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Research Unit
LINCOLN UNIVERSITY



California apple consumer consumption behaviours and product preferences: A Latent Class Analysis of New Zealand apples

Peter Tait
Caroline Saunders
Paul Dalziel
Paul Rutherford
Timothy Driver
Meike Guenther

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Agribusiness and Economics Research Unit
PO Box 85084
Lincoln University
Lincoln 7647
Canterbury
New Zealand

P: (64) (3) 423 0372
www.lincoln.ac.nz/AERU

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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 apples by consumers in California, 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 California residents in January 2021 using a research panel. The survey process achieved 914 responses with a suitable representation of key population demographics.
- As well as WTP values, this survey reports on:
 - Consumption frequency and behaviour by apple colour
 - Prices paid
 - Purchase frequency by country-of-origin
 - Country-of-origin quality ranking
 - Importance of reasons for NZ apple purchases
 - Apple varieties purchased, and perceptions of variety origin
 - Purchase behaviour of “ugly” fruit and vegetables
 - Importance factors in purchase decisions
 - Use of digital media and smart technologies for apple shopping
- Over two-thirds of respondents consumed apples at least *fortnightly*, with *red apples* the most frequently consumed, followed by green apples (34 per cent) and yellow apples (25 per cent). 21 per cent of consumers are eating whole apples daily, and 12 per cent pre-sliced apples daily. Whole green apples are used for cooking at least fortnightly by 10 per cent of consumers. When it comes to juicing, red apples are used more frequently. The most common apple varieties purchased included Fuji (54 per cent), Gala (43 per cent), Granny Smith (43 per cent), and Red Delicious (42 per cent).
- The most common price point paid for apples was between \$1 and \$2/lb. The average price usually paid is \$2.70/lb, while over a quarter of consumers usually paid more than \$3.30/lb. Supermarkets are the dominate retail channel for apple expenditure (66 per cent), followed by specialty stores (9 per cent), greengrocers (8 per cent), and farmers markets (5 per cent).
- Purchases by country-of-origin are dominated by USA apples (83 per cent), with a relatively even purchase frequency across other countries. 10 per cent of respondents purchase NZ apples frequently, another 13 per cent occasionally, and 13 per cent rarely. USA apple quality is ranked first among six in-market origins by 78 per cent of respondents, while NZ apple quality is ranked first by 5 per cent, second (23per cent) or third (29 per cent).
- Respondents were mostly unaware of the country that the apple varieties they consumed were grown or developed in, reporting they did not know, or possibly assumed that it was grown or developed in the USA.
- Over a quarter of respondents said that they have bought “ugly” apples (that were unusual, blemished or misshapen). However, 60 per cent said that they have only bought “perfect” apples.

- Factors that consumers considered were important in their decisions to purchase apples included freshness (63 per cent Very Important), high quality (49 per cent), personal health (48 per cent), food safety standards (47 per cent), and reduced chemical residuals (46 per cent).
- Important reasons for purchasing NZ apples included high quality (93 per cent), freshness (88 per cent), sweet taste (85 per cent), and high food safety standards (84 per cent).
- Many consumers use digital media and smart technologies related to apples. About 43 per cent of consumers use mobile devices to search for information on *how apples are produced*, and 29 per cent use mobile devices to make apple purchases. Barcodes are being used for information searching (26per cent) and to make purchases (20 per cent). QR code use is at a similar level, and RFID/NFC is also being used (18 per cent).
- Use of mobile apps related to apples could be considered modest, with one in five consumers using apps for discounts, purchasing, and rewards programmes. While current use may be low, there is substantial interest in potential use.
- The survey included a Discrete Choice Experiment to assess the willingness-to-pay by consumers for different attributes associated with apples. Using a Latent Class Modelling approach, the consumers were segmented into four classes, each with different characteristics and preferences.
- The first segment of consumers is only concerned with avoiding suboptimal apples. Members of this group are less likely to think environmental impacts are important to consider. Conversely, consumers in the second segment are primarily focused on social and environmental attributes in their apple choices, and have the highest WTP for these attributes of the segments. These consumers are indifferent to changes in appearance when choosing between apple options. Members of this group are more likely to be younger, and to believe that there are significant risks with the use of GE. Segment three consider the broadest set of attributes in their apple choices, despite having among the lowest WTP values of the segments. Segment four consumers have the highest WTP of the four segments for Organic production, but they also have the strongest preferences for avoiding deformed or injured apples.

Apple Attribute	Segment 1 (17%)	Segment 2 (27%)	Segment 3 (28%)	Segment 4 (28%)
15% Reduction in GHG		37% (10%, 63%)	10% (3%, 13%)	37% (0%, 73%)
30% Reduction in GHG		44% (17%, 73%)	5% (0%, 10%)	
Organic Production		88% (30%, 143%)	17% (10%, 23%)	104% (38%, 170%)
Care for Workers		74% (37%, 113%)	17% (7%, 23%)	
Contribute to Communities		64% (30%, 97%)	18% (10%, 27%)	
Support Growers		75% (37%, 113%)	7% (0%, 13%)	
GE-Free		96% (47%, 147%)	8% (0%, 17%)	
Moderate Injury	-23% (-33%, -10%)		-14% (-33%, -10%)	-151% (-200%, -67%)
Significant Injury	-49% (-63%, -37%)		-21% (-33%, -10%)	-250% (-333%, -100%)
Moderate Deformity			-31% (-33%, -10%)	-128% (-300%, -33%)
Significant Deformity	-60% (-80%, -43%)		-37% (-49%, -23%)	-272% (-400%, -167%)

Average % marginal WTP/lb. 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.

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. 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 Californian apple 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, and *experience attributes* such as flavour 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

Apple Survey Method

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

The survey was developed by the research team drawing from a literature review on consumer trends for apples, results from previous surveys examining consumer attitudes in overseas markets, a scoping survey of 199 Washington apple consumers (December 2020), survey pre-testing with recruited testers, and consultation with industry partners and stakeholders, especially those on the 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. Potential respondents were recruited by e-mail and were screened out if they purchased apples less than monthly.

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 and beverage 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 apples are described by appearance, 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 American consumers considered distinctive of NZ apples.

Table 2-1 Apple attribute descriptions used in the DCE

Apple attributes	Attribute descriptions
Appearance	Apples may have some blemishing such as coloring or spotting, or may be misshapen. Apples that are not perfect in appearance are still safe to eat and taste the same. However they are often considered as not saleable and therefore do not make it onto supermarket shelves. These apples are typically wasted and reduction in this food waste has the potential to improve sustainability
Social Responsibility	The apple may be labeled as being produced by growers that are socially responsible, with programs that actively care for workers, contribute to local communities, or support farmers
Organic Production	Apples grown organically avoid the use of synthetic pesticides and fertilizers, or genetic engineering
Reduction in Greenhouse gas emissions	Reduction in Greenhouse gas (GHG) emissions could be achieved through changes in production systems. Reduction in GHG, such as carbon and methane, is an important tool for reducing global warming and climate change
Genetic Engineering	Genetic engineering can be used to increase growing productivity and enhance the financial sustainability of the apple industry. It can also be used to improve disease resistance and reduce the use of agrichemicals
Price	Price per pound of apples

Changes in apple attributes are described using the labels in Table 2-2. Price levels were determined by market prices, and from what scoping survey respondents said that they usually paid. The different levels of apple appearance were expressed using images without description; these images are also included in Table 2-2.

Table 2-2 Apple attribute levels used in the DCE

Apple attributes	Attribute levels				
Appearance					
	Perfect	Moderately blemished	Significantly blemished	Moderately misshapen	Significantly misshapen
GHG reduction	No Label	15% less GHG	30% less GHG		
Genetic engineering	No Label	GE-free			
Organic production	No label	Organic			
Social Responsibility	No label	Care for workers	Contribute to local communities	Support farmers	
Price	\$1.50 / lb	\$3 / lb	\$4.50 / lb		

An example of alternative product offerings presented to respondents is shown in Figure 2-1. Each set of offerings comprises four options, of which respondents chose their preferred one. Three options present alternative apples, while the fourth is a 'none of these' option. Product choices are statistically analysed using Latent Class Models to identify consumers 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.

Set 1 of 10 Imagine that you are going to buy some apples from your usual shop, and there are **three types of New Zealand grown apples** available that you could purchase. All apples are the same weight, have equivalent nutritional content, and have been officially approved as safe for consumption by the Food and Drug Administration.

