Consumer Demand for Green Electricity: A study of Consumer Switching in New Zealand Retail Electricity Markets

A thesis

submitted in fulfilment

of the requirements for the degree

of

Doctor of Philosophy in Economics

at

The University of Waikato

by

TOM NDEBELE

THE UNIVERSITY OF
WAIKATO
Te Whare Wānanga o Waikato

2016

Abstract

The extent to which deregulation increases the competitiveness of retail electricity markets depends largely on consumer switching activity. The USA, UK, Norway, Sweden, and Australia have all implemented electricity market reforms but consumers have often been reluctant to switch suppliers. In New Zealand, most consumers have not switched suppliers despite potential annual power bill savings of $150. Campaigns promoting consumer switching rely on price differences and ignore the value of non-price attributes, including whether the electricity is generated from renewable energy sources.

This thesis improves our understanding of consumer switching and the demand for green electricity by analysing consumer preferences for the attributes of electricity services, estimating willingness to pay (WTP) for non-price attributes, and explaining consumer switching in terms of eight attributes:- power bill, call waiting time, fixed rate contract, discount, loyalty rewards, renewables, ownership of supplier, and supplier type. The analysis is based on a panel choice dataset generated using a choice experiment which was administered in 2014 to an online panel of 224 electricity bill payers in New Zealand. The multinomial logit, random parameter logit and latent class models are used to analyse the choice data with psychological constructs included to explain heterogeneity of preferences. The effect of attribute non-attendance (AN-A) and hypothetical bias on WTP estimates is investigated. We also explore whether using shorter versions of the New Ecological Paradigm (NEP) Scale to measure environmental attitudes (EA) affects estimates of WTP for green electricity.

The results indicate that non-price attributes of electricity services are significant determinants of consumer switching. Three latent classes with distinct preferences for the attributes are identified. Class 1 (40%) is mainly concerned about the power bill, and would switch supplier to save at least NZ$125 per year in power bills, *ceteris paribus*. This value mainly captures the status quo effect. Class 2 (46%) exhibits no status quo effect and values all the attributes offered including renewables, and particularly dislikes entrants from other sectors which have to charge at least NZ$135 less per year compared to a traditional retailer for a 50% chance of attracting customers. Class 3 (14%) consists of captive and loyal respondents who would not switch supplier for any realistic bill savings.

We find that failing to account for attribute non-attendance results in WTP estimates that are significantly lower for attributes that are not normally included in standard electricity plans. Also, respondents who claim to have ignored some attributes may not have done so; instead they assigned lower weights to these attributes. Respondents with low certainty scores are less sensitive to the power bill and are predicted to have significantly higher WTP. We find that using shorter versions of the NEP Scale to measure EA, increases bias in WTP for green electricity.

We conclude that price differences in retail markets reflect, in part, consumer preferences for non-price attributes, and that providing consumers with information on the levels of non-price attributes could influence switching rates, the uptake of green electricity and potentially the level of competition in the retail electricity sector.

Publications from this thesis

Conference papers

Ndebele, T., & Marsh, D. (2015, February 10-13). *The influence of attitudes on electricity supplier choice: Does it matter how green a supplier is?* Paper presented at the 59th National Australian Agricultural & Resource Economics Society, Rotorua, New Zealand. Abstract available at: http://www.aares.org.au/aares/documents/2015AC/Handbook.pdf

Ndebele, T., & Marsh, D. (2014, August 28-29). *Environmental attitude and the demand for green electricity in the context of supplier choice: A case study of the New Zealand retail electricity market*. Paper presented at the New Zealand Agricultural & Resource Economics Society, Nelson, New Zealand. Download from http://ageconsearch.umn.edu/handle/188376

Ndebele, T., & Marsh, D. (2013, August 28-30). *Consumer choice of electricity supplier: Investigating preferences for attributes of electricity services*. Paper presented at the New Zealand Agricultural & Resource Economics Society, Lincoln University, Canterbury, New Zealand. Download from http://ageconsearch.umn.edu/handle/160417

Dedication

I dedicate this thesis to my daughters, Thandazile Kholiwe, Thandeka Kholwani and Thandile Kholwekile Ndebele, and to my mother Sikholiwe Ndebele and late father Nkengiwa Johnson Ndebele. Throughout the study period, my children were deprived of quality time with their father and I thank them for their patience.

Acknowledgements

This thesis was mainly funded through the Waikato Doctoral Scholarship and the Internal Study Award granted by the University of Waikato. My PhD study would not have been possible without this support, for which I am greatly thankful. I would like to thank NZARES for sponsoring my conference presentation.

I am greatly indebted to a number of people who generously offered valuable advice, encouragement, inspiration, support and friendship throughout my study at the University of Waikato. I extend my sincere thanks and gratitude to my doctoral supervisory panel, Dr. Dan Marsh and Professor Riccardo Scarpa, for their support throughout my study. I am deeply indebted to my chief supervisor, Dr. Dan Marsh for his guidance, encouragement, insightful criticism, patience, accessibility and for sharing his knowledge. I thank Professor Riccardo Scarpa for his invaluable ideas and for pushing me to dig deeper into my research.

Many thanks to the following people for their help in the development of the survey questionnaire: Professor Murray Patterson, Associate Professor Marjan van den Belt, Derrylea Hardy, Vicky Forgie and Dr. Richard Yao. I would also like to thank Dr. Beverley Brereton for her comments and suggestions on earlier drafts of chapter 3. Also thanks to the staff in the Economics Department for their support, and special thanks to Maria Fitzgerald for her assistance. Many thanks to Judy McDonald for proofreading the final draft of this thesis.

To my fellow students, especially Stefania Mattea, Harold Valera, Alexey Kravchenko, Dr. Van Vu Huong, Dr. Haseeb Bhatti, Dr. Lena Mkwara, I say thank you for sharing some of your experiences with me. To all my friends, I appreciate all your moral support and for encouraging me to keep going.

Thank you all!

