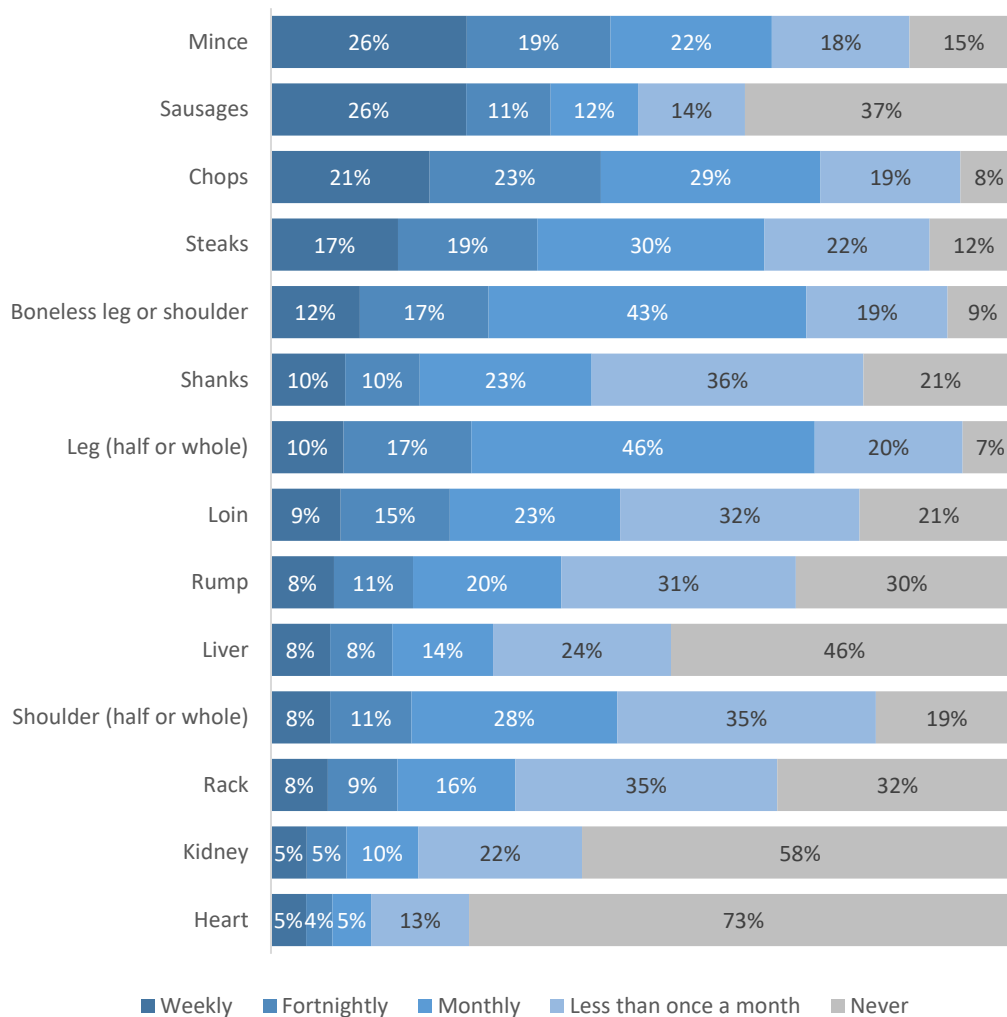


Figure 3-2 Lamb cut purchase frequency

3.2.2 Usual prices paid for lamb cuts

- Looking at how prices paid vary over the different lamb cuts shows that the highest average prices were paid for lamb leg, with the lowest for liver (Figure 3-3).
- A closer inspection of the prices usually paid for lamb leg shows that fifty percent of respondents usually pay between £6/kg and £11/kg, and about ten per cent of consumers pay £15/kg or more (Figure 3-4).

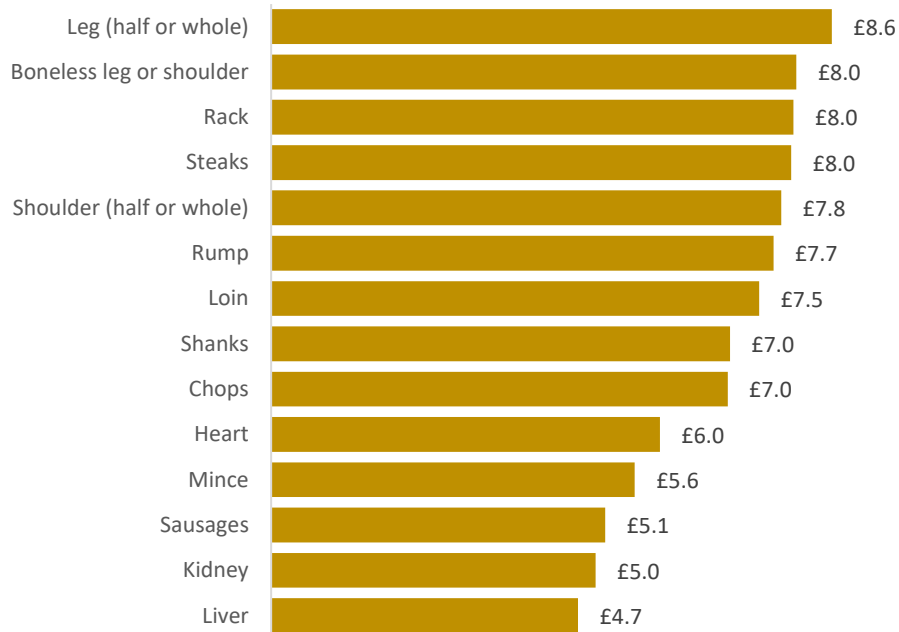


Figure 3-3 Average price usually paid by lamb cut £/kg

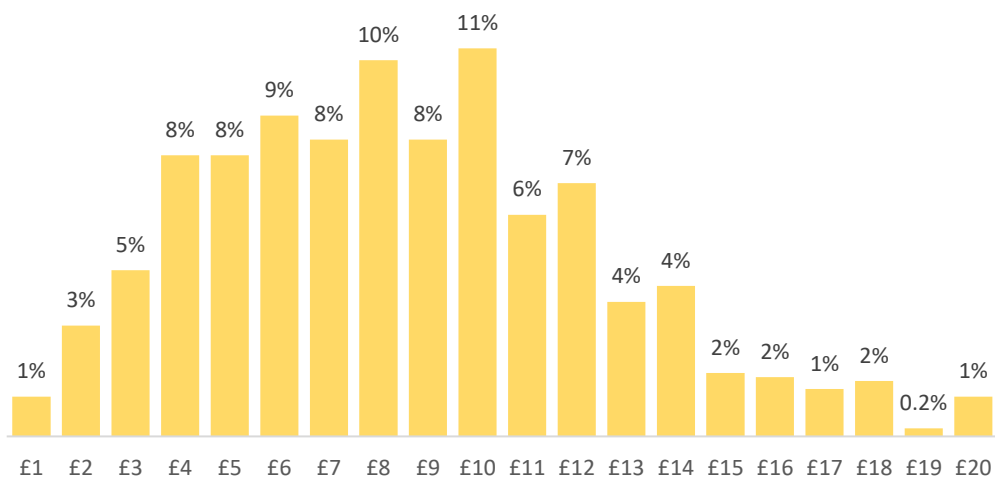


Figure 3-4 Range of prices usually paid for lamb leg £/kg

3.2.3 Country-of-origin purchase frequency

- New Zealand has the second highest country-of-origin purchase frequency overall behind lamb raised in England (Figure 3-5). Just ten per cent of respondents had never purchased New Zealand raised lamb.