Given the available selection, which apple would you purchase? [More Info](#)




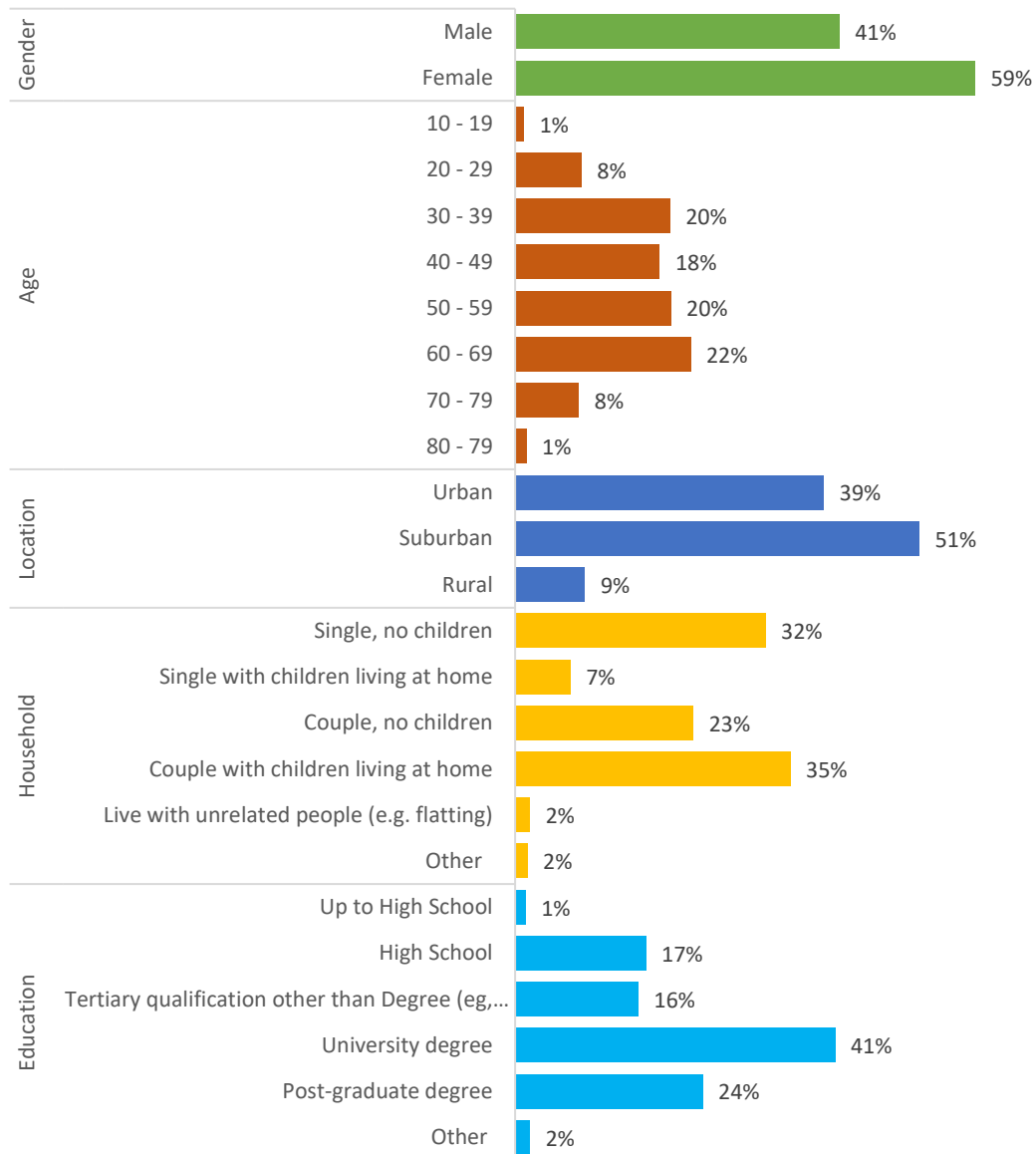
	Apple Option A	Apple Option B	Apple Option C	
Appearance of apple				
Organic Production		Organic		
Genetic Engineering			GE-free	
Social Responsibility	Support farmers			
Greenhouse Gases (GHG) Reduction		30% less GHG		
Price per pound	\$4.50 / lb	\$1.50 / lb	\$3 / lb	
Selection:	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/> I would not purchase any of these apples

Figure 2-1 Example of a DCE 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 Californian population, but rather those that purchase apples at least monthly.



Household Annual Income

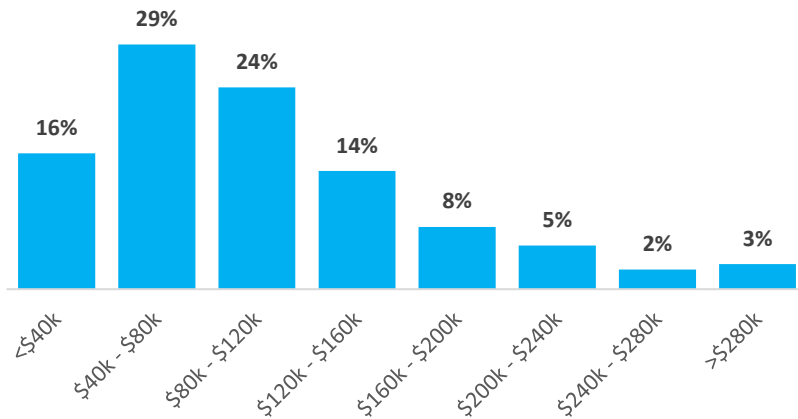


Figure 3-1 Sample demographics

3.2 Purchase and consumption behaviour

3.2.1 Purchase frequency by colour

- 69 per cent of respondents consumed apples at least fortnightly, with red apples the most frequently consumed (Figure 3-2).

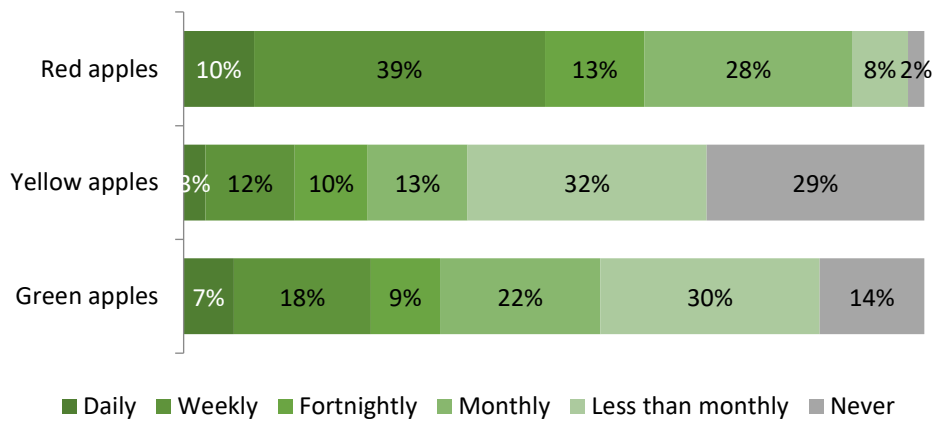


Figure 3-2 Purchase frequency by colour

3.2.2 Consumption uses for whole and pre-sliced apples by colour

- Consumers were asked to indicate how they consume apples. We split this into apples purchased as whole apples (Figure 3-3) and those apples purchased as pre-sliced (Figure 3-4).
- When purchasing whole apples, most respondents reported eating apples *whole*.

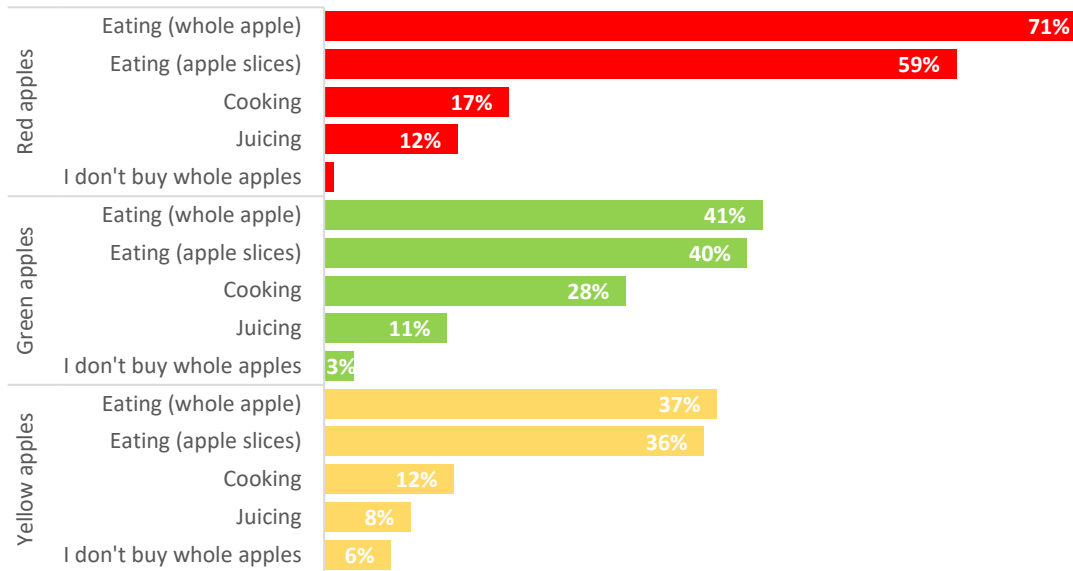


Figure 3-3 Use of whole apples by colour

- When purchasing pre-sliced apples, the most common use was for eating as they were, while consumers also purchased pre-sliced apples for cooking and juicing.

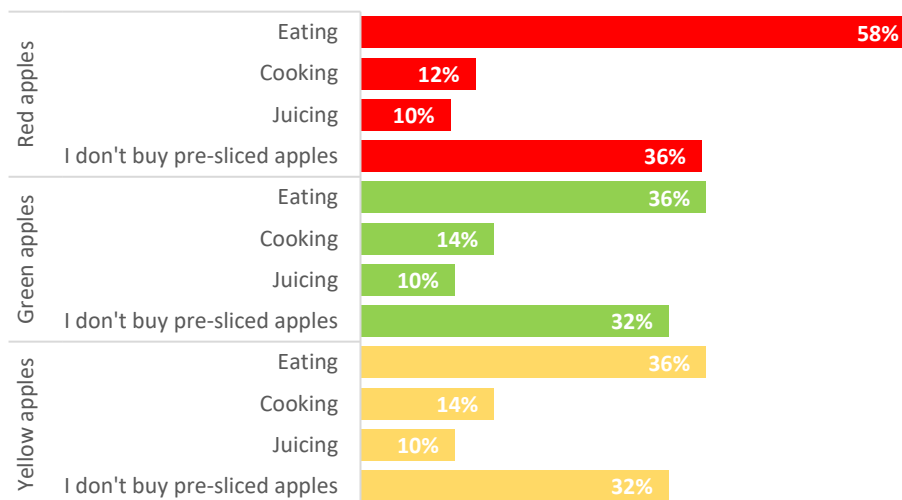


Figure 3-4 Use of pre-sliced apples by colour

- We then look more closely at the uses of whole and pre-sliced apples by asking consumers to indicate the frequency of use: eating as is, cooking, or juicing (Figure 3-5).
- This shows that 21 per cent of consumers are eating whole apple daily, and 12 per cent pre-sliced apples daily. Whole green apples are used for cooking at least fortnightly by 10 per cent of consumers. When it comes to juicing, red apples are used more frequently.