Table of Contents

Abstract iii

Publications from this thesis...v

Dedication vi

Acknowledgements vi

List of Tables..xi

List of Figures xiv

List of acronyms xv

Chapter 1. Introduction..1

1.0 Overview and background.. 1

1.1 Motivation and research questions 8

1.1.1 Motivation and contribution... 8

1.1.2 Research questions.. 10

1.2 Significance of this study 15

1.3 Outline of the thesis.. 17

Chapter 2. Methodology..18

2.1 Introduction 18

2.1.1 Hypotheses 21

2.2 Stated Choice experiments for the valuation of the attributes of electricity services 23

2.2.1 An overview of stated choice experiments......................... 23

2.2.2 The discrete choice model 26

2.2.3 Multinomial logit (MNL) model 27

2.2.4 Panel Latent class logit model 30

2.2.5 The panel logit with continuous mixing (MXL)................. 36

2.3 Conceptual model for integrating psychological constructs with stated choice 40

2.3.1 Background of the conceptual model 40

2.3.2 The model 42

2.4 Measuring psychological constructs based on attitude-behaviour theories 46

2.4.1 The New Ecological Paradigm (NEP) Scale...................... 48

2.4.2 The theory of planned behaviour (TPB): Application to consumer switching 50

2.4.3 Norm activation theory: Application to consumer switching........... 54

2.5 Experimental design and survey questionnaire development 55

2.5.1 Selection of decision-relevant attributes of electricity suppliers 56

2.5.2 Experimental design for pilot survey ... 60
2.5.3 Experimental design for the final survey ... 63
2.5.4 Simulation of experimental design for the final survey ... 68
2.5.5 Survey questionnaire ... 70
2.5.6 Choice data ... 73
2.5.7 Summary ... 73
Chapter 3. The New Zealand electricity market ... 74
3.1 Introduction ... 74
3.2 The New Zealand electricity market (NZEM) ... 74
3.3 Reasons for deregulating the electricity markets ... 75
3.4 Current market structure ... 76
3.5 Retail electricity prices ... 79
3.6 Promoting consumer switching in NZ retail electricity markets ... 81
3.7 Debate on the competitiveness of the New Zealand electricity market ... 82
3.7.1 Study contribution to the debate ... 85
3.8 Electricity as a product ... 88
3.9 Summary ... 88
Chapter 4. Consumer switching: Is price all that matters? ... 90
4.1 Introduction ... 90
4.2 What's My Number campaign ... 92
4.3 Overview of the switching literature and the contribution of this chapter ... 94
4.4 Consumer switching in the retail electricity market in New Zealand ... 97
4.4.1 Sample statistics ... 97
4.4.2 Reasons for choosing current supplier ... 99
4.4.3 Switching activity ... 101
4.4.4 Reasons for switching supplier ... 102
4.4.5 Reasons for not switching supplier in the past 24 months ... 103
4.4.6 Consumer sensitivity to the level of savings (power bill savings) ... 104
4.4.7 Attitudes towards switching ... 106
4.5 Preferences and WTP for the attributes of electricity services ... 111
4.5.1 Description of variables ... 112
4.5.2 Utility function ... 115
4.5.3 Hypotheses ... 115
4.6 Models ... 116
4.7 Results ... 117
4.7.1 Regression results ... 118

4.7.2 WTP estimates 128

4.7.3 Supplier type and switching inertia 133

4.7.4 Determinants of WTP for the attributes of electricity services 141

4.8 Chapter summary 144

Chapter 5. Attribute non-attendance and hypothetical bias in stated choice experiments for supplier choice 146

5.1 Introduction 146

5.2 Brief background and research questions 147

5.3 A brief review of the literature on attribute non-attendance and hypothetical bias 152

5.3.1 Attribute non-attendance 152

5.3.2 Hypothetical bias in stated choice experiments 155

5.4 Stated attribute non-attendance 157

5.4.1 Analysis of stated attribute non-attendance responses 157

5.4.2 How AN-A in this study compares with AN-A in other study contexts 161

5.4.3 Consistency of stated non-attendance with observed choices 164

5.4.4 The effect of inconsistent stated attribute non-attendance on model estimation 167

5.4.5 Alternative approaches for accounting for stated AN-A in model estimation 175

5.5 Inferred attribute non-attendance 186

5.5.1 A probabilistic decision process model for inferred AN-A 186

5.5.2 Model specification 187

5.5.3 Results 190

5.6 Hypothetical bias in choice experiments 194

5.6.1 Distribution of responses to the certainty statement 195

5.6.2 Models 195

5.6.3 Regression Results 196

5.7 Summary 204

Chapter 6. Environmental attitudes, altruism and the demand for green electricity 208

6.1 Introduction 208

6.2 Background and literature review 210

6.2.1 The demand for green electricity 213

6.2.2 How the NEP Scale has been used in previous studies. 216

6.3 New Zealanders’ environmental attitudes 219

6.3.1 Analysis of responses to the NEP Scale statements 219
6.3.2 Internal consistency of the NEP Scale statements 223
6.3.3 Heterogeneity in environmental attitudes 226
6.3.4 Constructing and testing subscales of the NEP Scale 232
6.4 Analysis of responses to questions based on the norm activation theory . 238
6.5 Environmental attitudes and WTP for green electricity 240
6.5.1 Methods 241
6.5.2 Results 243
6.6 Altruism and the demand for green electricity 248
6.6.1 Regression results 250
6.6.2 WTP for green electricity 252
6.7 The influence of shorter versions of the NEP Scale on WTP estimates ... 253
6.7.1 Regression results 254
6.8 Chapter summary 262
Chapter 7. Summary and conclusion 265
References 274
Appendix 1. Final survey questionnaire 293
Appendix 2. Pilot survey results 316
2.1. Analysis of responses to the NEP Scale statements 316
2.2. Analysis of responses to the TPB statements – pilot survey 321
2.3 Analysis of responses to the NAT statements – pilot survey 324
Appendix 3. Chronology of market reforms 326
3.1 NZ electricity market reforms 326
3.2 How the wholesale spot market price is determined 327
Appendix 4. Supplementary tables for Chapter 4 330
Appendix 5. Supplementary results for Chapter 5 333
Appendix 6. EA and WTP for green electricity: supplementary results 336
6.1 Analysis of responses to the NEP Scale statements: Supplementary analysis 336
6.1.1 Facets of ecological worldview 336
6.1.2 The dimensionality of the NEP Scale 337
6.2 Panel ordered probit model 339
6.3 WTP for green electricity 341
6.4 The influence of shorter versions of the NEP Scale on WTP estimates ... 341
6.4.1 Regression results for MNL and RPL-EC 341

List of Tables

Table 2-1: The New Ecological Paradigm Scale items 49
Table 2-2: Description of the TPB constructs and average scores: pilot survey[1] . 53
Table 2-3: NAT constructs and distribution of response: pilot survey (N =70) ... 55
Table 2-4: Attributes, attribute levels and the design codes used in the ED......... 58
Table 2-5: MNL efficiency measures for ED for the pilot survey 61
Table 2-6: Regression results for the pilot survey (z values are in parentheses) .. 63
Table 2-7: MNL Bayesian experimental design efficiency measures 67
Table 2-8: MNL probabilities 67
Table 2-9: Minimum sample estimates for individual priors 67
Table 2-10: MNL D-efficient design summary of iteration history 68
Table 2-11: Experimental design simulation results 69
Table 2-12: Quotas used for age and income groups 72
Table 4-1: Switching rates and benefits (2011-2013)[1] 94
Table 4-2: Summary statistics of SDCs and attitudinal covariates for sample and national populations 98
Table 4-3: Reasons for choosing current supplier (N = 224) 100
Table 4-4: Distribution of ratings on the importance of reasons for switching retail supplier (N = 224) 103
Table 4-5: Reasons for not switching supplier in the past two years (N = 177) . 104
Table 4-6: Level of savings and stated switching rates 105
Table 4-7: Average scores for the TPB constructs (N = 224) 109
Table 4-8: Correlation matrix (Pearson (n)) for the TPB constructs (N = 224).. 110
Table 4-9: Linear regression results for BI on ATT, SN, and PBC (N = 224) ... 111
Table 4-10: Variable description 114
Table 4-11: Criteria used to determine the number of classes for model M4 119
Table 4-12: MNL and LC model regression results (t values are in parentheses) (N= 224) 121
Table 4-13: Summary of preference classes 127
Table 4-14: Summary of characteristics of respondents in each class 128
Table 4-15: WTP for the attributes of electricity services (NZ$$_{2014}$)[1] 131
Table 4-16: Minimum savings required to induce a 50-50 chance of switching (NZ$$_{(2014)}$) 135
Table 4-17: OLS regression results (t values are in parentheses) 143
Table 5-1: Share of respondents who ignored a specific attribute 158
Table 5-2: Share of respondents who ignored a specific number of attributes... 160
Table 5-3: Proportion of respondents attending to each attribute and jointly with *Bill* 161
Table 5-4: Proportion of respondents attending to combinations of attributes ... 161
Table 5-5: Comparison of AN-A reported in previous studies. 163
Table 5-6: Characteristics of respondents who ignored the cost attribute 164
Table 5-7: Characteristics of respondents who ignored or considered the cost attribute 166
Table 5-8: Information criteria used to determine the number of classes 169