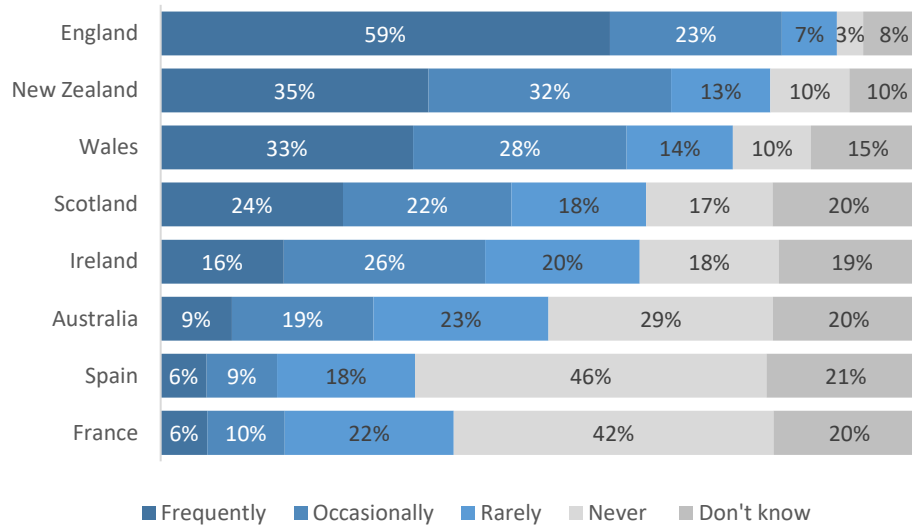


Figure 3-5 Country-of-origin purchase frequency

3.3 Perceptions of lamb quality, and important purchase characteristics

3.3.1 Country-of-origin quality ranking

- Consumers were asked to rank the quality of lamb produced by country-of-origin (
- Figure 3-6). We see that NZ is ranked first by 27 per cent of consumers, while Spanish and French lamb are more often ranked last than other countries.

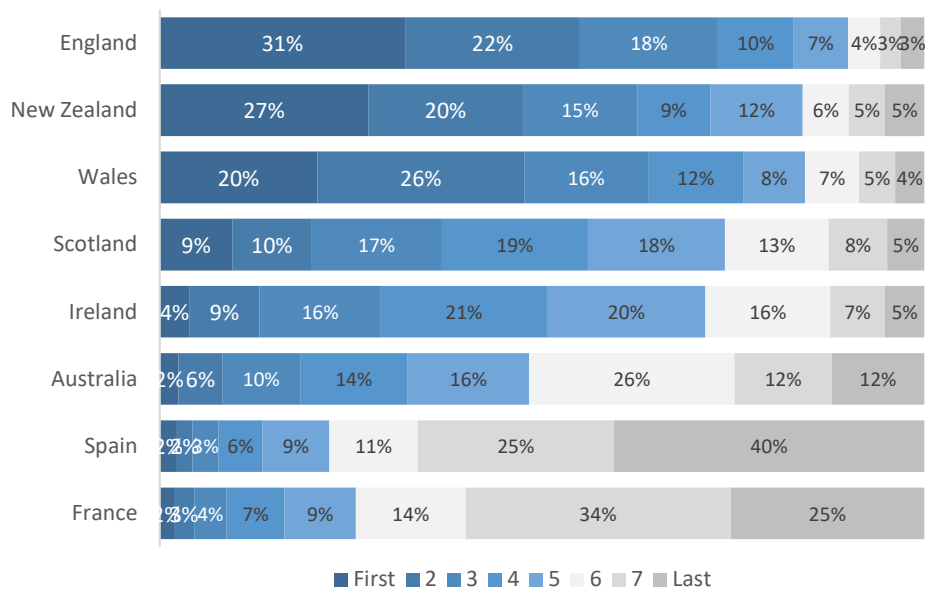


Figure 3-6 Country-of-origin quality ranking

- Looking at the number of times each country is ranked in the top three by each consumer shows that 61 per cent of respondents ranked New Zealand within the top three and practically the same as Welsh lamb (Figure 3-7).

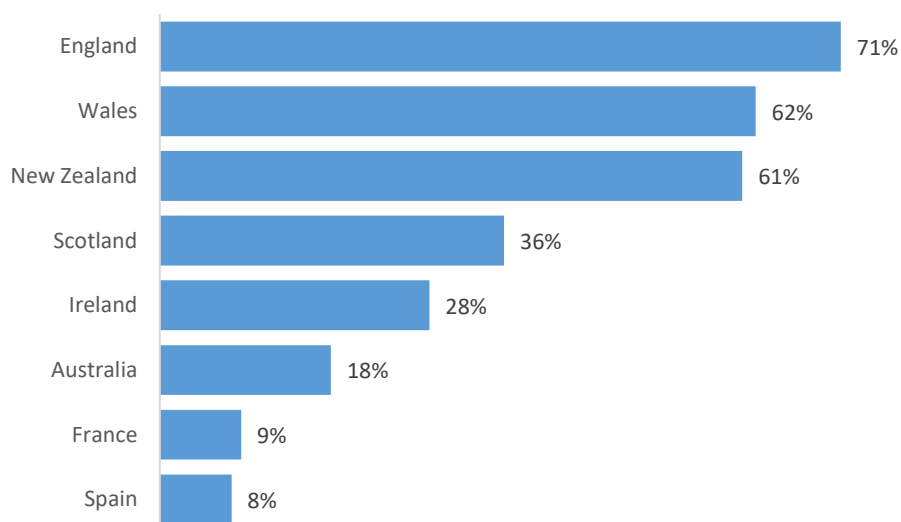


Figure 3-7 Top three country-of-origin quality ranking

3.3.2 Important of lamb characteristics in purchase decisions

- Consumers were asked to rate the importance of a set of lamb characteristics in their purchase decisions. Overall, it is most important to consumers that lamb tastes good, is safe to eat, and exhibit natural farming practices including the treatment of animals (Figure 3-8).

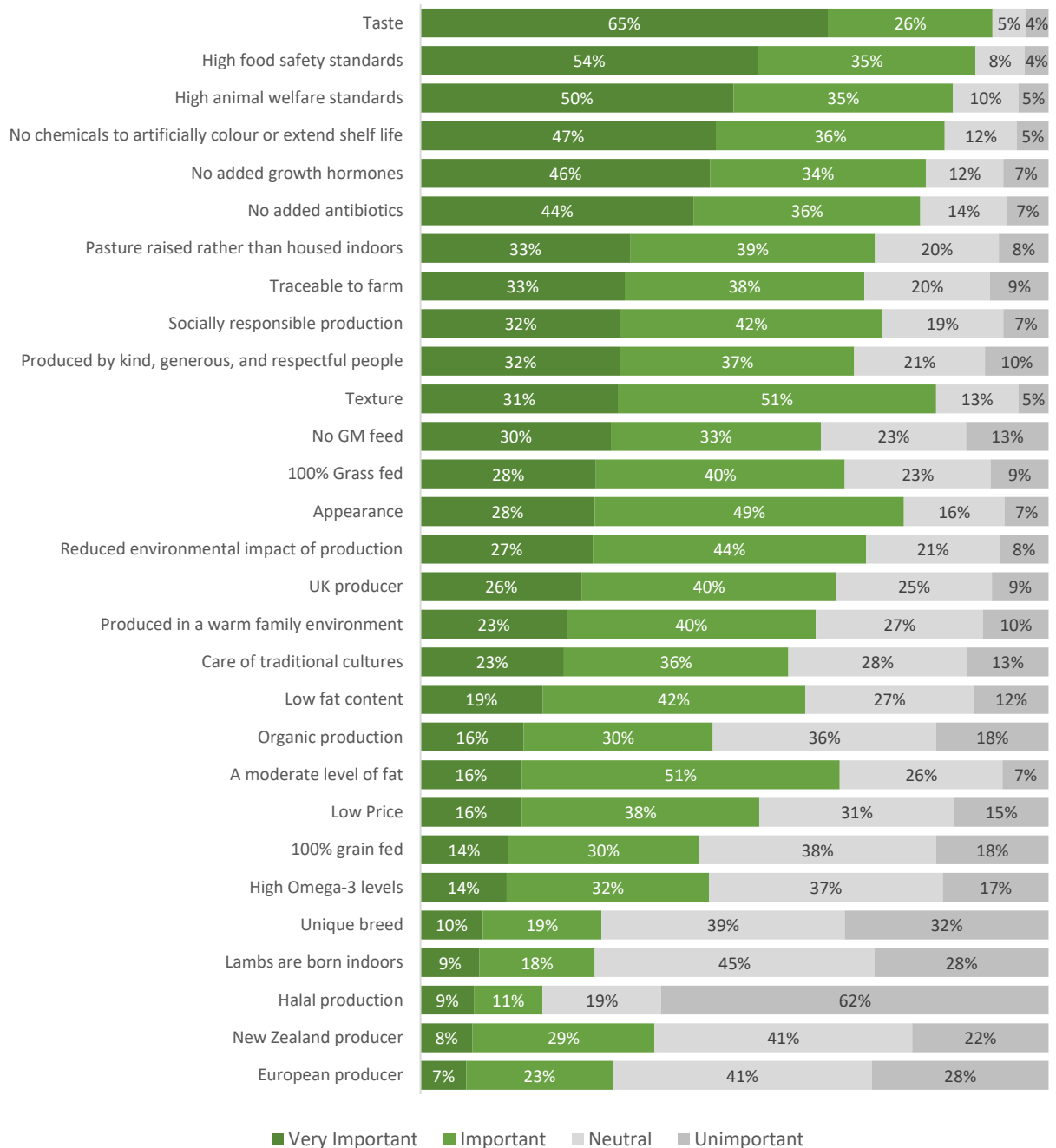


Figure 3-8 Importance of lamb product attributes when purchasing

3.4 Use of smart technology and digital media for lamb shopping

3.4.1 Internet access by device and use

- Consumers were asked how often they used the internet to help decide which lamb products to buy. We can see that use was consistent across home computers and mobile devices with about 40 per cent of respondents using the internet (Figure 3-9).