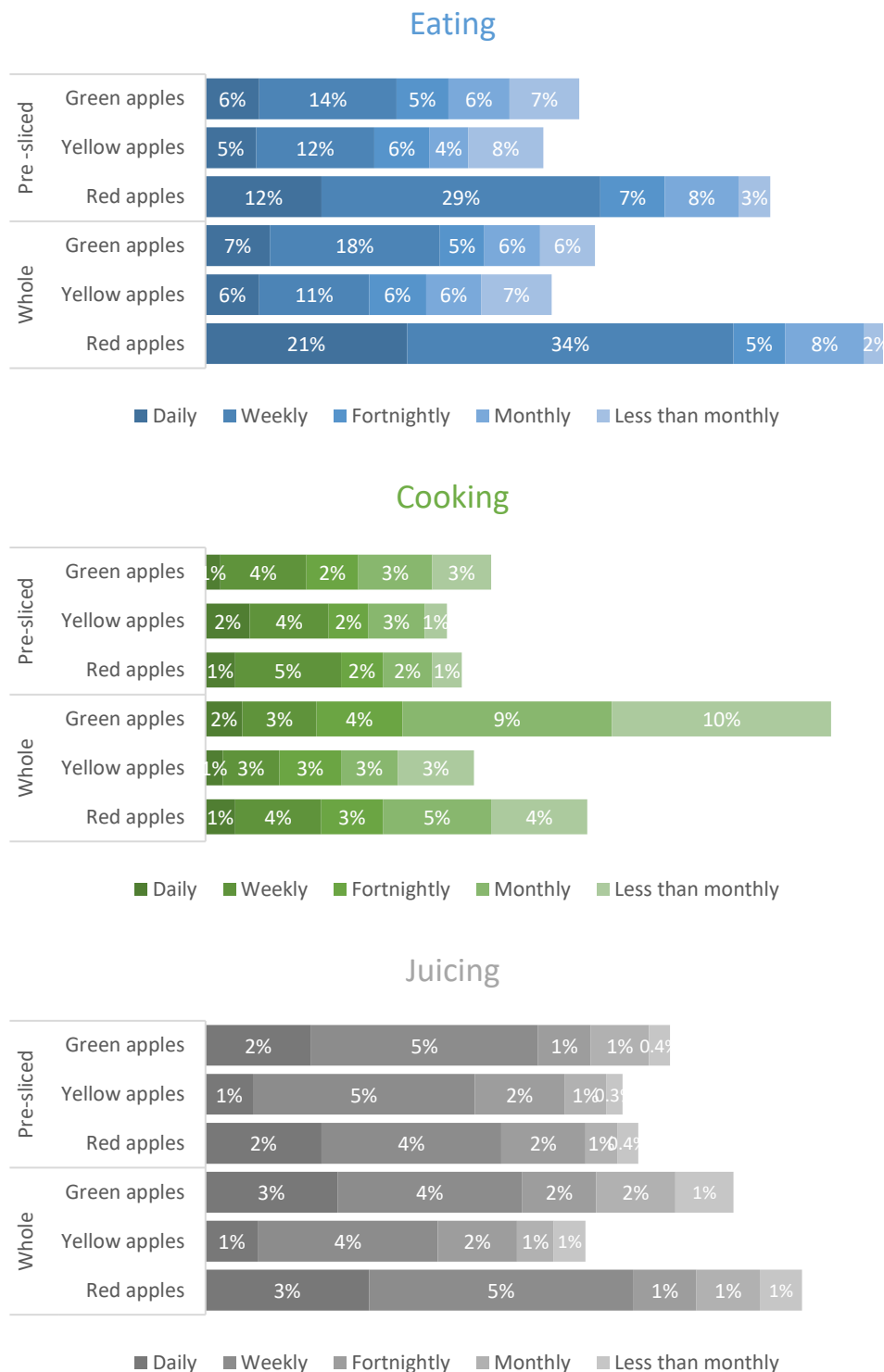


Figure 3-5 Frequency of apple uses by colour and format

3.2.3 Prices usually paid for apples

- The most common price point paid for apples was between \$1 and \$2/lb (Figure 3-6). The average price usually paid is \$2.70/lb, while over a quarter of consumers usually paid more than \$3.30/lb.

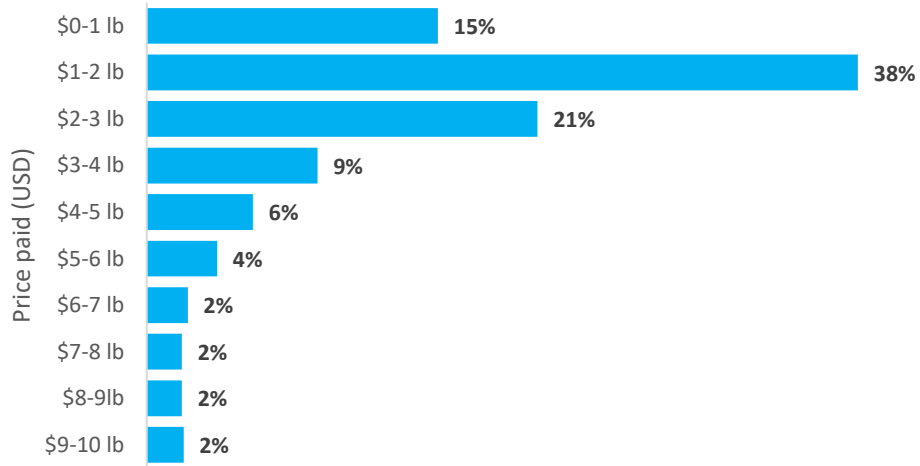


Figure 3-6 Usual price paid for apples

- A breakdown of apple prices by colour reveals that price does not vary much across colours (Figure 3-7).

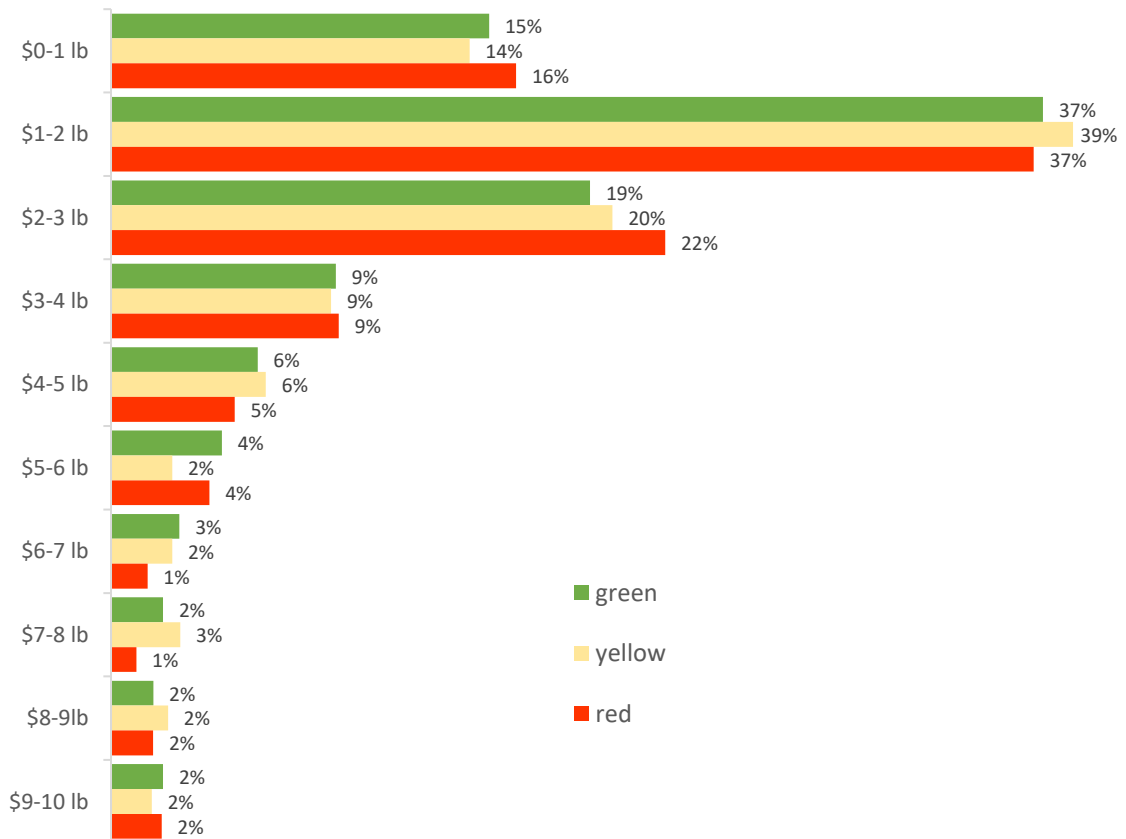


Figure 3-7 Breakdown by colour of usual price paid for apples

3.2.4 Country-of-origin purchase frequency and quality ranking

- New Zealand has the fourth-highest country-of-origin purchase frequency with about a quarter of consumers purchasing NZ apples at least occasionally (Figure 3-9).