Table 5-9: Class probabilities ... 170
Table 5-10: Latent class model results (z-values are in parentheses) ... 172
Table 5-11: Estimates of WTP for the attributes of electricity services ($NZ\$_{(2014)}$) ... 174
Table 5-12: Regression results for the MNL and RPL-EC models of supplier choice ... 178
Table 5-13: Estimates of average marginal WTP for the attributes of electricity services based on MNL and RPL-EC models ($NZ\$_{(2014)}$) ... 183
Table 5-14: Tests of equality of WTP estimates based on the MNL and RPL-EC models ... 185
Table 5-15: Structure of inferred attribute non-attendance classes ... 189
Table 5-16: Comparison of attribute processing rules ... 192
Table 5-17: WTP estimates for the MNL and LC models ($NZ\$_{(2014)}$ /month) ... 194
Table 5-18: Regression results for MNL and RPL-EC models ... 199
Table 5-19: WTP for respondents with different levels of certainty about their choices ($NZ\$_{(2014)}$ /month) ... 202
Table 5-20: Test of equality of WTP based on the asymptotically normal test statistic (ANTS)[1] ... 203
Table 6-1: Recent studies that use the NEP Scale ... 218
Table 6-2: Mean scores, percentage distribution of responses and item-total correlations (r_{i-t}) for the NEP Scale items ... 221
Table 6-3: Comparison of corrected item-total correlation (r_{i-t}) and Cronbach's alpha ... 224
Table 6-4: Factor loadings for NEP Scale items ... 225
Table 6-5: Frequencies and proportions of self-reported levels of environmental concern ... 229
Table 6-6: Marginal effects of respondents' SDCs on NEP Scale responses[*] ... 230
Table 6-7: Regression results for the ordered LCA model (N = 224) ... 231
Table 6-8: Item-total correlations and Cronbach's alpha for the sub-scales of the NEP Scale ... 233
Table 6-9: LCA model results for the full NEP Scale and constructed 10- and 5-item sub-scales ... 235
Table 6-10: Characteristics of respondents in the *weak*, *moderate* and *strong* environmental classes ... 237
Table 6-11: Percentage distribution of responses to AC and AR statements (N = 224) ... 239
Table 6-12: Summary statistics and the correlation matrix (Pearson (n)) for the NAT constructs ... 240
Table 6-13: Description of NEP score levels ... 242
Table 6-14: Information criteria used to determine the number of latent classes ... 244
Table 6-15: Regression results ... 245
Table 6-16: WTP for a 1% increase in generation from renewable energy sources ($NZ\$_{(2014)}$ / month) ... 247
Table 6-17: RPL-EC model regression results ... 251

Table 6-18: WTP to secure a 1% increase in green electricity (NZ$$_{(2014)}$ /month) 253
Table 6-19: Criteria for the number of classes 254
Table 6-20: LC model results for supplier choice with dummy coded levels for NEP scores 256
Table 6-21: WTP with Dummy coded levels for NEP score 258
Table 6-22: Test for equality of WTP for green electricity using ANTS[1] 259
Table 6-23: Comparison of estimated prior probabilities 260
Table 6-24: WTP for a 1% increase in green electricity (NZ$$_{(2014)}$ /month) 261
Table 6-25: Comparison and test for equality of WTP estimates 261

List of Figures

Figure 2-1: Schematic causal model of environmental concern 41
Figure 2-2: Conceptual framework integrating NEP Scale, TPB, NAT and stated choice analysis 43
Figure 2-3: Stated choice scenario and example of a choice task. 62
Figure 3-1: A schematic of the NZ electricity industry (Source: NZ Energy Data File 2012) 77
Figure 3-2: Components of the residential retail price in 2010 (Source: NZX Ltd, 2014) 80
Figure 3-3: Real retail electricity prices by consumer category ($NZ\$_{2013}$) 81
Figure 3-4: Price differences between highest- and lowest-priced regional retailers 87
Figure 4-1: Distribution of ratings of satisfaction with current supplier 101
Figure 4-2: Search activity: (*Question: How often do you look for opportunities to switch supplier?*) 102
Figure 4-3: Distribution of responses to the TPB constructs 108
Figure 4-4: Distribution of responses for behavioural intentions (BI) 109
Figure 4-5: Stated choice scenario and example of a choice task. 112
Figure 4-6: Information criteria and segment retention for M4 119
Figure 4-7: Predicted probability of switching [MNL model ($switch_1$, $\alpha = \alpha_1$)] . 136
Figure 4-8: Probability of switching to any competitor for bargain hunters (class 1) 137
Figure 4-9: Probability of switching to different supplier types [class 2 ($switch_1$, $\alpha = \alpha_1$)] 138
Figure 4-10: Probability of switching to different supplier types [class 2 ($switch_2$, $\alpha = \alpha_2$)] 138
Figure 4-11: Probability of switching to different supplier types [class 2 ($switch_3$, $\alpha = \alpha_3$)] 139
Figure 4-12: Probability of switching to different supplier types [class 2 ($switch_4$, $\alpha = \alpha_4$)] 139
Figure 4-13: Probability of switching to different supplier types [class 3 ($switch_1$, $\alpha = \alpha_1$)] 140
Figure 5-1: Distribution of certainty scores 195
Figure 5-2: WTP estimates at various cut-off points on the certainty scale 197
Figure 6-1: Distribution of responses to the NEP Scale statements 222
Figure 6-2: Average item scores 223
Figure 6-3: Information criteria used to determine the number of classes 244
Figure 6-4: Histogram of randomly drawn normal distribution with mean zero and standard deviation one 252
Figure 6-5: Histogram of the sampling distribution of WTP for green electricity 253

List of acronyms

AC	Awareness of the consequences of a behaviour
AN-A	Attribute non-attendance
ANTS	Asymptotically normal test statistic
AR	Ascription of responsibility
ATT	Attitude
AVC	Asymptotic variance-covariance matrix
CE	Choice experiment
CVM	Contingent valuation method
DC	Dichotomous choice
EA	Environmental attitudes
ED	Experimental design
HB	Hypothetical bias
LC	Latent class model
LCA	Latent class attitudinal model
MBIE	Ministry of Business, Innovation and Employment
MNL	Multinomial logit model
MRS	Marginal rate of substitution
NAT	Norm activation theory
NEP	New Ecological Paradigm Scale
NZ	New Zealand
PBC	Perceived behavioural control
PRL-EC	Random parameter logit with error components model
RP	Revealed preference
RUM	Random utility maximization
RUT	Random utility theory
SDCs	Socio-demographic characteristics
SN	Social norms
SP	Stated preference
TPB	Theory of planned behaviour
WMN	What's My Number campaign
WTP	Willingness to pay

Chapter 1. Introduction

1.0 Overview and background

New Zealand, the USA, the UK, Norway, Sweden, and Australia have all implemented electricity market reforms since the 1980s aimed at replacing monopolies with efficient and competitive markets. In some cases these reforms have had limited success, particularly in the retail electricity sector. An important issue has been the apparent reluctance of consumers to consider changing their electricity supplier, leading to a lack of effective competition (Electricity Authority, 2010). Brennan (2007) reports that most jurisdictions have experienced very low switching rates, and attributes this to customers' reluctance to move from their default supplier. A similar finding is reported by Defeuilley (2009), who attributes low switching rates and suboptimal behaviour of households to risk aversion, and other behavioural biases that encourage customers to stick with the status quo (SQ). In contrast, Littlechild (2009) asserts that most deregulated markets have experienced growing switching rates, and argues that low switching rates do not necessarily indicate that the markets are non-competitive, but could be a result of increased competition where retailers offer better packages and counter-offers to retain customers. However, under current market conditions, where seemingly unjustifiable large price dispersions are observed, Littlechild's (2009) argument could be challenged.

The willingness of consumers to change their supplier is an important factor in determining the extent to which deregulated retail electricity markets become competitive. Goett, Hudson, and Train (2000, p. 1) assert that "The power of competitive pressures to lower prices depends on the degree to which customers are willing to switch suppliers in response to offers of lower prices." A better understanding of consumer preferences and switching behaviour is required to inform regulation and the effective promotion of switching in retail electricity markets, and this is what this thesis provides.