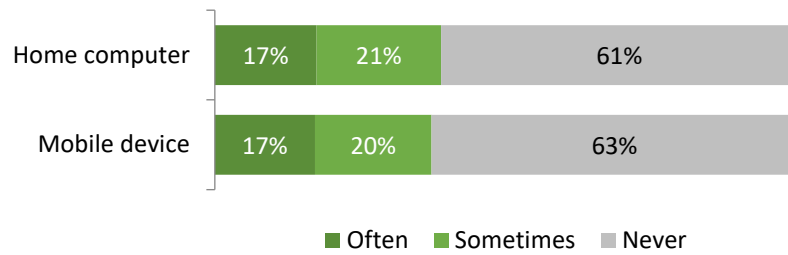


Figure 3-9 Use of internet to decide lamb purchase decision

- Focusing on mobile device use, nearly half of respondents stated that they use mobile devices to search for information about lamb, and almost a third use their mobile device to make lamb purchases (Figure 3-10).

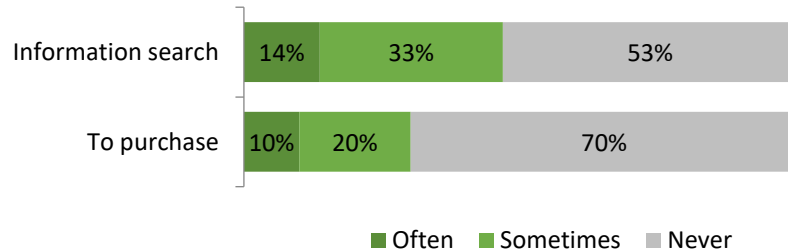


Figure 3-10 Use of mobile device for lamb info and purchases

3.4.2 Use of mobile device apps in relation to lamb

- Respondents were asked which mobile apps they currently used for lamb related purposes, and which apps they were interested in using (Figure 3-11). While current use of mobile apps is relatively low, there is an indication of strong interest across a variety of potential uses. Access to discounts/coupons and dietary information are the most popular reason for respondents currently using mobile apps.

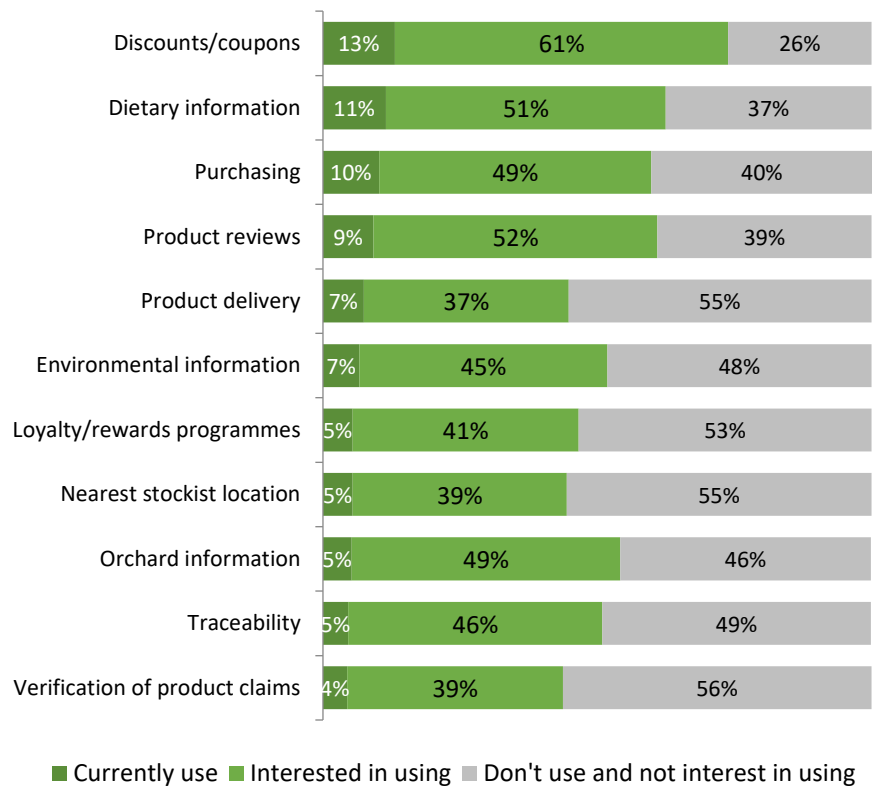


Figure 3-11 Reasons for using mobile apps for in relation to lamb

3.4.3 Lamb expenditure by purchase channel

- Respondents were asked to allocate their lamb expenditure according to their usual purchase channels (Figure 3-12). The graph below shows the average expenditure by channel.
- Almost half of expenditure occurs at supermarkets making this the most popular retail channel for lamb purchases.
- While online expenditure is relatively low at about seven per cent over domestic and international retailers, over 30 per cent of respondents purchased lamb online.

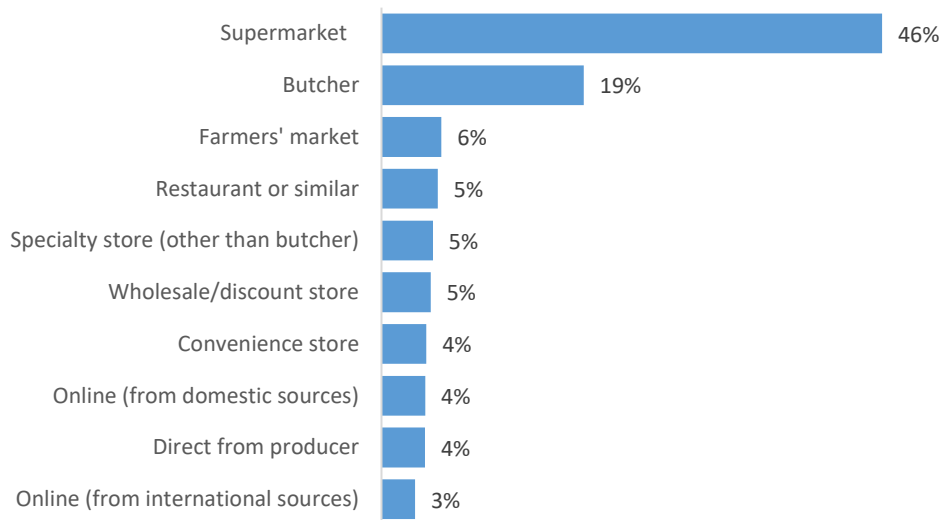


Figure 3-12 Percentage of lamb expenditure by retail channel

- Consumers who purchase lamb online spend on average, about a quarter of their lamb expenditure via this retail channel (Figure 3-13).