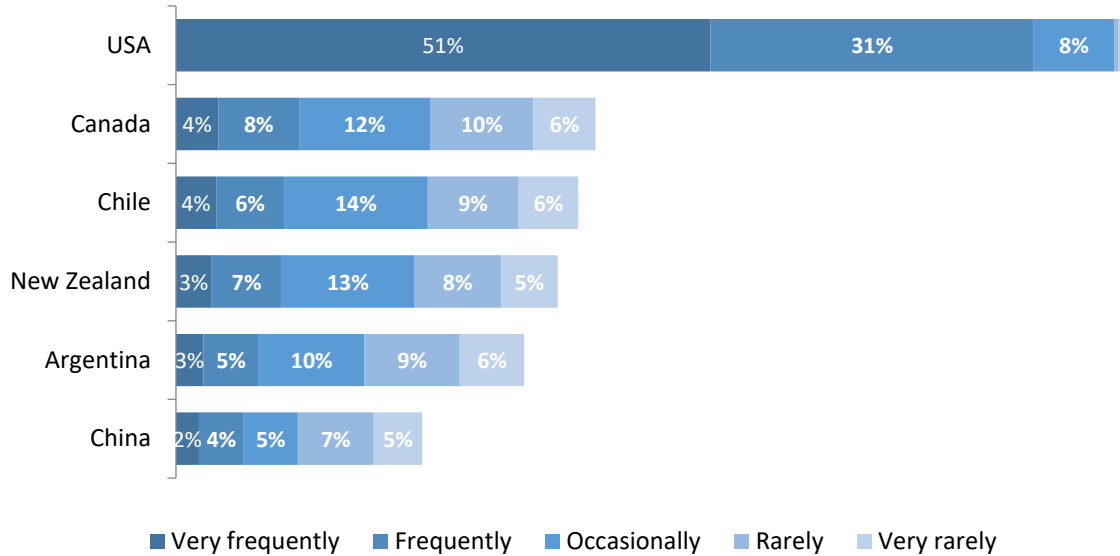


Figure 3-8 Country-of-origin purchase frequency

- When asked to rank countries according to which produced the best quality apples, 57 per cent ranked New Zealand in the top 3 apple producers (Figure 3-9).

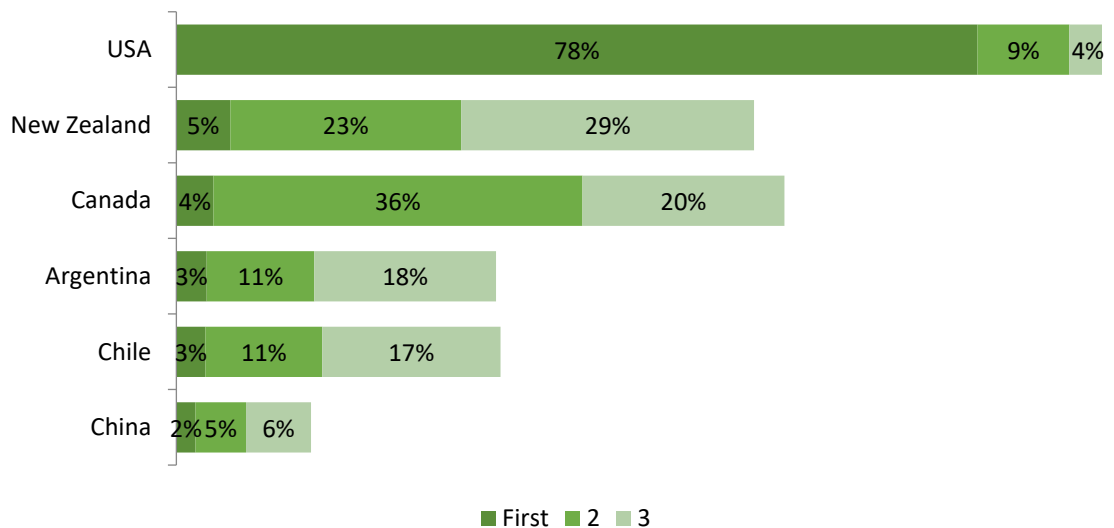


Figure 3-9 Ranking of countries by apple production quality

3.2.5 Apple varieties purchased

- From the following list of varieties, 55 per cent of consumers had purchased at least one in the previous month. This means that 45 per cent had not purchased any of these varieties. The most frequently purchased apple varieties were *Fuji*, *Gala*, *Granny Smith*, and *Red Delicious* (Figure 3-10).

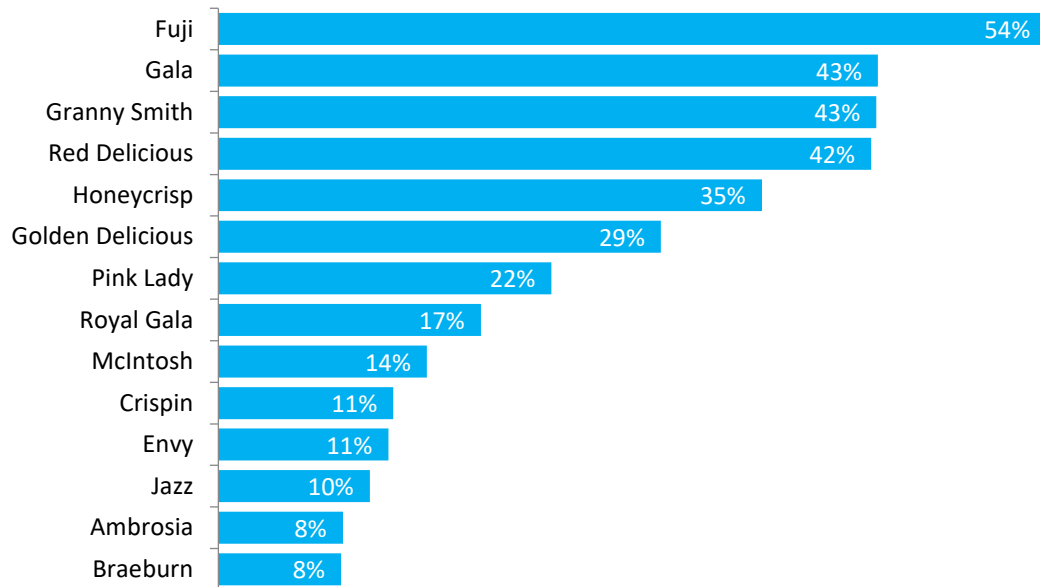


Figure 3-10 Varieties of apples purchased in the previous month

- Suboptimal apples typically have visual imperfections and are sold in various retail settings. Over a quarter of respondents said that they have bought “ugly” apples (that were unusual, blemished or misshapen) (Figure 3-11).

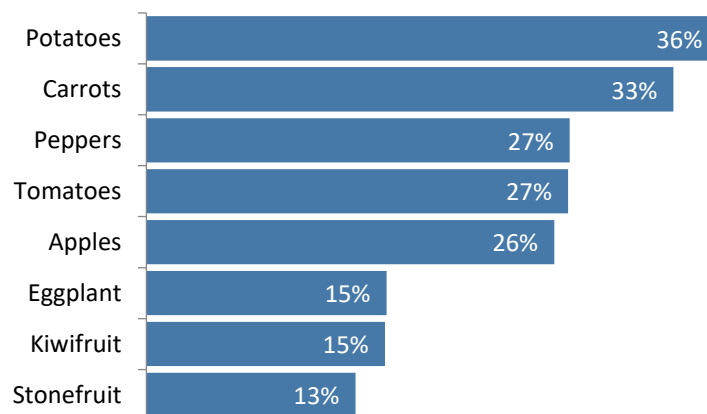


Figure 3-11 Purchase of “ugly” fruit and vegetables

3.3 Perceptions, preferences and attitudes

3.3.1 Awareness of where apple varieties are grown

- Respondents who had purchased at least one of the varieties (Figure 3-10) were asked to indicate where they thought the apple was grown.
- The figure below shows how respondents' *perception* of where the variety is grown matches up to where it is *actually* grown (Figure 3-12). This analysis reveals that up to 25 per cent of respondents did not know where their apples were grown, depending on the variety.
- Most respondents thought that the apples they consumed were grown in the USA and, that could have been correct as the USA produces all varieties considered here. Conversely, few knew where the Australasian varietal *Braeburn* is grown.