New Zealand (NZ) introduced retail competition in 1998 under the Electricity Industry Reform Act 1998 (Ministry of Business, Innovation & Employment

[MBIE], 2010). The main objective of the Act was “to increase consumer choice, encourage innovation, and ultimately result in lower prices than would otherwise be charged” (Electricity Authority, 2010, p. 3). However, a decade later, a ministerial review of the performance of the electricity market conducted in 2009 determined that: (1) the current levels of consumer switching were insufficient to curb non-competitive behaviour by retailers; and (2) the full benefits of retail competition had not yet been realised, particularly for domestic customers who continued to face rapidly increasing prices (Electricity Authority, 2010). Based on price differences between retailers in each region, the total benefits of switching to the cheapest available retailer were estimated to be about $150 million per annum across all consumers (Electricity Authority, 2011a). To address the issue of customer ‘stickiness’, the government set up a $15 million consumer Switching Fund to promote switching, as recommended by the ministerial review (Electricity Authority, 2010)[1].

The Electricity Authority spent $15 million (2011-2014) on the “What’s My Number” (WMN) campaign promoting consumer switching by increasing awareness of the benefits of switching, and encouraging consumers to shop around for lower prices (Electricity Authority, 2011a, 2012b). Also, an independent complementary one-stop-shop website called “Powerswitch” was revamped to allow consumers to compare prices and switch to the supplier offering the lowest price (Electricity Authority, 2010). The benefits promoted under this campaign were based only on price differences between retailers. This ignored the value that consumers place on non-price attributes of electricity supply (or services) and any possible influence these attributes may have on switching behaviour and supplier choice. However, information on the values of non-price attributes has not been available in the past. Obtaining reliable estimates of these values or willingness to pay (WTP), and explaining the variability of consumer preferences for this class of goods remains a challenge for researchers and policy makers.

[1] Customer ‘stickiness’ was defined as the observed tendency of the majority of electricity customers to stay with their default or incumbent retailers, which were allocated all customers within a particular region at the time the market was opened up for competition. For example, Mercury Energy was allocated all customers in central Auckland, while Meridian Energy got all customers in Northland.

Results from international studies indicate that factors such as attitudes, loyalty to incumbent supplier, lack of information, perceived information search costs, and perceived low economic benefits from switching, among others, may prevent consumers from switching to the cheapest supplier (e.g., Gamble, Juliusson, & Gärling, 2007, 2009; Gärling, Gamble, & Juliusson, 2008; Giulietti, Price, & Waterson, 2005; Rowlands, Parker, & Scott, 2004). The WMN campaign and Powerswitch addressed some of these issues.

A number of NZ studies and reviews were commissioned under the Switching Fund to provide the Electricity Authority and Ministry of Consumer Affairs with research that underpins the fund (see Electricity Authority, 2010), and to conduct market research to assess the performance of the WMN campaign and Powerswitch website (see Electricity Authority, 2011a, 2012a, 2012b, 2013b, 2013c). Although the studies show an increase in switching activity compared to the pre-campaign period, they also show that more than 79% of consumers did not switch in any particular year despite high bill savings available in the market. The latter suggests that customer 'stickiness' remained despite improved access to information, increased awareness of the right and ability to switch, ease of switching and higher bill savings.

These studies also report on consumers' attitudes towards switching, barriers to switching, and retailer activity. They also identify important non-price attributes of electricity services and groups of customers with similar switching behaviour, and explain differences between groups in terms of socio-demographic characteristics (SDCs). However, none of these studies attempt to value these attributes, but rather limit the analysis to a ranking of the attributes in terms of importance to consumers. Furthermore, it appears that no detailed analysis has been conducted to provide insight into the perceived customer 'stickiness' that may arise as a result of a number of unknown factors and the SQ effect – a tendency to stick with the current retailer.

Although the rankings provided in the above studies convey the relative importance of the non-price attributes of electricity supply, they do not provide information on how consumers trade-off these attributes. This thesis provides information on the trade-offs consumers make among a sub-set of important attributes of electricity services, and explains consumer “stickiness” in terms of SQ and “supplier type” effects[2]. Knowledge of the trade-offs consumers make amongst the attributes, including power bill savings, increases our understanding of consumer preferences and helps in explaining switching behaviour in the NZ retail electricity markets. For example, we are able to assess the likelihood of a given level of bill savings inducing switching, given differences in the levels of non-price attributes for different suppliers. This allows policy makers to more accurately predict likely outcomes of future campaigns promoting switching. Knowledge of the trade-offs also offers electricity retailers an opportunity to design offers that suit their customers, and to maintain or increase their market share. Retailers may be able to compensate customers for lower levels of some desirable attributes by changing the levels of other desirable or undesirable attributes. Furthermore, the dollar values estimated for the attributes allow for all attributes to be reduced to a common metric, which helps in evaluating policies that deliver different attribute levels, e.g., privatization of electricity companies, and renewable energy policy targets.

Promoting switching on the basis of price differences (bill savings) appears to be based on the belief that: (1) consumers are price-sensitive, and small changes in price will induce switching, given the homogeneous nature of the product (Cai, Deilami, & Train, 1998; Price, 2004); (2) brand value and service factors are likely to be very small for electricity retailing (Electricity Authority, 2010); and (3) consumers are more likely to view suppliers to be the same except for the price (Gärling et al., 2008). Promoting competition then focuses on price instead of other dimensions, which reflects the belief that “only the price matters.” This belief seems to have been fundamental in the Switching Fund in NZ. The belief is echoed in a statement by the chief executive of the Electricity Authority that “When the Electricity Authority launched the *What’s My Number* programme in 2011, it was with a strong belief that encouraging New Zealanders to shop around for their electricity – on a scale that had not been done before – had the potential to change the retail electricity landscape.” (Electricity Authority, 2012b, p. 1).

The way switching has been promoted in New Zealand conforms to the practice that relies entirely on values based on market prices to evaluate welfare benefits.

[2] “Supplier type” effects are the preferences for different types of electricity suppliers

Such practice has been criticized and shown to deliver sub-optimal welfare outcomes, especially in the evaluation of public projects, by ignoring all welfare benefits and costs that are not priced in the market (Bennett & Adamowicz, 2001; Costanza et al., 1997). Non-market valuation studies have shown that ignoring non-market values in decision-making either under-states or over-states welfare benefits. Therefore, the benefits of switching, quantified as bill savings, advertised under the WMN campaign may not reflect the true welfare benefits, if consumers value non-price attributes.

Switching rates have averaged about 20% per year over the period 2011-2013 (Electricity Authority, 2013b). While this is a positive outcome of the WMN campaign, the authorities are still not satisfied with the level of switching, as a large proportion of consumers have not actively participated and continue to be passive or indifferent. This suggests that the strategy of promoting switching benefits based on price alone is not effective enough. Estimates of WTP for non-price attributes provided in this thesis suggest that a more comprehensive approach that recognizes the values of these attributes may be required to induce higher switching rates.

Non-market valuation techniques, particularly choice experiments (CEs) and the contingent valuation method (CVM), have increasingly been used to provide welfare estimates of the attributes of non-market goods. Many important policy decisions in NZ have been supported by estimates obtained from non-market valuation techniques, transforming them "from mainly an academic exercise, ……. into a government decision support tool for policy decision making…" (Yao & Kaval, 2007, p. 7). However, CEs and the CVM rely on responses to hypothetical questions designed to elicit responses that are expected to convey information about the respondents' true preferences for the specific attributes under consideration. These techniques have been criticised for their reliance on responses to hypothetical questions.

Critics of non-market valuation techniques once argued that estimates based on these techniques should be rejected on the basis of unreliability of responses to hypothetical questions (e.g., Diamond & Hausman, 1994; McFadden, 1994)[3]. Some studies have shown that responses to real and hypothetical questions may differ significantly (e.g., Brownstone & Small, 2005; Champ, Bishop, Brown, & McCollum, 1997; Hensher, 2010; Isacsson, 2007), while others find no significant differences (e.g., Carlsson & Martinsson, 2001; Carson, Flores, Martin, & Wright, 1996; Lusk & Schroeder, 2004). However, it has been shown that properly designed surveys and elicitation formats, and mitigating hypothetical bias in model estimation can reduce the gap between hypothetical and real choices (Arrow et al., 1993; Champ et al., 1997; Champ, Moore, & Bishop, 2009; Cummings & Taylor, 1999).