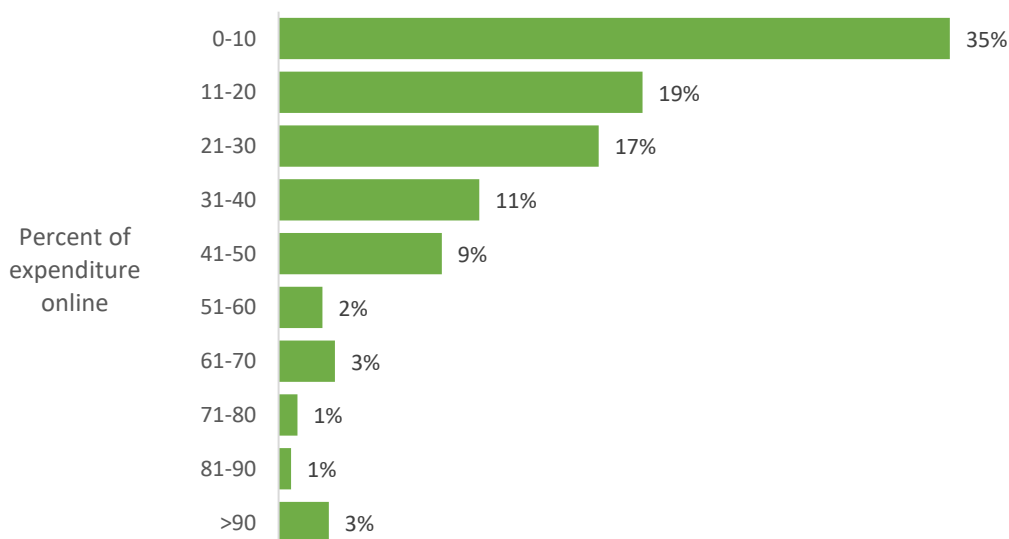


Figure 3-13 Distribution of online expenditures

- The main benefits of online shopping were avoiding having to go in-store, and access to products not available domestically (Figure 3-14).

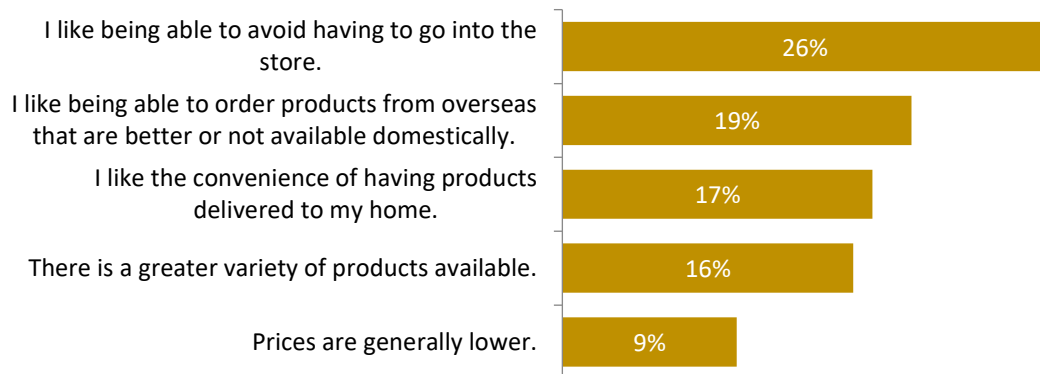


Figure 3-14 Main benefit of shopping online for lamb

3.5 Discrete Choice Experiment analysis of lamb choices

In this section we present findings of the Discrete Choice Experiment. Our aim is to identify which lamb leg attributes drive lamb choice, by how much, and by who. We do this by segmenting the sample of consumers into groups based on which product offerings they preferred using a Latent Class Modelling method (Appendix B). Discrete Choice Experiments can be somewhat more difficult to answer compared with the usual question formats that people have typically seen before, so it is important to check whether respondents have been able to complete the exercise reliably. Overall, task and attribute understanding were relatively high, and most respondents felt certain that their responses reflected real-world choices if these lamb leg products were available (Figure 3-15).

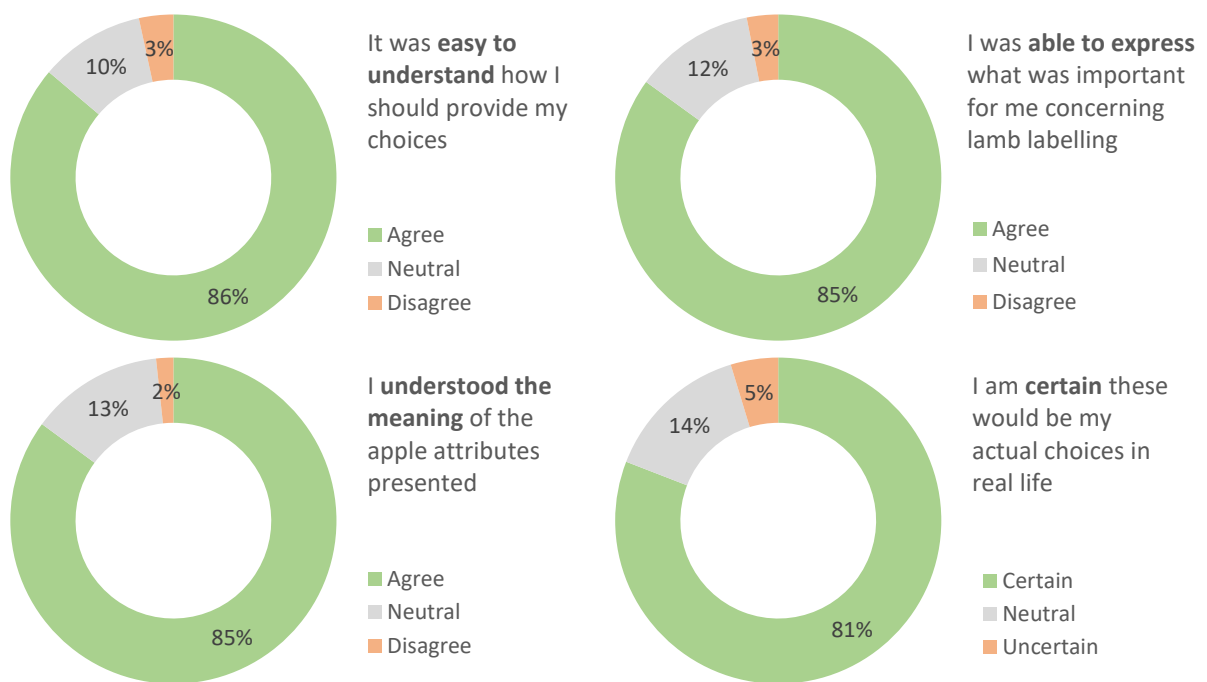


Figure 3-15 DCE task and attribute understanding, ability to express preferences, and choice certainty

3.5.1 Consumer willingness-to-pay values

Estimates of WTP tell us how much more the average consumer is willing to pay for a lamb leg with a particular attribute, over a lamb leg that does not have this attribute (Table 3.1, Figure 3-16). For example, consumers in the first segment are willing to pay, on average, £2.29/kg more for a lamb leg raised without added antibiotics over lamb that does not have this claim. There is some uncertainty in WTP estimates, and the Confidence Intervals reported in Table 3.1 indicate that we can be 95 per cent sure that the true average WTP falls within this interval, in this case between £0.24/kg and £4.35/kg.

We can see that three distinct consumer groups have been identified, the first has an estimated size of 49 per cent, the second group's size is 32 per cent and the third is 19 per cent. These segment sizes tell us the probability that a randomly selected UK lamb leg purchaser belongs to that consumer group.

Table 3-1 UK lamb leg attribute willingness-to-pay by consumer segment

Lamb Attribute	Segment 1 49% of consumers	Segment 2 32% of consumers	Segment 3 19% of consumers
No added antibiotics	£2.29*** (0.24,4.35)	£1.23*** (0.75,1.69)	£1.54*** (0.47,2.61)
No added growth hormones	£2.04*** (-0.34,4.44)		£1.65*** (0.44,2.86)
Enhanced Animal Welfare	£4.28*** (0.09,8.47)		£1.45*** (0.54,2.36)
Māori farming system	£1.68*** (0.18,3.18)	£2.30*** (1.52,3.07)	
Organic farming system	£2.05*** (0.17,3.94)	£0.72*** (0.21,1.22)	
Water Quality Protection	£1.13*** (0.08,2.19)	£0.64** (0.06,1.22)	
100% Pasture Raised	£3.03*** (0.01,6.04)	£0.56*** (0.14,0.98)	£2.04*** (1.24,2.84)
Biodiversity Enhancement	£3.78*** (-0.31,7.88)	£2.92*** (0.54,5.00)	
Carbon Neutral	£4.41*** (-0.29,9.12)	£2.35** (0.34,4.35)	
No GM Feed	£1.24*** (0.14,2.35)		£2.05*** (0.99,3.11)
100% Grass Fed	£2.64*** (-0.10,5.37)		£3.64*** (2.34,4.93)

Average WTP per kg lamb leg in £2021.