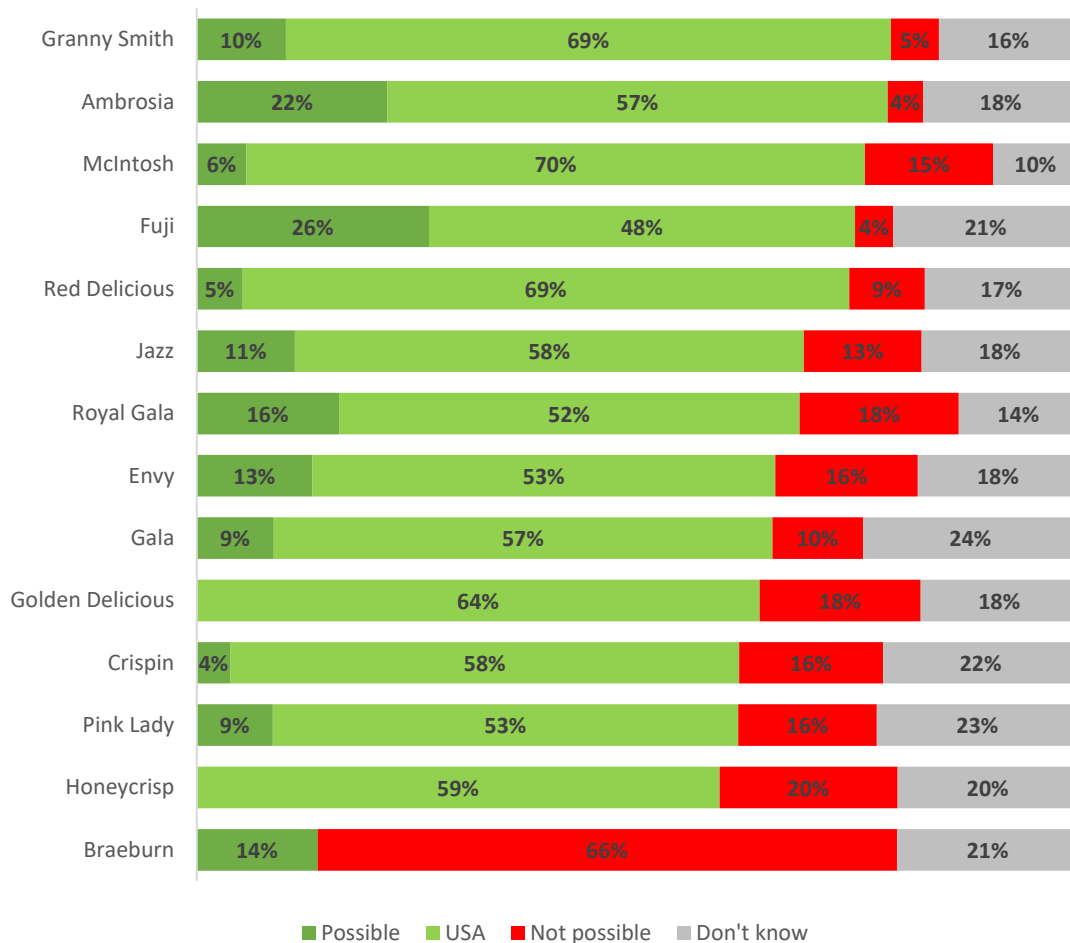


Figure 3-12 Perception of where varieties are grown

3.3.2 Importance of factors on apple purchase decisions

- Respondents were asked to indicate which of the following factors were important considerations in their purchasing decisions for apples. The most important factors included freshness, quality, improving personal health, and crispness (Figure 3-13).

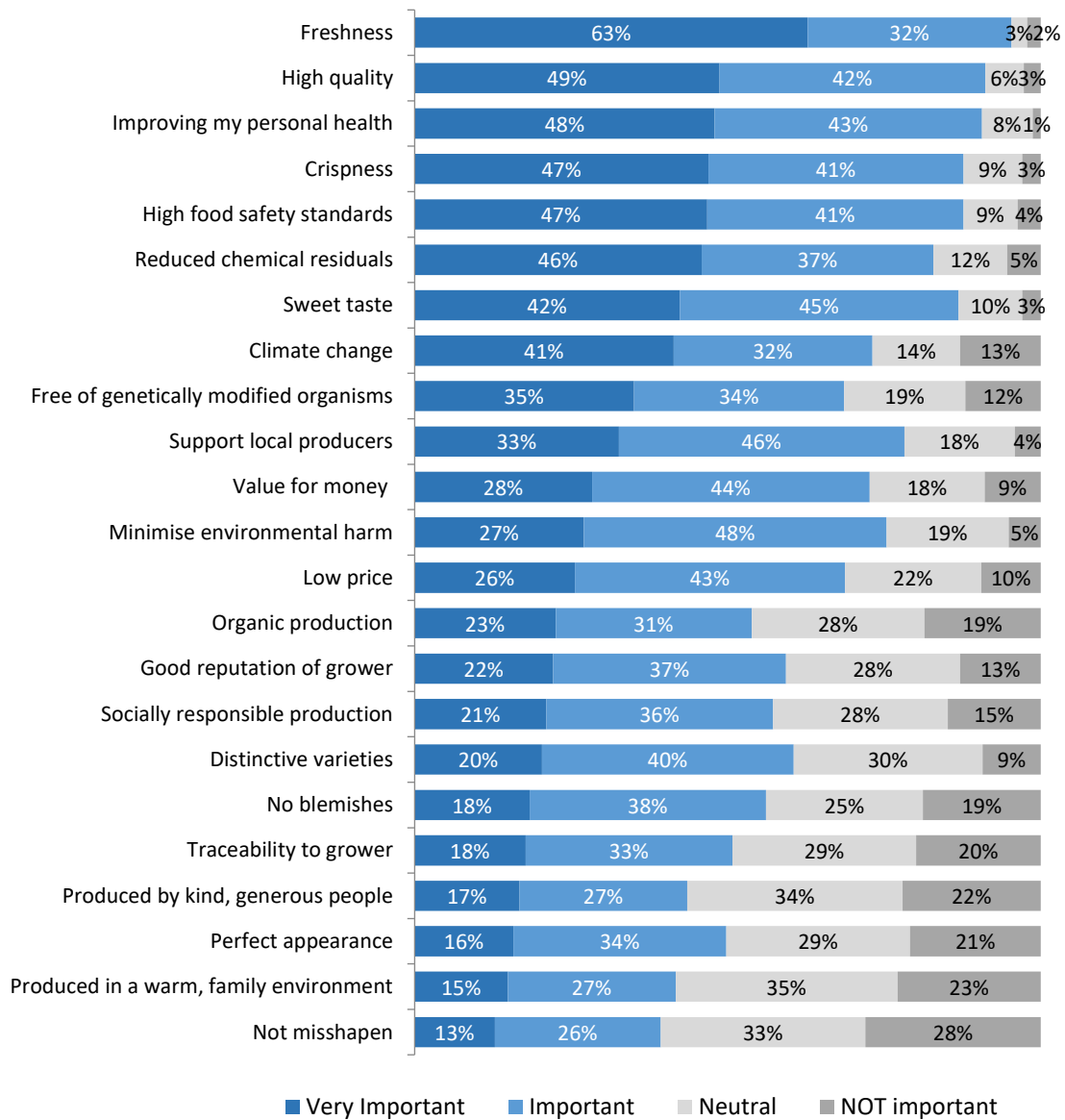


Figure 3-13 Importance of factors in purchasing decision

3.3.3 Reasons for purchasing New Zealand apples

- Respondents who had bought NZ apples at least occasionally (23 per cent of respondents) were asked which to indicate which of the following attributes were important factors in deciding to purchase NZ apples. *High quality, freshness, sweet taste, and food safety* were the four most important attributes (Figure 3-14).

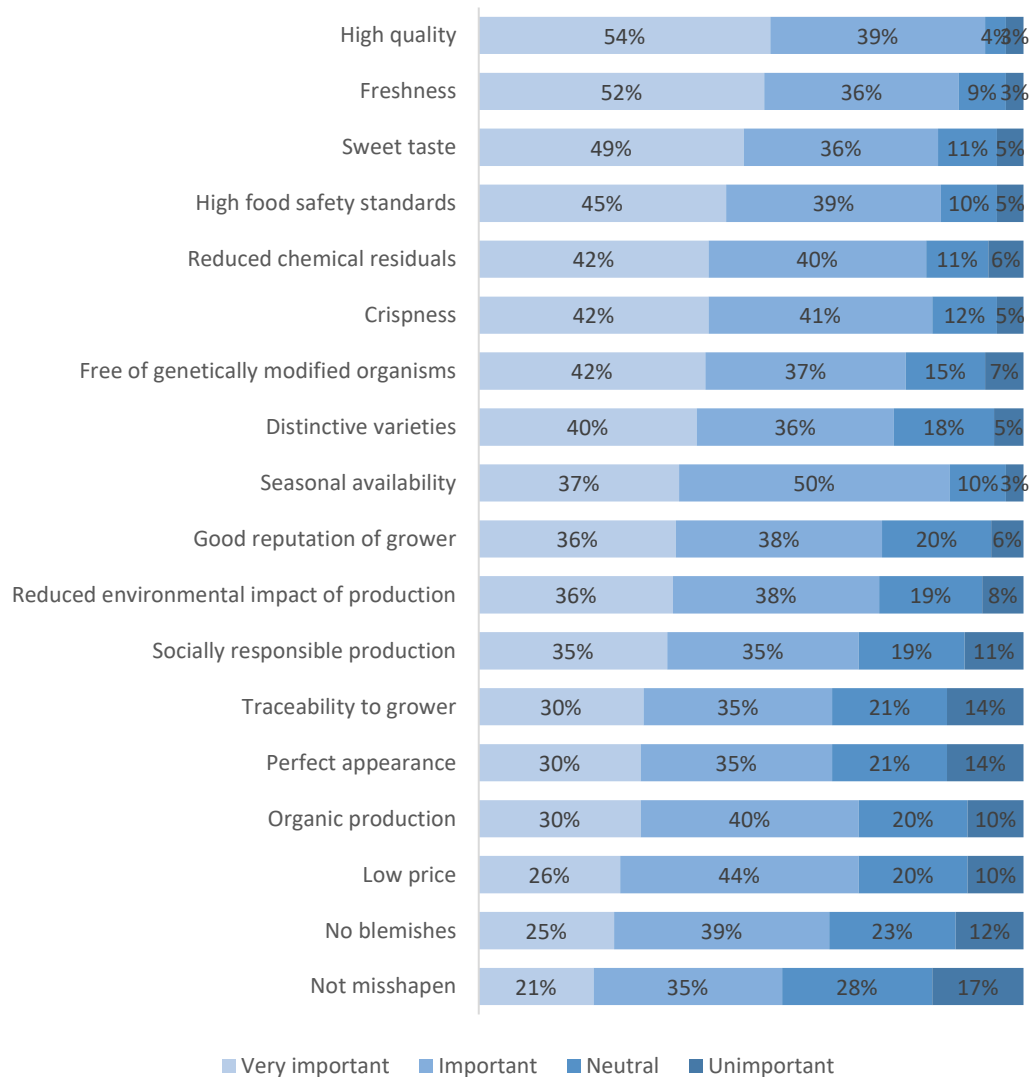


Figure 3-14 Importance of attributes for purchasing New Zealand grown apples

3.4 Use of digital media and smart technology for apple shopping

3.4.1 Internet access by device and use

- Mobile devices (e.g. smartphone) are used more frequently to access the internet than home computers (e.g. desktop/laptop) on at least a monthly basis (Figure 3-15).