The widespread use of non-market valuation techniques over the years has seen increasing attention paid to methods that seek to close the gap between WTP estimates obtained from hypothetical choices and those obtained from real choices. This increases the validity and acceptability of the welfare estimates. The gap between real and hypothetical WTP estimates is referred to as hypothetical bias (HB). Two important issues addressed by some of these methods are HB and attribute non-attendance (AN-A) in stated CEs. For example, a number of studies have developed statistical models that infer attribute processing rules supported by the choice data (e.g., Campbell, Hensher, & Scarpa, 2011; Hensher, Rose, & Greene, 2012; Scarpa, Gilbride, Campbell, & Hensher, 2009). AN-A identified in this manner is referred to as inferred AN-A. Other studies have incorporated respondent self-reported non-attendance, which is referred to as serial AN-A or choice task AN-A (e.g., Campbell, Hutchinson, & Scarpa, 2008; Carlsson, Kataria, & Lampi, 2010; DeShazo & Fermo, 2004; Hensher, Rose, & Greene, 2005b; Scarpa, Thiene, & Hensher, 2010). These studies demonstrate that explicitly accounting for ignored attributes in model estimation improves model fit and results in WTP estimates that are significantly different.

Another fairly recent development that has resulted from increased use of non-market valuation techniques is the specification of discrete choice models that more realistically represent the choice process by incorporating respondents' perceptions and attitudes in the utility functions of choice alternatives. The

[3] The criticism was mainly directed at the use of the CVM in estimating existence and non-use values in accessing environmental damage. Stated CEs were developed to address some of the major shortcomings of the CVM.

motivation behind this development is the increased realisation that preference heterogeneity is in part due to underlying attitudes and convictions (Alvarez-Daziano & Bolduc, 2009; Hess & Beharry-Borg, 2011). This approach adds another dimension to explaining preference heterogeneity, where unobserved latent variables that influence choice behaviour are measured using carefully designed attitudinal questions aimed at eliciting responses that reflect the underlying latent variables. A number of attitude-behaviour theories such as the theory of planned behaviour (TPB) (Ajzen, 1988, 1991), norm activation theory (NAT) (Schwartz, 1977), and the New Ecological Paradigm (NEP) Scale (Dunlap, Van Liere, Mertig, & Jones, 2000) offer non-market valuation practitioners an opportunity to use attitudinal questions that provide measurements with a valid theoretical foundation. However, only a limited number of valuation studies actually use these theories in the design of attitudinal question.

The values of some of the non-price attributes of electricity services have been estimated in previous studies using non-market valuation techniques (e.g., Abdullah & Mariel, 2010; Amador, Gonzalez, & Ramos-Real, 2013; Blass, Lach, & Manski, 2010; Cai et al., 1998; Giulietti et al., 2005; Goett et al., 2000; Hensher, Shore, & Train, 2014; Kaenzig, Heinzle, & Wuestenhagen, 2013). These studies show that consumers place significant value on non-price attributes of electricity services. This suggests that a better understanding of consumer switching in retail electricity markets may be achieved through research that includes these attributes in the analyses. Benefit transfer of estimates of non-price attributes from international studies may be problematic. For example, the retail markets covered by these studies have different structures to that of NZ, and may not reflect local conditions and experiences of local consumers. Research specifically targeting the NZ retail market is warranted as it contributes a unique set of values for the attributes of electricity services.

As discussed above, deeper insight into consumer switching in the retail electricity market in NZ may be gained by investigating consumers' preferences for non-price attributes. We achieve this by applying the stated CEs approach to identify and estimate monetary values for non-price attributes that influence residential consumers' choice of electricity supplier. Furthermore, we incorporate attitudes in model estimation to explain any heterogeneity of preferences uncovered in the analysis. We focus attention on the residential retail electricity market because it has been identified by the authorities as the market worst affected by rapidly increasing prices. The authorities attribute the rapid increase in prices in this market to low switching activity, which is insufficient to induce competitive behaviour among retailers (Electricity Authority, 2010).

The arguments introduced above spell out the need for better understanding of consumer preferences and switching behaviour. This motivates the overall question addressed in this thesis, namely:

What are the determinants of supplier choice and how can preference heterogeneity be explained?

The specific research questions are explained in the next section.

1.1 Motivation and research questions

The main objective of this thesis is to assess consumer preferences for the attributes of electricity services, estimate monetary values for non-price attributes, and to explain preference heterogeneity using psychological constructs based on valid attitude-behaviour theories in order to gain a better understanding of switching behaviour in retail electricity markets. To achieve this objective we:

a. Identify the main factors that influence consumer switching in NZ retail electricity markets.
b. Develop an appropriate instrument to generate the data that is required for the analysis.
c. Develop a framework for modelling consumer switching.
d. Estimate WTP for non-price attributes of electricity services, and explain preference heterogeneity using psychological constructs.
e. Explore the effect of AN-A and HB on WTP estimates.

1.1.1 Motivation and contribution

So far, all annual reviews of the WMN campaign show that despite a simplified switching process, reduced information search costs, and the quantified and widely publicized economic benefits of switching to the cheapest available supplier, most consumers have not switched supplier. Currently, no detailed research has been conducted to provide empirical evidence that sheds light on the underlying determinants of the observed customer ‘stickiness’ or inertia, and whether or not non-price attributes matter. This thesis identifies determinants of supplier choice, provides an explanation of the observed customer ‘stickiness’, and also provides the first set of New Zealand-specific monetary values of important attributes of electricity services.

International literature investigating consumer preferences in retail electricity markets is relatively limited. For example, the literature estimating values of the attributes of electricity services consists of a handful of well-known American and British studies which are now dated (e.g., Cai et al., 1998; Goett, 1998; Goett et al., 2000; Revelt & Train, 2000). These early studies were conducted at the start of deregulation of the retail markets to evaluate the likely response of consumers to the entry of new suppliers in the market. As such, respondents in these studies had no previous experience of choosing an electricity supplier. Current conditions in deregulated markets differ from the pre-deregulation era as consumers have a choice and some have actually switched supplier before. This thesis provides current values for the attributes of electricity services and contributes to the academic literature on switching.

Growing interest in consumer switching and valuation of non-price attributes has resulted in a small but increasing number of recent studies investigating the influence of attitudes on switching (e.g., Gamble et al., 2007, 2009; Gärling et al., 2008); estimating WTP for supply reliability (e.g., Abdullah & Mariel, 2010; Blass et al., 2010; Carlsson, Martinsson, & Akay, 2011; Hensher et al., 2014); and estimating WTP for a small subset of attributes (e.g., Amador et al., 2013; Kaenzig et al., 2013; Zhang & Wu, 2012). This thesis contributes to this growing literature by explaining preference heterogeneity using psychological constructs based on specific attitude-behaviour theories, and evaluating a different subset of attributes. Furthermore, this thesis provides, to the best of our knowledge, the first application of the latent class model in the context of switching, to uncover latent segments with homogeneous preferences for the attributes.

1.1.2 Research questions

The first research question that we answer in this thesis is:

Question 1: Do consumers perceive all electricity retailers to be the same except for the price?