95% Confidence Intervals in brackets

***, **, * indicates statistical significance at 1%, 5%, 10% level.

United Kingdom Consumer Willingness-to-pay Segments

1. Environmentally Engaged

49% of consumers

This segment is the largest of the three consumer groups. They have a broad set of considerations but preferences focus on environmental and animal health attributes. They have the highest WTP for these claims of the three segments.

Consumers in this segment are more likely to:

- Have higher usual spend on lamb
- Try to make purchases that minimise environmental harm
- Be younger

2. Cultural Consumers

32% of consumers

These consumers have significant preferences for environmental claims but importantly that have the highest WTP for Māori farmed lamb of the three segments.

Consumers in this segment are more likely to:

- Have higher awareness of Māori culture
- Be more open to cultures other than their own

3. Natural Necessary

19% of consumers

These consumers preferences encompass attributes which could be considered as representing natural farming systems, they value a 100% grass-fed claim the most, and highest of the three segments.

Consumers in this segment are more likely to:

- Be older
- Have higher NZ purchase frequency
- Rank NZ lamb highly

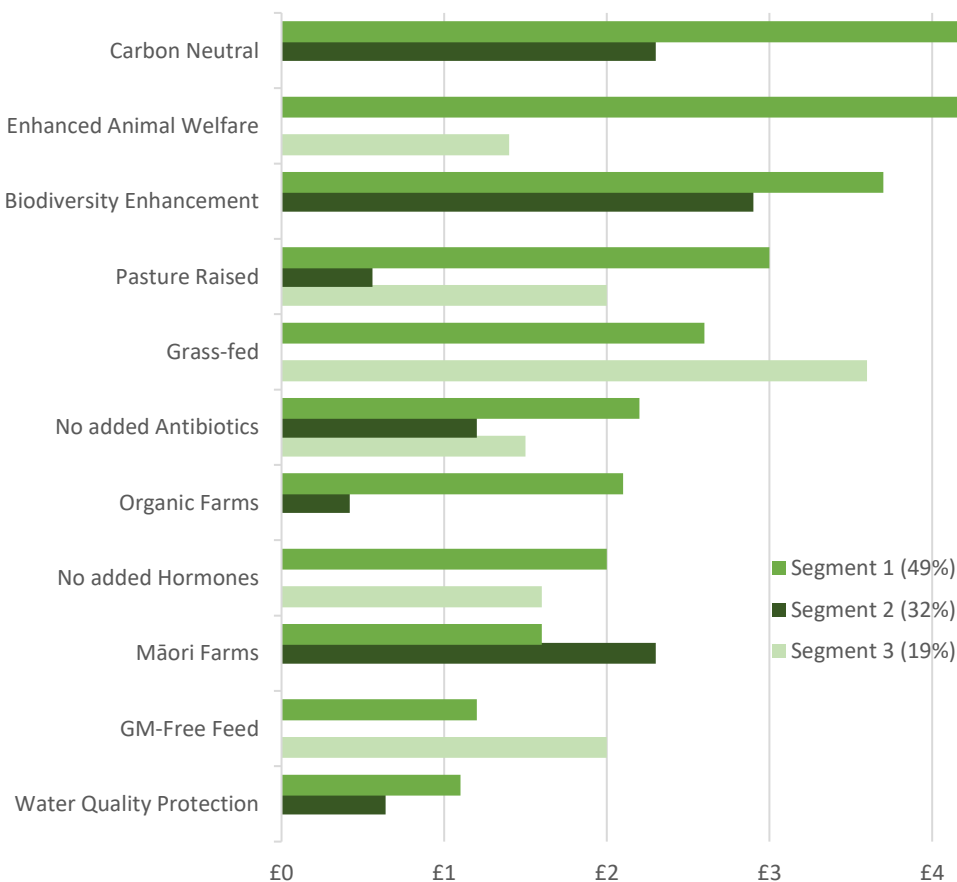


Figure 3-16 UK consumer willingness-to-pay for lamb attributes

To provide an indication of overall willingness-to-pay values, the individual segment values presented above are combined to form a weighted aggregate value (Figure 3-17 **Error! Reference source not found.**). These estimates are formed by weighting each willingness-to-pay value for each segment, by their segment size and summing across segments. These weighted values are then divided by the average price usually paid over the sample. What this shows is that:

- Consumers lamb choices can be significantly influenced by environmental claims
- Preferences for animal welfare claims are important
- Pasture-raised and grass-fed claims are important to many consumers

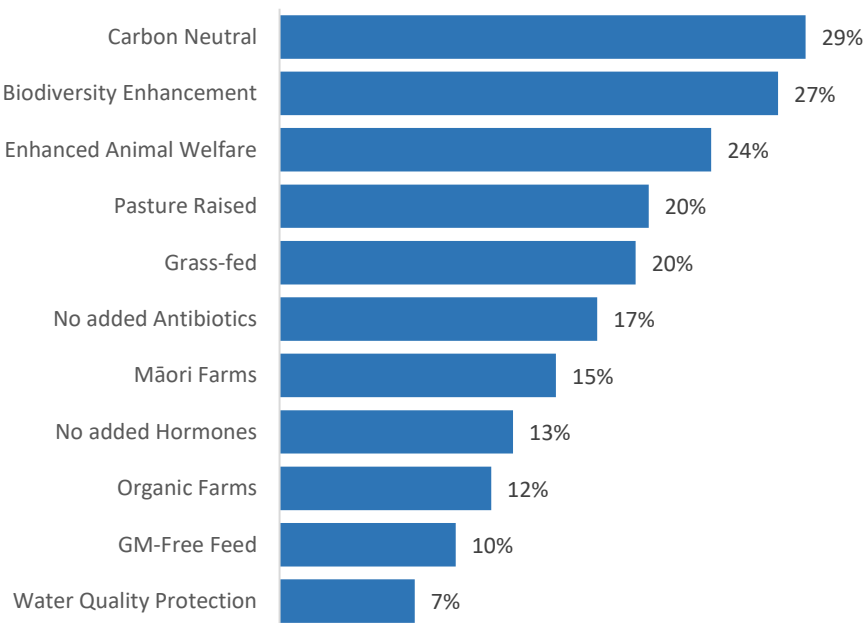


Figure 3-17 Weighted aggregate WTP as percent of average price paid

Chapter 4

Conclusions

This report presents the findings of a structured online survey of United Kingdom lamb leg consumers. The survey objective was to provide insights into consumers' purchase and consumption behaviours. The information gathered included examining perceptions of important drivers of product characteristics, the role of digital media and smart technologies, and consumer preferences for distinctively New Zealand credence attributes.

Overall, results clearly indicate that New Zealand lamb is held in high regard as a high-quality offering, with characteristics that consumers prefer and value. The statistical analysis of consumers' lamb leg choices using the Discrete Choice Experiment and Latent Class Modelling provides a robust analytical framework to identify consumer segments with differing characteristics and product preferences. Profiling high value consumers informs marketing strategy aimed at engaging consumers with highest willingness-to-pay for the product attributes that New Zealand can deliver.

This survey is the third in the research programme to survey UK lamb consumers with the first survey in 2019¹ and the second in 2020². The three samples are consistent on demographic measures, although relative to the 2020 and 2021 samples, the 2019 sample has a higher proportion of households without children, is older cohorts, and males. Comparing results found here to the previous surveys show that:

- Purchase frequency of different lamb cuts mainly unchanged, with sausages, mince and chops the top three in all three surveys.
- Average prices usually paid for different lamb cuts are stable across surveys, particularly for higher priced cuts. For example, lamb leg is £8.6/kg in 2019, £8.4/kg in 2020, and £8.6/kg in 2021. While for lower priced cuts we see a moderate level of variation, for example for the lowest priced cut liver was £3.9/kg in 2019, £5.02/kg in 2020, £4.7/kg in 2021.
- Purchase frequency by country-of-origin ordering is the same across the three surveys: England first, NZ second, then Wales third.
- Country-of-origin quality ranking inside the top three is unchanged across surveys: England first, NZ and Wales tied third equal.
- Ranking of important factors in purchase decision are consistent between surveys.
- Comparing estimates of consumer willingness-to-pay for lamb attributes in the Discrete Choice Experiment reveals some consistencies and significant changes over the three surveys (**Error! Reference source not found.**).