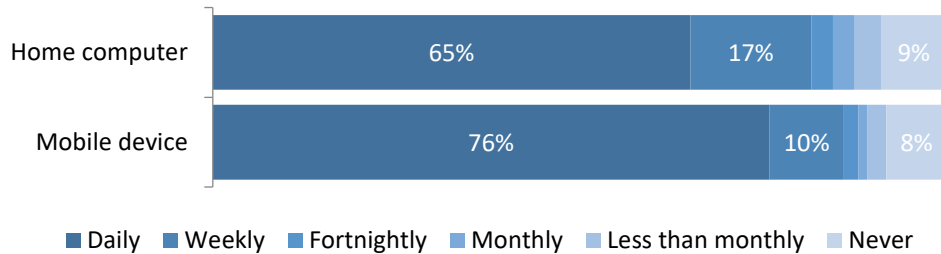


Figure 3-15 Frequency of internet access across device types

- Respondents were asked to indicate if they used online digital media sources to help decide which apples to purchase (Figure 3-16).

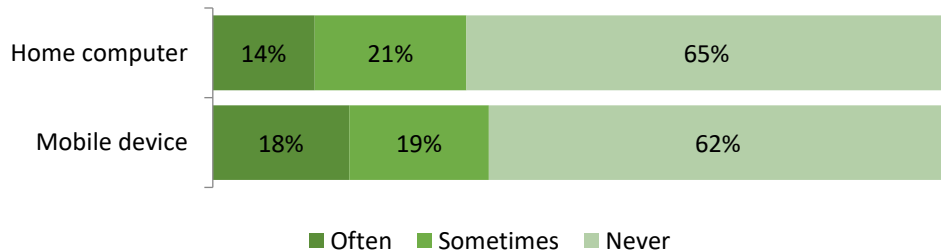


Figure 3-16 Use of digital media in making purchase decisions

- About 43 per cent of consumers use mobile devices to search for information on *how apples are produced* and 29 per cent use mobile devices to make purchases (Figure 3-17).

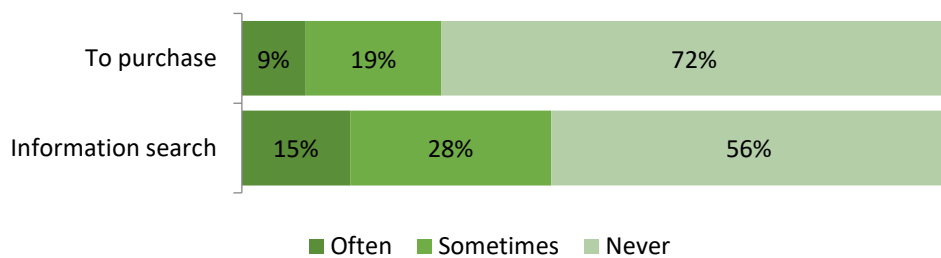


Figure 3-17 Use of mobile device for purchasing and production information

3.4.2 Use of mobile device smart technologies in relation to apples

- Looking at the **use of mobile device smart technologies** shows that barcodes are the most used technology for purchasing, and information searching (Figure 3-18).

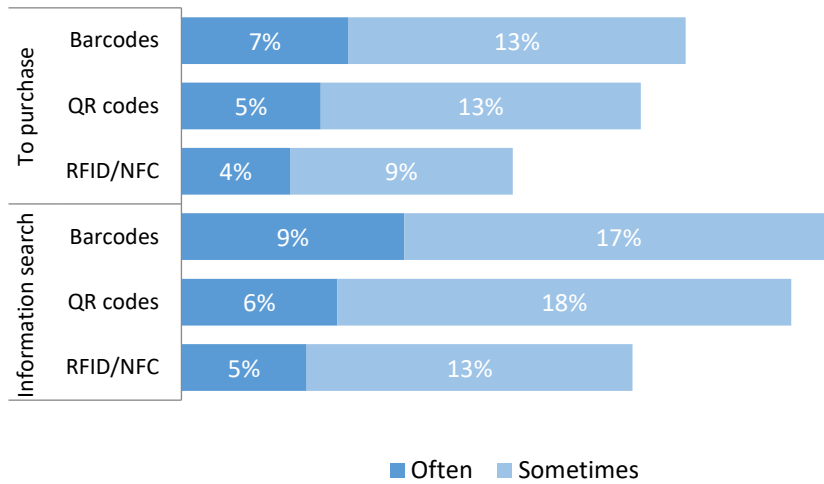


Figure 3-18 Use of mobile smart technologies for information searching and purchase

3.4.3 Mobile app use related to apples

- Consumers were asked if they **currently use, or were interested in using mobile apps** for a variety of apple related reasons (Figure 3-19). Access to discounts was ranked the highest use, and also had the highest interest in potential use.

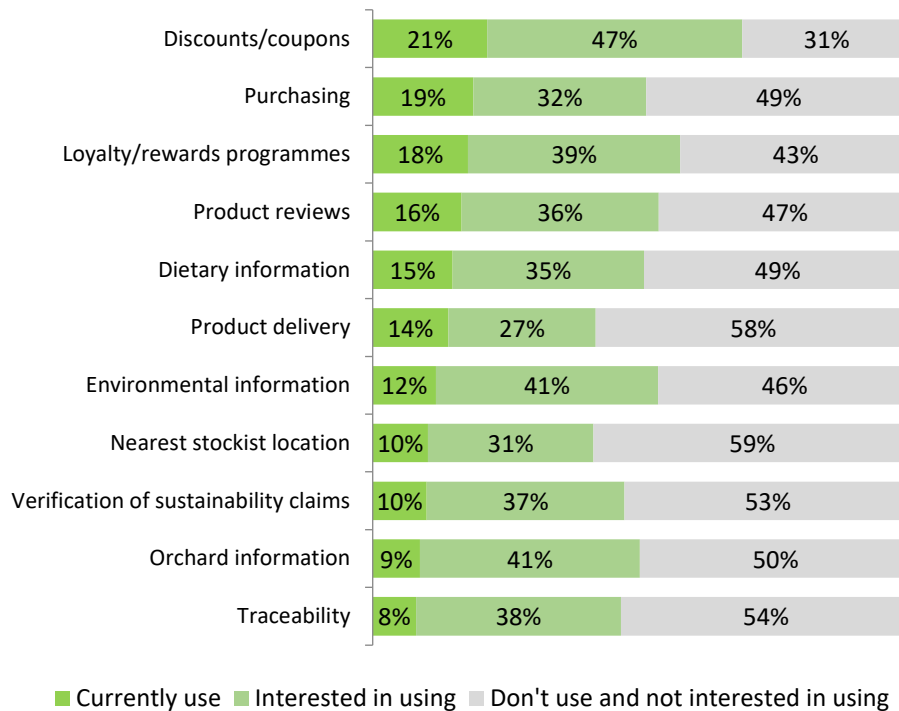


Figure 3-19 Current and potential uses of mobile applications related to apples

3.4.4 Apple expenditure by purchase channel

- Respondents were asked to allocate their **apple expenditure according to their usual purchase channels** (Figure 3-20). The graph below shows the average expenditure by channel.
- Supermarkets attract the largest share of expenditure by a considerable margin, with an average of 66 per cent of apple expenditure.

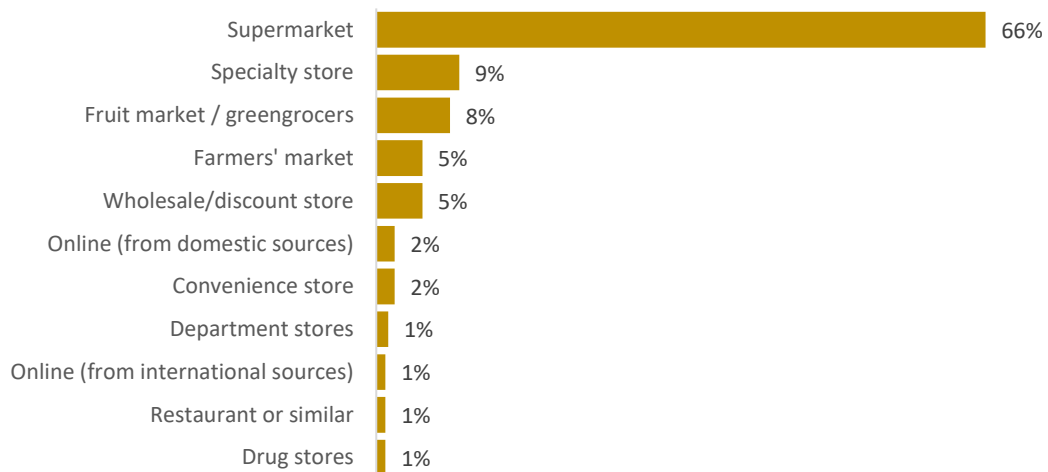


Figure 3-20 Percentage of apple expenditure by retail channel

- About 12 per cent of consumers purchased some apples online. The most cited main reason for buying apples online was a preference to avoid going in-store (Figure 3-21).



Figure 3-21 Main benefit of shopping online for apples

3.5 Discrete Choice Experiment analysis of apple choices

In this section we present findings of the Discrete Choice Experiment. Our aim is to identify which apple attributes drive product choices, by how much, and by who. We do this using a statistical method called Latent Class Modelling that identifies consumer segments in the data based on which product offerings consumers preferred. The model parameter estimates can be found in 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 was high, and most respondents felt certain that their responses reflected real-world choices if these apples were available (Figure 3-22).