We question whether electricity prices should converge in NZ retail markets as implied by concerns over large differences in retail prices within regional markets. For a homogeneous product like electricity, small price differences or a single price is expected to prevail in a competitive market[4]. Our main hypothesis is that non-price attributes matter; hence price differences alone may not fully explain switching in electricity retail markets. The above question is broken down into the following components:

(a) *Are non-price attributes of electricity services important determinants of supplier choice? If so, what values do residential consumers place on these attributes?*
(b) *What are the determinants of WTP for the attributes?*
(c) *Do preferences for power bill savings differ across respondents? If so how do these preferences influence switching?*
(d) *Do attitudes towards switching play a systematic role in explaining preference heterogeneity?*

Revealed preference (RP) data required to answer these questions are not available. We generate a unique stated choice dataset using an online CE survey administered to an online panel of residential bill payers in NZ. Advances in non-market valuation techniques, particularly experimental designs (EDs) for stated CEs allow researchers to jointly estimate the values of multiple attributes of a good or service simultaneously. CEs can be used to investigate preferences and obtain WTP values for individual attributes of electricity service in a multi-attribute setting. In the CE developed for this thesis, respondents were asked to make a series of choices (12 choice tasks) from a set of three alternatives described in terms of attribute levels. This produced a panel choice dataset with 2,688 observations from 224 respondents, which is used for the analysis.

[4] In New Zealand, electricity prices are based on nodal pricing so that different locations or regional markets have different prices. The law of one price is expected to apply, to some degree, in each regional market.

Econometric analysis is applied to the choice dataset to tease out taste intensities or parameters for the individual attributes. These taste intensities are used to estimate marginal rates of substitution (MRS), which are ratios of these parameter estimates, and average marginal WTP estimated as the ratio of each parameter to the parameter for the power bill savings attribute. The MRS and WTP estimates reveal the trade-offs among the attributes, which are implied by the observed pattern of choices. The application of CEs and the specific models estimated are discussed in more detail in Chapter 2. Research *Question 1* is the main focus of Chapter 4. The specific models estimated to provide answers to this question are: the multinomial logit (MNL) model, which is used as a base model; the latent class (LC) model used to identify latent groups with homogeneous preferences for the attributes of electricity services; and the random parameter logit with error components (RPL-EC) model, which estimates distributions for preferences.

Previous studies show that the information processing strategies adopted by respondents in CEs, and the hypothetical nature of the choice questions have an effect on model fit and WTP estimates obtained using the models mentioned above. The next two research questions focus on these issues in the context of supplier choice.

> *Question 2: Do respondents consider all the attributes of alternatives in making their choices? If not, how does this affect model fit and WTP estimates?*

This question is broken down into a set of related questions as follows.

(a) *Are non-price attributes of electricity services ignored in choice experiments of switching or supplier choice? If so, which attributes are ignored?*

(b) *Are attributes ignored individually or in combinations?*

(c) *Are the choice responses of respondents who claim to have ignored the cost attribute consistent with their claim?*

(d) *Do preferences of respondents who ignore an attribute differ from those who consider it?*

(e) *What are the effects of attribute non-attendance on WTP?*

It has been argued in the literature on customer switching that electricity consumers are more likely to perceive all electricity suppliers to be the same except for the price (e.g., Electricity Authority, 2010; Gärling et al., 2008). Given that switching in NZ has been promoted through the WMN campaign, it is likely that respondents, particularly those who were influenced by this campaign to switch supplier, ignored all non-price attributes and related their choices in the experiment to their recent experiences. Although care was exercised in the development of the choice tasks to make them as realistic as possible and to mimic real supplier choices, there were no guarantees that respondents would take the choice tasks seriously and/or consider all the information provided in making their choices[5]. Furthermore, hypothetical choices have no financial commitment.

The second question relates to HB in stated CEs.

Question 3: What are the effects of response uncertainty on WTP estimates?

The problems of HB and AN-A in stated CEs bring to question the validity and reliability of WTP estimates obtained from data collected using this technique as reasonable estimates of consumers' true preferences. It is therefore prudent for researchers employing stated CEs to investigate the influence of HB and AN-A on WTP estimates. None of the literature reviewed for this study estimating WTP for the attributes of electricity services explicitly addresses AN-A and HB, yet these are more likely to be present given the nature of the product and the way switching has been promoted so far.

Questions (2) and *(3)* are answered in Chapter 5. The two main approaches that have been used in the literature to incorporate AN-A in model estimation are stated AN-A and inferred AN-A. Stated AN-A relies on self-reported non-attendance, where respondents are asked to state the attributes they ignored, if any, in making their choices (e.g., Campbell et al., 2008; Carlsson et al., 2010; Hensher et al., 2005b; Lockwood, 1999; Scarpa, Gilbride, et al., 2009; Yao, 2012). In this approach, ignored attributes are assigned zero weights in model estimation to reflect their assumed neutrality to the choices made. An alternative method of dealing with ignored attributes is to estimate different parameters for respondents stating non-attendance to specific attributes (e.g., Carlsson et al.,

[5] Details of the ED and survey questionnaire development are provided in chapter 2.

2010). An unresolved issue in the literature on AN-A is which of the two methods is preferred. To make a contribution in this area, we use both approaches and test whether it is reasonable to assign zero weights to ignored attributes in the context of this study. The approach that uses inferred AN-A applies a statistical model based on a latent class framework to uncover latent classes of non-attendance to single or combinations of attributes that are supported by the data (e.g., Campbell et al., 2011; Hensher et al., 2012; Scarpa, Gilbride, et al., 2009). Attributes that are inferred to have been ignored are assigned zero weights as in the first approach, while the parameters of considered attributes are constrained to be equal across the classes. A detailed discussion of these approaches is given in Chapter 5.

A number of mechanisms for mitigating HB such as the National Oceanic and Atmospheric Administration (NOAA) panel's suggested rule of thumb - 'the divide by 2 rule'; cheap talk script (Cummings & Taylor, 1999; List, 2001; Lusk, 2003); certainty statements (Bollino, 2009; Champ & Bishop, 2001; Ready, Champ, & Lawton, 2010); short opt-out reminders (Ladenburg, Olsen, & Nielsen, 2007); and provision point mechanism (Poe, Clark, Rondeau, & Schulze, 2002) have been suggested and tested in previous studies. Evidence on the effectiveness of these mechanisms in mitigating HB is mixed, leaving researchers without any specific guidance in terms of selecting among the available mechanisms for mitigating HB.

For this research we adopt the approach developed by Champ et al. (1997), which uses self-reported certainty statements to calibrate hypothetical choice responses to bring them closer to real world choices. Certainty statements are designed to directly mitigate against HB (Ready et al., 2010). The choices of respondents who state a high level of certainty are taken to be more likely to approximate real market behaviours. An unresolved issue, particularly in stated CEs involving multiple choices, is how to recode or calibrate responses from respondents with low certainty scores, and the certainty threshold or cut-off points used. For example, in dichotomous choice (DC) contingent valuation studies, "yes" responses for respondents with certainty scores below the threshold, typically below 7, are recoded as "no" responses (e.g., Champ & Bishop, 2001; Champ et al., 1997). However, recoding uncertain responses in choice experiments is complicated, especially where each choice set has more than two alternatives and/or no “opt-out” or status quo alternatives are included. The question is to which alternative should the uncertain responses be recoded (Ready et al., 2010). The answer is clearer where an opt-out alternative is included in the choice set and an uncertain respondent selects one of the other two alternatives; the response is recoded as an opt-out choice (e.g., List, Sinha, & Taylor, 2006; Taylor, Morrison, & Boyle, 2010).

To overcome the problem of choosing a threshold for recoding responses for respondents who are less certain about their choices, we apply an approach based on the assumption that respondents who are less certain about their choices select more expensive alternatives than they would in real market situations. We postulate that these respondents are less sensitive to the cost attribute (power bill) compared to those who are more certain, and that this lower sensitivity results in higher WTP estimates. To this end, we estimate different parameters for respondents with different levels of certainty and estimate WTP using these parameters as the denominator. This approach differs from the standard approaches of recoding uncertain responses as “no” or omitting these responses in model estimations.

The next research question that we address relates to environmentally-related WTP and how heterogeneity of preferences may be explained using psychological constructs based on the NEP Scale and the NAT. The question also looks at the use of different versions of the NEP Scale in measuring environmental attitudes (EA) and how this impacts on welfare estimates. We apply this to WTP for changes in the proportion of electricity generated from renewable energy sources (green electricity).