¹ Tait, Peter, Caroline Saunders, Paul Dalziel, Paul Rutherford, Timothy Driver and Meike Guenther (2020). *United Kingdom lamb consumer consumption behaviours and product preferences: A Latent Class Analysis*. AERU Research Report No. 362, prepared for Unlocking Export Prosperity Research Programme. Lincoln University: Agribusiness and Economics Research Unit.

² Tait, Peter, Caroline Saunders, Paul Dalziel, Paul Rutherford, Timothy Driver and Meike Guenther (2022). *United Kingdom lamb consumer consumption behaviours and product preferences: A Latent Class Analysis (2020)*. AERU Research Report No. 371 prepared for Unlocking Export Prosperity Research Programme. Lincoln University: Agribusiness and Economics Research Unit.

- A notable observation is that most attributes WTP estimates are reasonably consistent over the three surveys. Particularly relevant to New Zealand, we see that consumer preferences are stable for 'Pasture Raised' and 'Grass-fed' production claims, remaining highly valued attributes by UK consumers. Similarly, preferences for 'No added antibiotics' 'No added hormones' and 'Organic' have been consistent across both surveys.
- WTP for Several attributes went up in the 2020 round from what was observed in 2019, and then dropped in 2021 to levels more consistent with initial 2019 estimates. These are 'Water Quality protection', 'GM-free Feed', and 'Māori farming system'.
- Consumer preferences that have seen a significant increase in WTP in the 2021 survey round include 'Carbon Neutral', and 'Biodiversity Enhancement'. Both of these environmental attributes were not significant in respondents lamb choices in the 2019 round, and played only a minor role in 2020.

At the time of the first survey in December 2019, the COVID-19 pandemic had not reached the UK. The pandemic officially started in the UK in March 2020 when the first confirmed case was recorded. By the time the second survey was conducted in April 2020, the seven-day average death rate was approaching 1,000 people. And when the third round of surveying was undertaken in August of 2021, that rate was sitting at round 100 people. Each phase of the pandemic has created a range of influences on consumers, and has affected changes in consumer food and eating behaviours. Some of the changes in WTP between 2019 and 2021 estimates may be attributable to these factors. Initially, consumers exhibited some panic buying and stockpiling behaviours which saw consumer demand for foods become less responsive to prices. Therefore, the jump in higher WTP from 2019 to 2020 could be at least partially attributable to this effect. Some of that behaviour had softened by the time the 2021 survey was completed, contributing to the falling back of WTP estimates that we see here.

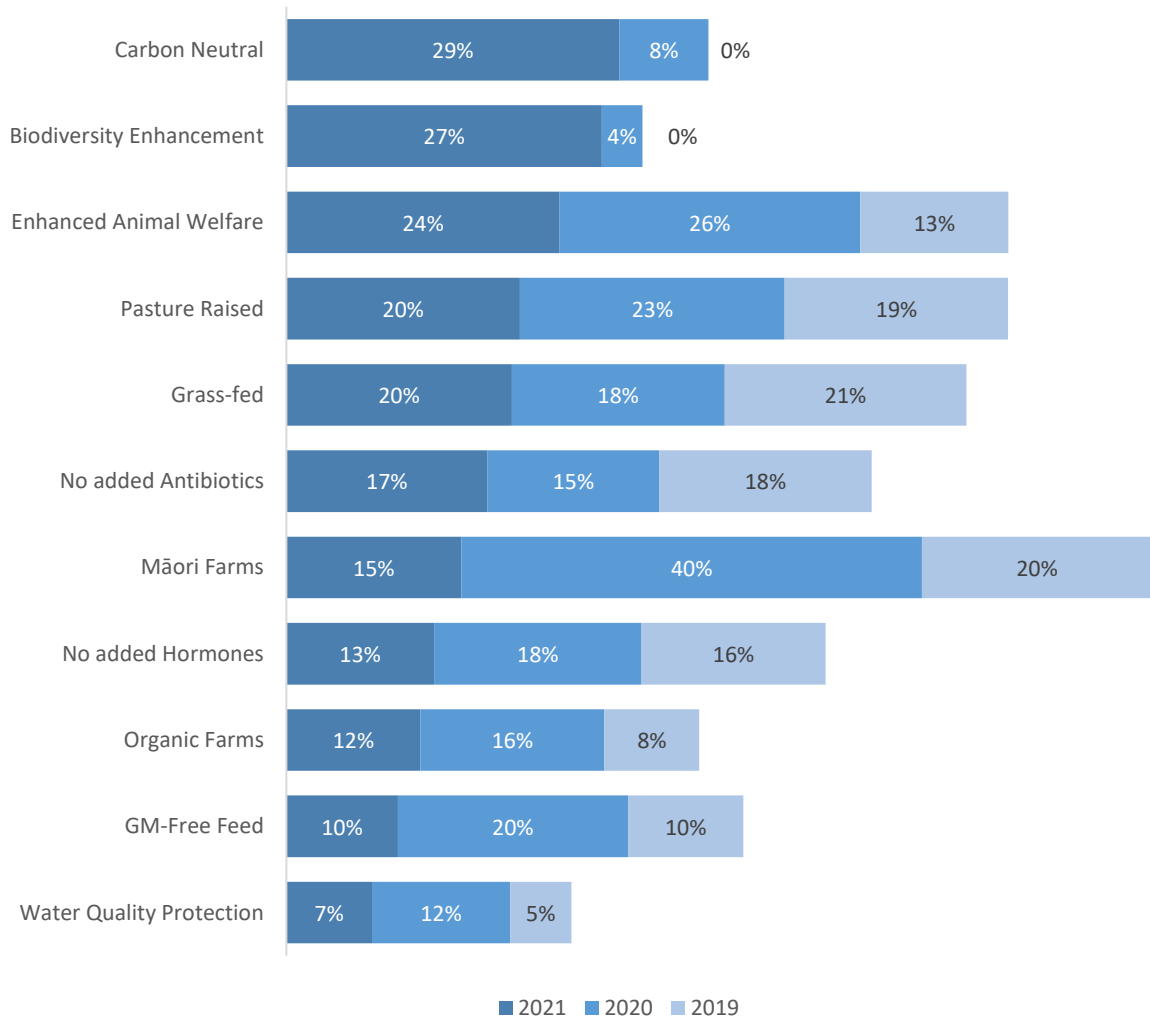


Figure 4-1 Comparing 2021 and 2019 WTP



Appendix A

Statistical Method

This appendix provides technical details of statistical analysis of choice data. The appendix includes a brief description of the theoretical foundations of choice analysis followed by statistical probability estimation approaches, focusing on contemporary models applied in this report. Lastly, the method used in generating monetary estimates is described.

A-1 Conceptual Framework

In Choice Experiments (CEs), researchers are interested of what influences, on average, the survey respondents' decisions to choose one alternative over others. These influences are driven by people's preferences towards the attributes but also the individual circumstances such as their demographics or perceptions of the choice task (e.g., the level of difficulty or understanding) (Hensher et al. 2015).

Each alternative in a choice set is described by attributes that differ in their levels, both across the alternatives and across the choice sets. The levels can be measured either qualitatively (e.g., poor and good) or quantitatively (e.g., kilometres). This concept is based on the characteristics theory of value (Lancaster 1966) stating that these attributes, when combined, provide people a level of utility³ U hence providing a starting point for measuring preferences in CE (Hanley et al. 2013; Hensher et al. 2015). The alternative chosen, by assumption, is the one that maximises people's utility⁴ providing the behavioural rule underlying choice analysis:

$$U_j > U_i \tag{0.1}$$

where the individual n chooses the alternative j if this provides higher utility than alternative i . A cornerstone of this framework is Random Utility Theory, dated back to early research on choice making (e.g., Thurstone 1927) and related probability estimation. This theory postulates that utility can be decomposed into systematic (explainable or observed) utility V and a stochastic (unobserved) utility ε (Hensher et al. 2015; Lancsar and Savage 2004).