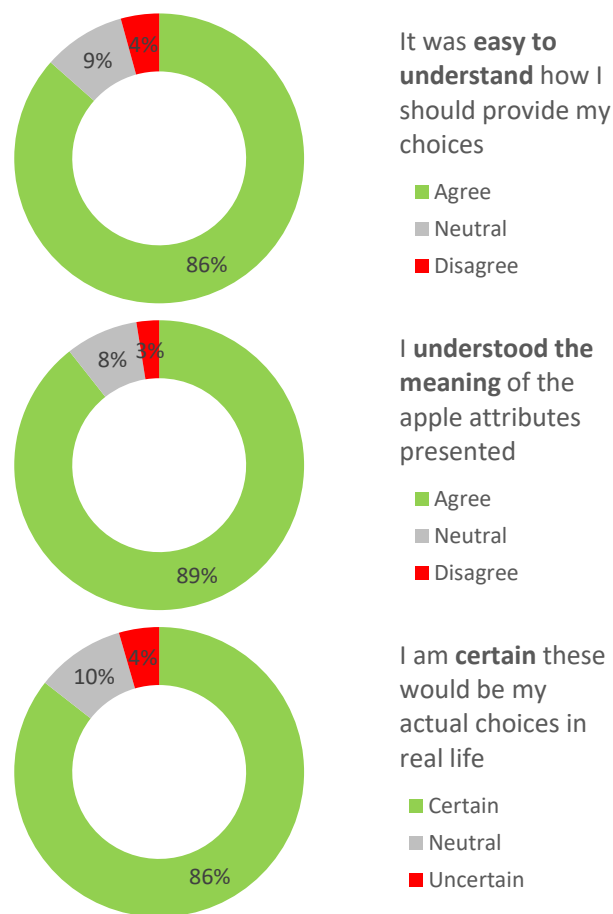


Figure 3-22 DCE debriefing questions around task and attribute understanding, and choice certainty

3.5.1 Consumer willingness-to-pay values

Estimates of WTP tell us how much more the average consumer is willing to pay for apples with a particular attribute, over apples that do not have this attribute (Table 3-1, **Error! Reference source not found.**). For example, members of Segment Two are willing to pay, on average, \$1.11/lb more for apples that are grown with practices that generate 15 per cent less GHG than conventional methods. There is some uncertainty in WTP estimates, and the Confidence Intervals reported indicate that we can be 95 per cent sure that the true WTP falls within this interval, in this case between \$0.33/lb and \$1.88/lb.

We can see that the Latent Class Modelling has identified four distinct consumer groups. Reported under each segment column heading is the size of each segment, Segment One has an estimated size of 17 per cent, the second segments size is 27 per cent, the third and fourth are both 28 per cent each. These segment sizes tell us the probability that a randomly selected Californian apple purchaser belongs to that consumer group.

Table 3-1 Apple attribute willingness-to-pay by consumer segment

Apple Attribute	Segment 1 (17%)	Segment 2 (27%)	Segment 3 (28%)	Segment 4 (28%)
Moderate Injury	-\$0.68*** (-1.02:-0.34)		-\$0.41*** (-1.02:-0.34)	-2.53*** (-4.5:-0.61)
Significant Injury	-\$1.47*** (-1.87:-1.07)		-\$0.62*** (-1.02:-0.34)	-\$5.49*** (-10.1:-3.92)
Moderate Deformity			-\$0.92*** (-1.02:-0.34)	-\$4.45*** (-7.87:-1.83)
Significant Deformity	-\$1.81*** (-2.35:-1.27)		-\$1.12*** (-1.47:-0.78)	-\$6.50*** (-10.2:-3.1)
15% Reduction in GHG		\$1.11*** (0.33:1.88)	\$0.29*** (0.12:0.46)	\$1.12** (0.02:2.22)
30% Reduction in GHG		\$1.31*** (0.45:2.17)	\$0.16*** (0.02:0.31)	
Organic Production		\$2.63*** (0.97:4.30)	\$0.52*** (0.33:0.72)	\$3.13*** (1.15:5.11)
Care for Workers		\$2.23*** (1.08:3.38)	\$0.50*** (0.26:0.73)	
Contribute to Communities		\$1.93*** (0.89:2.98)	\$0.53*** (0.28:0.77)	
Support Growers		\$2.24*** (1.11:3.37)	\$0.22*** (0.04:0.40)	
GE-Free		\$2.87*** (1.39:4.35)	\$0.25*** (0.02:0.48)	

Average marginal WTP/lb US2021

***, **, * denotes statistical significance at 1%, 5%, and 10% level respectively

95% Confidence Intervals in brackets

Californian Consumer Willingness-to-pay Segments

1. Appearance Only

17% of consumers

This segment is the smallest of the four consumer groups. These consumers are only concerned with avoiding suboptimal apples and do not value the credence attributes presented to them.

Consumers in this segment are:

- More likely to be older
- Less likely to think environmental impacts are important to consider

2. Conscious Consumer

27% of consumers

These consumers are primarily focused on the social and environmental attributes in their apple choices and have the highest WTP for these attributes of the segments. These consumers are indifferent to changes in appearance.

Consumers in this segment are more likely to:

- Believe that there are significant risks with the use of GE
- Be younger

3. Broad Considerations

28% of consumers

These consumers have the broadest set of attributes that they consider in their apple choices. However WTP values are the lowest of the segments.

Consumers in this segment are more likely to:

- Believe appearance is not important
- Be middle aged

4. Strong Preferences

28% of consumers

These consumers have the highest WTP of the three segments for Organic production. But they also have the strongest preferences for avoiding deformed or injured apples.

Consumers in this segment are more likely to:

- Believe apple appearance is important
- Believe GE has low risk

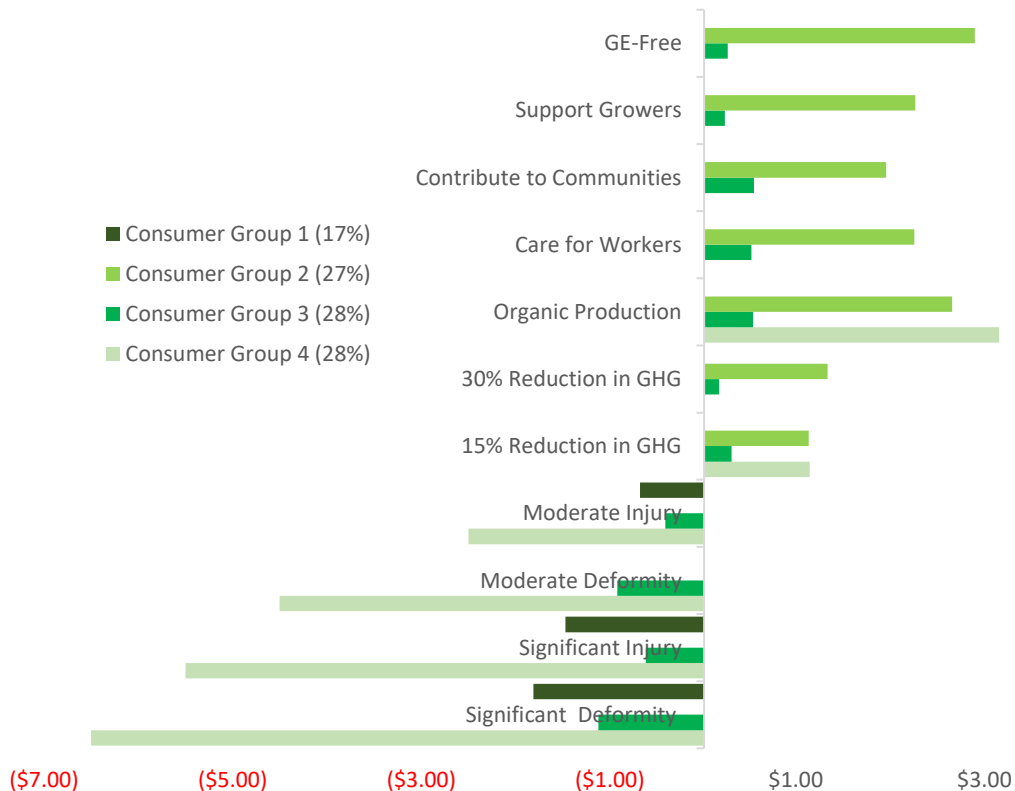


Figure 3-23 Apple attribute WTP by consumer segment

To provide an indication of the overall preferences ranking across the entire sample, we form a weighted aggregate estimate of WTP by adding up the weighted willingness-to-pay values for each class size (Figure 3-24). This shows that Organic production is the most valued attribute by consumers, followed by GE-free, social responsibility claims, and GHG reductions last. Consumers prefer to avoid purchasing apples with suboptimal appearance characteristics, with significant deformities having the strongest negative effect on consumer apple choice.