Question 4: (a) How much are electricity consumers willing to pay for green electricity and how can differences in WTP be explained?

(b) Does the use of shorter versions of the NEP Scales influence WTP estimates?

The first part of this research question assesses the potential for a consumer-driven renewable energy development through green marketing. NZ-specific information on consumer preferences for green electricity is currently limited and this thesis makes a contribution in this area. The second part of the research question is motivated by concerns over the proliferation of measures of EA, which has been observed over the years (Dunlap, 2008; Hawcroft & Milfont, 2010). An additional motivating factor is that relatively few studies in non-market valuation use well-established attitude-behaviour theories in constructing attitudinal questions, or use tried and tested scales such as the NEP Scale. In studies that estimate environmentally-related WTP, investigating the systematic role of EA in explaining preference heterogeneity requires the use of consistent and reliable measures of EA. To allow for comparisons across similar studies, the use of a standard measure of EA would benefit such endeavours.

Question 4 is addressed in Chapter 6. Before EA is used in model estimation to explain preference heterogeneity, we conduct an analysis based on responses to the NEP Scale to provide insight into New Zealanders' EA. An ordered probit model of EA is fitted to the data and the marginal effects of SDCs on EA are estimated. To identify latent environmental preference groups, an ordered latent class attitudinal (LCA) model of EA is estimated. A relatively small number of studies have used LCA models in analyzing responses to attitudinal questions to identify market segments for a variety of goods (e.g., Morey, Thacher, & Breffle, 2006; Morey, Thiene, De Salvo, & Signorello, 2008; Scarpa, Thiene, & Galletto, 2009; Ward, Stedman, Luloff, Shortle, & Finley, 2008). The MNL, RPL-EC and LC models of supplier choice are estimated for each version of the NEP Scale and WTP estimates from each model specification are tested for statistical differences across the versions of the NEP Scale. We provide a detailed discussion of the construction of the shorter versions of the NEP Scale in Chapter 6.

1.2 Significance of this study

Evidence from a number of previous studies indicates that all deregulated markets are experiencing the segregation of retail electricity markets into two segments; active and inactive customers. Consumer switching is seen as one of the main drivers for a competitive retail market. In NZ, about 79% of retail electricity customers have been found to be inactive or passive, which promotes non-competitive behaviour among retailers. A better understanding of consumer preferences is required to inform policies targeted at promoting switching. The Electricity Authority is currently looking for ways to increase consumer propensity to switch. This thesis provides evidence that non-price attributes of electricity services are important determinants of switching, which partly explains why some retailers are able to charge higher prices without losing significant market shares.

This thesis also provides the first set of WTP estimates for non-price attributes of electricity services based on CEs in NZ energy markets, and highlights the importance of accounting for differences in consumer sensitivity to the level of power bill savings in models of supplier choice. The results help to predict willingness to switch supplier and may be used for comparison with other jurisdictions with deregulated markets.

Most well-known non-market valuation studies that investigate supplier choice in electricity retail markets are now dated and this thesis contributes to a small number of recent studies in this area. Unlike most previous studies that have employed the mixed logit model, we apply the LC model in the context of consumer switching. This thesis provides valuable information on consumer preferences for the incumbent retailers and for three types of new market entrants. This identifies one possible source of the observed customer inertia and offers a window into the level of savings that are required to induce switching from incumbents to competitors. This information is important to both retailers and policy makers.

The analysis of the influence of psychological constructs on welfare estimates conducted in this thesis differs from previous academic non-market valuation literature in a number of ways. First, we use constructs based on valid attitude-behaviour theories and demonstrate how these may be integrated with choice data in a model of consumer switching. Second, the results show the impact of using shorter versions of the NEP Scale in classifying respondents into classes of homogeneous environmental preferences, and on WTP estimates. The results are important to researchers in that they provide guidance on the selection of the version of the NEP Scale. The NEP Scale is the most widely used measure of EA in the social sciences, but very few studies in non-market valuation studies have used it. We are not aware of any previous non-market valuation studies that have investigated the impact of using shorter versions of the NEP Scale on WTP estimates.

The thesis also contributes to the literature investigating HB by testing whether choice responses for respondents who are less certain about their hypothetical choices reveal less sensitivity to the cost attribute. We are currently unaware of previous similar studies.

1.3 Outline of the thesis

The rest of the thesis is organized as follows. Chapter 2 presents the methodology used for this research. It provides details of the experimental design used to generate the choice sets and survey questionnaire development. The main models used to analyze data are developed and the hypotheses to be tested are stated.

Chapter 3 provides an overview of the New Zealand electricity market to provide a context for the research. Chapter 4 presents results of the MNL and LC models of consumer switching in the residential electricity market. Sample statistics are also provided and an analysis of responses to questions assessing respondents' attitudes towards switching is presented to highlight possible barriers to switching.

Chapter 5 explores the effect of attribute non-attendance and hypothetical bias on WTP estimates. Two approaches of treating ignored attributes in model estimation are used to investigate whether assigning zero weights to ignored attributes may be justified in this case. In Chapter 6 we present results from MNL, RPL-EC, and LC models where different versions of the NEP Scale are used in model estimation to determine whether WTP estimates differ significantly when shorter versions of the scale are used. Chapter 7 provides a brief discussion of the research, conclusions and recommendations for future research.

Chapter 2. Methodology

2.1 Introduction

In this chapter we describe the methodology employed for this research. We start by providing an overview of choice experiments. The standard MNL, LC, and RPL-EC models used in the analysis of responses to the choice questions are formally stated. Next, we present a conceptual framework developed for this thesis for integrating psychological constructs with stated choice. The experimental design used to construct choice tasks is outlined, and the structure and content of the survey questionnaire and sampling procedure are discussed.

In this thesis, we use a family of discrete choice models which are based on random utility maximisation (RUM) to analyse consumer preferences for the attributes of electricity services. Preferences for the attributes of electricity services have important implications for promoting consumer switching required to achieve efficient and competitive retail markets, and for electricity retail marketing. The objective of using the above models is to assess how residential electricity consumers value the attributes of electricity services, characterise the heterogeneity of valuations or preference intensities, and explain heterogeneity of preferences using psychological constructs based on attitude-behaviour theories, and whether the use of different versions of the New Ecological Paradigm (NEP) Scale affect welfare estimates.

The MNL model is used as the base model in the analysis. The analysis is extended to capture preference heterogeneity by estimating LC and RPL-EC models. The LC model is used to identify groups with homogeneous preferences, which would assist policy makers and retailers as refining and targeting policies and marketing strategies often require sorting individuals into different groups. Furthermore, a comparison of the LC model with the MNL and RPL-EC models allows us to explore the effect of failing to account for groups with homogeneous preferences on WTP estimates. All the models are extended to capture systematic heterogeneity of preferences by including interaction effects of the NEP Scale and NAT scores.

The models are extended to capture systematic heterogeneity of preferences for green electricity by including interactions of EA and NAT constructs with a design attribute measuring the proportion of electricity generated from renewable energy sources. Results from these models explain heterogeneity of preferences for green electricity and allow for the testing of the null hypothesis that adopting different versions of the NEP Scale has no influence on WTP estimates. The results also explain preference heterogeneity for the attributes of electricity services using psychological constructs based on the TPB. The conceptual model for integrating psychological constructs with stated choice is presented in section 2.3.