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{0.2}$$

where j belongs to a set of J alternatives. The importance of this decomposition is the concept of utility only partly being observable to the researcher, and remaining unobserved sources of utility can be treated as random (Hensher et al. 2015). The observed component includes information of the attributes as a linear function of them and their preference weights (coefficient estimates).

$$V_{nsj} = \sum_{k=1}^K \beta_k x_{nsjk} \tag{0.3}$$

with k attributes in vector x for a choice set s . Essentially, the estimated parameter β shows "the effect on utility of a change in the level of each attribute" (Hanley et al. 2013, p. 65). This change can be specified as linear across the attribute levels, or as non-linear using either dummy coding or effect coding

³Related terminology used in psychology discipline is *the level of satisfaction* (Hensher et al. 2015).

⁴In choice analysis, utility is considered as *ordinal utility* where the relative values of utility are measured (Hensher et al. 2015).

approaches. The latter coding approach has a benefit of not confounding with an alternative specific constant (ASC) when included in the model (Hensher et al. 2015).

A-2 Statistical Modelling of Choice Probabilities

The statistical analysis aims to explain as much as possible of the observed utility using the data obtained from the CE and other relevant survey data. In order to do so, the behavioural rule (eq. 1.1) and the utility function (eq. 1.2) are combined (Hensher et al. 2015; Lancsar and Savage 2004) to estimate the probability of selecting an alternative j :

$$\Pr_{nsj} = \Pr(U_{nsj} > U_{nsi}) = \Pr(V_{nsj} + \varepsilon_{nsj} > V_{nsi} + \varepsilon_{nsi}) = \Pr(\varepsilon_{nsi} - \varepsilon_{nsj} < V_{nsj} - V_{nsi}) \forall j \neq i \quad (0.4)$$

where the probability of selecting alternative j states that differences in the random part of utility are smaller than differences in the observed part. A standard approach to estimate this probability is a conditional logit, or multinomial logit (MNL) model (McFadden 1974). This model can be derived from the above equations (1.2 and 1.3) by assuming that the unobserved component is independently and identically distributed (IID) following the Extreme Value type 1 distribution (see e.g. Hensher et al. 2015; Train, 2003). Although the MNL model provides a “workhorse” approach in CE, it includes a range of major limitations (see e.g. Fiebig et al. 2010; Greene and Hensher 2007; Hensher et al. 2015):

- Restrictive assumption of the IID error components
- Systematic, or homogenous, preferences allowing no heterogeneity across the sample
- Restrictive substitution patterns, namely the existence of independence of irrelevant alternatives property where introduction (or reduction) of a new alternative would not impact on the relativity of the other alternatives
- The fixed scale parameter obscures potential source of variation

Some or all of these assumptions are often not realised in collected data. These restrictive limitations can be relaxed in contemporary choice models. In particular, the random parameter logit (RPL) model (aka, the mixed logit model) has emerged in empirical application allowing preference estimates to vary across respondents (Fiebig, et al. 2010; Hensher et al. 2015; Revelt and Train, 1998). This is done by specifying a known distribution of variation to be parameter means. The RPL model probability of choosing alternative j can be written as:

$$\Pr_{nsj} = \frac{\exp(\beta_n' x_{nsj})}{\sum_J \exp(\beta_n' x_{nsj})} \quad (0.5)$$

where, in the basic specification, $\beta_n = \beta + \eta_n$ with η being a specific variation around the mean for k attributes in vector x (Fiebig, et al. 2010; Hensher et al. 2015). Typical distributional assumptions for the random parameters include normal, triangular and lognormal distributions, amongst others. The normal distribution captures both positive and negative preferences (i.e., *utility* and *disutility*) (Revelt and Train, 1998). The lognormal function can be used in cases where the researcher wants to ensure the parameter has a certain sign (positive or negative), a disadvantage is the resultant long tail of estimate distributions (Hensher et al. 2015). The triangular distribution provides an alternative functional form, where the spread can be constrained (i.e., the mean parameter is free whereas spread is fixed equal to mean) to ensure behaviourally plausible signs in estimation (Hensher et al. 2015). Further specifications used in modelling include parameters associated with individual specific characteristics (e.g, income) that can influence the heterogeneity around the mean, or allowing correlation across the random parameters. The

heterogeneity in mean, for example, captures whether individual specific characteristics influence the location of an observation on the random distribution (Hensher et al. 2015). In this study, the frequency of visits to rivers, streams and lakes was used to explain such variance.

Another way to write this probability function (in eq. 1.4) (Hensher et al. 2015) involves an integral of the estimated likelihood over the population:

$$L_{njs} = \int_{\beta} \text{Pr}_{nsj}(\beta) f(\beta|\theta) d\beta \quad (0.6)$$

In this specification, the parameter θ is now the probability density function conditional to the distributional assumption of β . As this integral has no closed form solution, the approximation of the probabilities requires a simulation process (Hensher et al. 2015; Train, 2003). In this process for data X , R number of draws are taken from the random distributions (i.e. the assumption made by the researcher) followed by averaging probabilities from these draws; furthermore these simulated draws are used to compute the expected likelihood functions:

$$L_{nsj} = E(\text{Pr}_{nsj}) \approx \frac{1}{R} \sum_R f(\beta^{(r)}|X) \quad (0.7)$$

where the $E(\text{Pr}_{nsj})$ is maximised through Maximum Likelihood Estimation. This specification (in eq. 1.6) can be found in Hensher et al. (2015). In practice, a popular simulation method is the Halton sequence which is considered a systematic method to draw parameters from distributions compared to for example, pseudo-random type approaches (Hensher et al. 2015).

A-3 Econometric Extensions

Common variations of the RPL model include specification of an additional error component (EC) in the unobserved part of the model. This EC extension captures the unobserved variance that is alternative-specific (Greene and Hensher 2007) hence relating to substitution patterns between the alternatives (Hensher et al. 2015). Empirically, one way to explain significant EC in a model is SQ-bias depicted in the stochastic part of utility if the EC is defined to capture correlation between the non-SQ alternatives (Scarpa et al., 2005).

Another extension which has gained increasing attention in recent CE literature, is the Generalized Mixed Logit (GMXL) model (Czajkowski et al. 2014; Hensher et al. 2015; Juutinen et al. 2012; Kragt 2013; Phillips 2014). This model aims to capture remaining unobserved components in utility as a source of choice variability by allowing estimation of the scale heterogeneity alongside the preference heterogeneity (Fiebig et al. 2010; Hensher et al. 2015). This scale parameter is (inversely) related to the error variance, and in convenient applications such as MNL or RPL, this is normalised to one to allow identification (Fiebig et al. 2010; Louviere and Eagle 2006). However, it is possible that the level of error variance differs between or within individuals, due to reasons such as behavioural outcomes, individual characteristics or contextual factors (Louviere and Eagle 2006).

Recent GMXL application builds on model specifications presented in Fiebig et al. (2010), stating that β_n (in eq. 1.4) becomes:

$$\beta_n = \sigma_n \beta + \gamma \eta_n + (1-\gamma) \sigma_n \eta_n \quad (0.8)$$

where σ is the scale factor (typically = 1) and $\gamma \in \{0,1\}$ is a weighting parameter indicating variance in the residual component. In the case the scale factor equals 1, this reduces to the RPL model. The importance of the weighting parameter is the impact on the scaling effect on the overall utility function (population means) versus the individual preference weights (individual means): when γ parameter approaches zero the scale heterogeneity affects both means, whereas when this approaches one the scale heterogeneity affects only the population means (Hensher et al. 2015; Juutinen et al. 2015). Interpretation of these parameters includes

- If γ is close to zero, and statistically significant, this supports the model specification with the variance of residual taste heterogeneity increases with scale (Juutinen et al. 2012); and
- If γ is not statistically significant from one, this suggests that the unobserved residual taste heterogeneity is independent of the scale effect, that is the individual-level parameter estimates differ in means but not variances around the mean (Kragt, 2013)

The scale factor specification (eq. 1.7) can also be extended to respondent specific characteristics associated with the unobserved scale heterogeneity (Hensher et al. 2015; Juutinen et al. 2015):

$$\sigma_n = \exp\{\bar{\sigma} + \tau\omega_n\} \quad (0.9)$$

where $\bar{\sigma}$ is the mean parameter in the error variance; and ω is unobserved scale heterogeneity (normally distributed) captured with coefficient τ (Hensher et al. 2015; Juutinen et al. 2015; Kragt, 2013). Juutinen et al. (2012), for example, in context of natural park management found that respondents' education level and the time spent in the park explained the scale heterogeneity ($\tau > 0$, p-value < 0.01). In this study, the respondents indicated levels of choice task understanding and difficulty were used to explain scale heterogeneity.