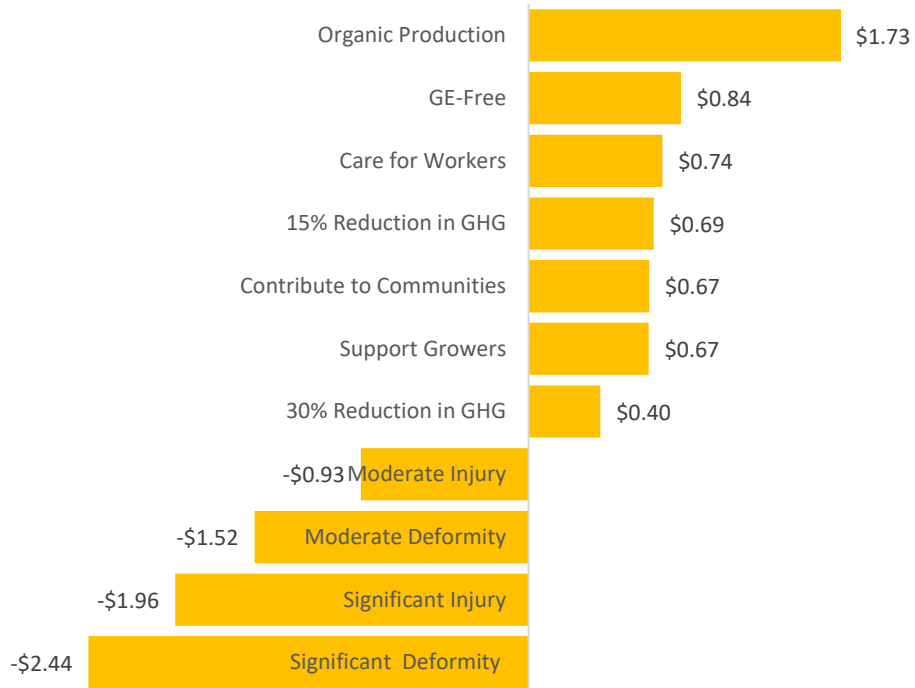


Figure 3-24 Segment weighted aggregate willingness-to-pay

Chapter 4

Conclusions

This report presents the findings of a structured online survey of Californian apple 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 consumers preferences for distinctively New Zealand credence attributes.

Overall, results indicate that New Zealand apples are held in high regard as a high-quality offering with characteristics that consumers prefer and value. The statistical analysis of consumers apple 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 second in the research programme to survey Californian apple consumers with the first survey in 2020. The two samples are very similar on demographic measures including income, gender, location, education, age, and household composition. Comparing results found here to the previous survey show that:

- Overall purchase frequencies largely unchanged across colour type, but an increase in average prices usually paid rising from \$2.45/lb to \$3.30/lb.
- In both surveys, purchase frequency of New Zealand apples sits around 24 percent purchasing at least occasionally. New Zealand apple quality is ranked second behind the USA in both surveys.
- The ranking of apple varieties purchased is unchanged. Consistent across both surveys was the low awareness of where apples were grown.
- The factors that consumers considered important in their decisions to purchase apples remained unchanged: freshness, high quality, personal health, crispness.
- Likewise, the reasons for purchasing NZ apples remained unchanged: high quality, freshness, sweet taste and high food safety.
- Comparing estimates of consumer willingness-to-pay for apple attributes in the Discrete Choice Experiment reveals that consumers relative preferences over the range of attributes considered are broadly consistent between the two survey rounds (Figure 4-1). The graph illustrates some modest reductions in WTP levels other than for Organic and GE-free, which saw moderate increases. Consumers relative preferences to avoid suboptimal appearance characteristics are consistent across both surveys with moderate injuries (blemish) having least affect, and significant deformities (misshapen) having the greatest negative influence on consumers apple choice. However, in 2021 we see a significant reduction in these negative affects across all suboptimal levels. COVID-19 pandemic impacts have included contraction in consumer spending, and supply constraints leading to increasing prices. Both of these factors are likely at play in the movements down that we see here. Conversely, demand for Organic and GE-free attributes is bolstered by consumer focus on health and immune enhancing foods.

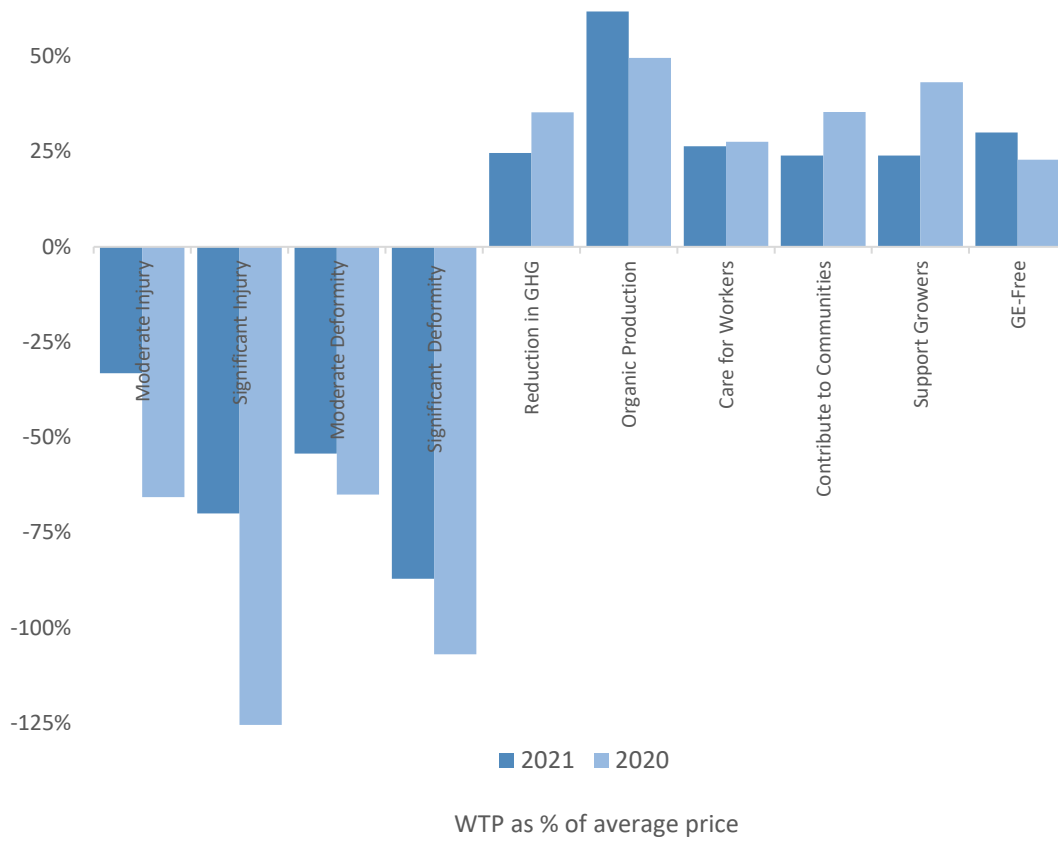


Figure 4-1 Comparing 2021 and 2020 WTP

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 utility¹ 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 utility² 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

¹Related terminology used in psychology discipline is *the level of satisfaction* (Hensher et al. 2015).

²In 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 Apple choices

Table B-1 California Apple choice Latent Class model

Apple Attributes	Class 1		Class 2		Class 3		Class 4	
Moderate Injury	-0.78***	(0.21)	0.18	(0.14)	-0.89**	(0.38)	-1.65***	(0.18)
Significant Injury	-1.69***	(0.24)	0.24	(0.17)	-1.36***	(0.46)	-2.64***	(0.28)
Moderate Deformity	-0.11	(0.22)	0.08	(0.15)	-1.99***	(0.47)	-1.25***	(0.28)
Significant Deformity	-2.08***	(0.33)	-0.01	(0.16)	-2.43***	(0.55)	-3.13***	(0.35)
15% Reduction in GHG	0.17	(0.15)	0.26**	(0.12)	0.64***	(0.20)	0.20*	(0.20)
30% Reduction in GHG	-0.26*	(0.15)	0.30***	(0.07)	0.36**	(0.16)	0.01	(0.20)
Organic Production	0.28	(0.18)	0.61***	(0.11)	1.14***	(0.18)	0.57***	(0.19)
Care for Workers	-0.35	(0.27)	0.52***	(0.16)	1.08***	(0.27)	0.10	(0.36)
Contribute to Communities	-0.42***	(0.16)	0.45***	(0.13)	1.14***	(0.27)	0.09	(0.25)
Support Growers	-0.05	(0.15)	0.52***	(0.11)	0.48***	(0.19)	0.05	(0.21)
GE-Free	0.05	(0.14)	0.66***	(0.13)	0.55**	(0.22)	0.06	(0.16)
Price \$/lb	-1.15***	(0.08)	-0.23***	(0.09)	-2.16***	(0.19)	-0.18***	(0.06)
Opt-out Choice	- 2.15***	(0.26)	- 2.28***	(0.30)	- 6.47***	(0.79)	- 3.67***	(0.21)
Class Membership								
Constant	1.57	(0.07)	3.95***	(0.88)	3.92***	(0.79)		
Appearance is important	-0.24***	(0.06)	-0.31***	(0.06)	-0.39***	(0.05)		
Environmental impact important	-0.52***	(0.27)	0.36	(0.26)	0.37	(0.24)		
Significant risks with use of GE	0.08	(0.32)	1.13***	(0.38)	0.62**	(0.29)		
Age	0.46***	(0.01)	-0.01	(0.01)	0.03***	(0.01)		
Female	-0.03	(0.28)	0.04	(0.25)	0.31	(0.22)		
Education	0.13	(0.16)	0.01	(0.17)	-0.25*	(0.15)		
Average Class Probability	0.17		0.27		0.28		0.28	
Log Likelihood	-8,216							
McFadden Pseudo-R ²	0.344							
Number of observations	9,140							
AIC/N	1.85							

***, **, * denotes statistical significance at 1%, 5%, and 10% level respectively
Standard errors in brackets

- 350 Unlocking Export Prosperity: The distinctive cultural attributes of food.**
Rout, M and Reid J 2019
- 351 Credence attributes and New Zealand country of Origin: A review.**
Dalziel P, Saunders C, Tait P and Saunders J 2018
- 352 Value-Based Leadership in New Zealand Agri-foods Exporting Enterprises: Literature Review.**
Mayes J, Wall G and Cammock P 2019
- 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