A-4 Estimation of Monetary Values

Typically the final step of interest in the CE application is the estimation of monetary values of respondent preferences for the attributes considered in utility functions. These are commonly referred to as marginal willingness-to-pay (WTP). WTP estimation is based on the marginal rate of substitution expressed in dollar terms providing a trade-off between some attribute k and the cost involved (Hensher et al. 2015) and is calculated using the ratio of an attribute parameter and the cost parameter. WTP can take into account interaction effects, if statistically significant, such as with the respondent demographics. WTP of attribute j by respondent i is calculated as the ratio of the estimated model parameters accommodating the influence of the random component (Cicia et al. 2013) as:

$$WTP_i^j = - \left(\frac{\beta_j + \varepsilon_{ij}}{\beta_{price} + \varepsilon_{ip}} \right) \quad (0.10)$$

The estimated mode parameters can also be used to estimate compensating surplus (CS) as a result of policy or quality change in a combination of attributes, using (Hanemann, 1984):

$$CS = \frac{-1}{\beta_{cost}} \left[\ln \sum_{j=1}^J \exp\{V_j^0\} - \ln \sum_{j=1}^J \exp\{V_j^1\} \right] \quad (0.11)$$

which calculates the difference in utilities before the policy or quality change (V_0) and after the policy or quality change (V_1) (Hanley et al. 2013; Lancsar and Savage 2004). Similar to WTP, the monetary estimation of this change is possible by using the estimate for the monetary attribute β_{cost} . Lastly, there are some challenges associated with the empirical estimation of the WTP in the RPL based models. One approach is to use a fixed cost, which simplifies the WTP estimation (Daly et al. 2012) but which may not be as behaviourally a plausible consideration as allowing heterogeneous preferences towards the cost attribute (Bliemer and Rose, 2013; Daziano and Achtnicht, 2014). Conceptually, the estimated cost parameter is a proxy for the marginal utility of income for respondents and economic theory suggests individuals will respond differently to varying income levels. The use of a random cost parameter however, presents complications in deriving population distribution moments from the ratio of two random parameters.

Appendix B

Latent Class Model of Lamb Choices

Table B-1 UK lamb leg choice Latent Class model

Utility parameters ¹	Class 1	Class 2	Class 3
No added antibiotics	0.30***(0.06)	0.52***(0.10)	0.31***(0.12)
No added hormones	0.26** (0.12)	0.21 (0.28)	0.34***(0.13)
Enhanced animal welfare	0.55***(0.04)	0.13 (0.9)	0.29***(0.09)
Māori farming system	0.22***(0.06)	0.98***(0.19)	0.15 (0.12)
Organic farming system	0.26***(0.06)	0.31***(0.11)	0.07 (0.13)
Water quality protection	0.15** (0.06)	0.27** (0.13)	0.05 (0.14)
Pasture raised	0.39***(0.04)	0.24***(0.09)	0.42***(0.08)
Biodiversity enhancement	0.49***(0.13)	1.24***(0.46)	0.10 (0.14)
Carbon neutral	0.57***(0.13)	0.99** (0.44)	0.12 (0.14)
No GM feed	0.16***(0.05)	0.09 (0.13)	0.42***(0.12)
100% grass fed	0.34***(0.01)	0.41 (0.26)	0.74***(0.13)
Price/Kg	- 0.013***(0.01)	- 0.43***(0.02)	- 0.20***(0.02)
Opt-Out	- 1.90***(0.19)	- 7.32***(0.38)	- 0.85***(0.19)
Class Membership			
Ethnocentric score		- 0.02*	
Age	- 0.04***(0.01)		
Knowledge of Māori	1.42** (0.66)		
Environment important	1.07***(0.22)		
Usual Purchase Price	0.06***(0.02)		
NZ quality ranking	0.36* (0.23)		
NZ purchase frequency			
Average class probability	0.49	0.32	0.19
Model Fit Statistics			
Log Likelihood function	- 7,210		
Log Likelihood chi ² stat (55 d.f.)	7,543***		
McFadden Pseudo R ²	0.34		
Number of observations	9,990		
Number of respondents	999		

***, **, * denote statistical significance at the 1%, 5% and 10% levels respectively for the null hypothesis that a parameter estimate is not significantly different from zero.

Standard errors in brackets.

¹ Parameter mean estimates indicates the estimated average value in the model for each different parameter

- 353 Culture, Wellbeing, and the Living Standards Framework.**
Dalziel P, Saunders C and Savage C 2019
- 354 Consumer preferences and willingness-to-pay for sustainable wine products: Incentives for improving environmental management practice for New Zealand winegrowers.**
Driver T, Tait P, Rutherford P, Li X, Saunders C, and Dalziel P 2019
- 355 Governing value creation and capture in New Zealand agribusiness value chains: A case study. McIntyre T, Wilson MJ, Saunders C, Childerhouse PHJ, Dalziel P, Kaye-Blake W, Kingi T, Mowat A, Reid J and Saunders J 2019**
- 356 Agri-food Leadership Case Study: John Brakenridge and the New Zealand Merino Company**
Mayes J, Wall G, Cammock P. 2020
- 357 Agri-food Leadership Case Study: Mike & Sharon Barton and Taupō Beef and Lamb**
Mayes J, Wall G, Cammock P. 2020
- 358 Cultural Attributes of Ngāi Tahu Food and the International Consumer Cultures that will recognise them.**
Rout M and Reid J 2020
- 359 United Arab Emirates beef consumer consumption behaviour and product preferences: A Latent Class Analysis.**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T and Guenther M 2020
- 360 Beijing beef consumer consumption behaviour and product preferences: A Latent Class Analysis**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T and Guenther M 2020
- 361 Japanese Kiwifruit consumer consumption behaviours and product preferences: A Latent Class Analysis.**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T and Guenther M 2020
- 362 United Kingdom lamb consumer consumption behaviour and product preferences: A Latent Class Analysis.**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T and Guenther M 2020
- 363 Beijing UHT Milk consumer consumption behaviour and product preferences: A Latent Class Analysis.**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T and Guenther M 2020
- 364 New York Sauvignon blanc wine consumer consumption behaviour and product preferences: A Latent Class Analysis.**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T and Guenther M 2020
- 365 Texas Sauvignon blanc wine consumer consumption behaviour and product preferences: A Latent Class Analysis.**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T and Guenther M 2020
- 366 California apple consumer consumption behaviour and product preferences: A Latent Class Analysis.**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T and Guenther M 2021
- 367 UK and USA alternative proteins consumer consumption behaviours and product preferences.**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T and Guenther M 2021
- 368 Agri-food Leadership Case Study: Alex Guichard & Monique Kelly and Revology**
Mayes J, Wall G, Cammock P. 2020
- 369 Agri-food Leadership Case Study: Pegasus Bay Wines**
Avery H, Mayes J, Wall J, Cammock P October 2021
- 370 Trade Implications for Consumer Attitudes to New Zealand Food Attributes in Key Export Countries**
Saunders JT, Guenther M, Saunders C 2021
- 371 United Kingdom lamb consumer consumption behaviour and product preferences: A Latent Class Analysis (2020)**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T, Guenther M 2022
- 372 In progress.**
- 373 In progress.**
- 374 Shanghai and Beijing UHT Milk consumer consumption behaviour and product preferences: A Latent Class Analysis**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T, Guenther M 2022
- 375 Beijing beef consumer consumption behaviour and product preferences: A Latent Class Analysis of New Zealand beef tenderloin**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T, Guenther M 2022
- 376 California apple consumer consumption behaviour and product preferences: A Latent Class Analysis of New Zealand apples**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T, Guenther M 2022
- 377 Californian wine consumer consumption behaviour and product preferences: A Latent Class Analysis of New Zealand Sauvignon blanc**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T, Guenther M 2022
- 378 Japanese Kiwifruit consumer consumption behaviour and product preferences: A Latent Class Analysis**
Tait P, Saunders C, Dalziel P, Rutherford P, Driver T, Guenther M 2022