The LC model specifies that the distribution of the stated preferences, estimated from responses to the choice experiments, is a mixture of a finite number of underlying distributions thus accommodating preference heterogeneity while allowing the number of segments to be determined endogenously by the data (McLachlan & Peel, 2000), i.e., the number of classes retained is the one that provides the best model fit for the data. One key advantage of using the LC model is that any continuous "distribution can be approximated arbitrarily closely by a discrete distribution with a sufficiently large number of points" (McLachlan & Peel, 2000; Train, 2009, p. 356). On the other hand the MNL and RPL-EC models ignore the possibility of more than one class of utility representation (up to a probability) in the sampled population. The standard MNL model assumes homogeneity of preferences while the RPL-EC model assumes that preferences are heterogeneous and are distributed with a continuous distribution typically assumed to be triangular, normal, uniform, or lognormal over the population. RPL-EC models thus explicitly incorporate and account for heterogeneity by allowing model parameters to vary randomly over individuals. However, Boxall and Adamowicz (2002) point out that these models are not well-suited to explaining the sources of heterogeneity. For the LC model, the number of classes in the population is not known *a priori* and is determined based on information criteria.

The LC model endogenously assigns individuals to classes with identical preferences and estimates class membership probability along with class-specific taste intensities (Scarpa & Thiene, 2005). Although there is no consensus on the determination of the optimum number of classes, literature suggests the use of information criteria in determining the number of classes. Researchers typically use information criteria such as AIC, AIC3, crAIC, CAIC, BIC, HQC, and log likelihood to determine the number of classes (Andrews & Currim, 2003a, 2003b; Greene & Hensher, 2013; Lin & Dayton, 1997; Yang & Yang, 2007). A practical guidepost noted by Heckman and Singer (1984) is that if a model is fitted with too many classes, the estimates become imprecise and vary wildly, class probability estimates become very small, and estimated standard errors become huge. A detailed discussion of information criteria is presented in section 2.2.4.

Greene and Hensher (2003) systematically contrast the mixed logit with the LC model in terms of criteria such as choice elasticities, distributions of predicted choice probabilities, and changes in absolute choice shares and conclude that no unambiguous recommendation can be made as to the superiority of either approach. However, they find stronger statistical support overall for the LC approach with three preference segments. In chapters 4 to 6, we apply both models to a choice data set and select the best model based on model fit and the ability of each model to address specific research questions.

Louviere Hensher, and Swait (2000) argue that stated choice experiments closely simulate real-world purchasing decisions where a respondent has to select an alternative from a set of options. The methodology used for this thesis allows for the estimation of respondents' trade-offs among the attribute levels of experimentally designed alternatives presented in a series of choice tasks. The main aim is to tease out marginal WTP estimates for the attributes and their relative importance and explore the implications of failing to adopt the proper NEP Scale on welfare estimates. This thesis therefore adds to the growing literature that investigates environmentally-related WTP, and also contributes to the current debate on the use of psychological constructs based on different versions of the NEP Scale, and competing theories in investigating consumer preferences.

In recent research exploring preference heterogeneity, Campbell and Doherty (2012) and Greene and Hensher (2013) have estimated models combining discrete and continuous mixing distributions to identify additional dimensions of heterogeneity within latent classes (within-class heterogeneity). While allowing for preference heterogeneity in a latent class framework, Greene and Hensher (2013) add a second dimension of preference heterogeneity within each class by assuming that preferences within each class are distributed with a continuous distribution. This method allows for the analysis of heterogeneity between and within classes. The decomposition of, or systematic variation in, class membership probability is based on one of the attributes of the alternatives (‘freight rate’ – which is the unit cost of transportation). Campbell and Doherty (2012) adopt a similar approach when they allow for heterogeneity of preferences within the niche market segment by combining a discrete mixture and a RPL-EC model specification to simultaneously uncover the size of the niche market and the heterogeneity in preferences within these segments as well as substitution patterns.

In the next section we state the main hypotheses that will be tested in chapters 4 to 6 of this thesis.

2.1.1 Hypotheses

In this thesis we postulate that non-price attributes of electricity services are important determinants of supplier choice and argue that information on the levels of these attributes should be provided in campaigns aimed at promoting consumer switching. Environmentally-related WTP is an important input into both the policy decision-making process and policy evaluation. Using realistic and reliable WTP estimates is therefore important. If the selection of a version of NEP Scale influences WTP estimates, it is important for researchers to be aware of the effect. Knowledge of how attitudes influence demand for the attributes of electricity services is important. Electricity suppliers may use this knowledge for marketing purposes especially in evolving deregulated markets characterised by free movement of consumers. Empirical evidence shows that not all respondents in stated choice experiments adopt attribute processing rules that involve full attribute preservation in making their choices. How the violation of full attribute preservation is treated in model estimation, especially where the objective is to estimate marginal WTP is important. Therefore, we test the following hypotheses.

Hypothesis I: *Non-price attributes of electricity suppliers are important determinants of supplier choice.*

H_0: $\beta_1 = \beta_2 = \cdots = \beta_K = 0$ (non-price attributes are not significant determinants of supplier choice)

H_1: $\beta_k \neq 0$ (non-price attributes are significant determinants of supplier choice) where k = 1, 2, …, K, and β_k is the parameter estimate for the k^{th} attribute.

Hypothesis II: Preferences of respondents who ignore an attribute differ from those who attend to it.

H_0: $\beta_{dk} = 0$ (respondents who ignore an attribute in making their choices and those who consider it have similar preferences for the attribute).

Where, β_{dk} is the parameter for the interaction between a dummy variable indicating non-attendance to the k^{th} attribute and its levels.

H_1: $\beta_{dk} \neq 0$ (respondents who ignore an attribute and those who consider it have different preferences for the attribute)

Hypothesis III: Environmentally-related WTP is sensitive to the versions of the New Ecological Paradigm (NEP) Scale.

H_0: $WTP_{k\_NEP5} = WTP_{k\_NEP10} = WTP_{k\_NEP15}$ (marginal WTP for the k^{th} attribute is invariant to the version of the NEP Scale used).

H_1: $WTP_{k\_NEP5} \neq WTP_{k\_NEP10} \neq WTP_{k\_NEP15}$ (marginal WTP for the k^{th} attribute is sensitive to the version of the NEP Scale used).

Where, the subscripts $_{\_NEP5}$, $_{\_NEP10}$, and $_{\_NEP15}$ indicate the length of the version of the NEP Scale used, i.e., the number of statements used to construct the scale.

A likelihood ratio-test (LRT) statistic estimated as $-2(LL_R - LL_{UR})$ (Hensher, Rose, & Greene, 2005a) will be used to test *Hypothesis I*. LL_R and LL_{UR} are the log likelihood functions of the restricted and unrestricted models, respectively. For *Hypothesis II*, the t-test is used to test the significance of each β_{dk}. For *Hypothesis III*, we test whether marginal WTP estimates are statistically different across any two models using the asymptotically normal test statistic (ANTS) suggested by Campbell et al. (2008). This test is based on comparing marginal WTP estimates of the same attribute across two models using different versions of the NEP Scale. It is important to note that the betas from the different models are confounded with the scale parameter, hence it is only meaningful to compare MRS or marginal WTP estimates which are the ratios of the coefficients of the attributes to the coefficient of the cost attribute. Campbell et al. (2008) provide a formula for ANTS used to test for differences in WTP estimates from two models specified as:

$$ANTS = \frac{\left(WTP_k^1 - WTP_k^2\right)}{\sqrt{\left(Var\left(WTP_k^1\right) - Var\left(WTP_k^1\right)\right)}} \quad , \tag{2-0}$$

where, WTP_k^1 and WTP_k^2 are WTP estimates for attribute k obtained from competing models 1 and 2 respectively.

2.2 Stated Choice experiments for the valuation of the attributes of electricity services

2.2.1 An overview of stated choice experiments

Stated choice experiments (CEs) are widely used to study consumer preferences in the fields of transportation, marketing, psychology, health economics, and environmental economics because of their ability to mimic real markets. The MNL model and other more advanced models such as the mixed MNL, LC, and RPL-EC have been estimated on data from stated CEs and applied for planning and policy purposes. Studies employing CEs provide insight regarding the determinants of consumer choice and allow researchers to introduce new attributes or to vary attribute levels beyond those available in the market. Stated preferences are elicited using constructed hypothetical choice situations in which two or more alternatives are described in terms of attribute levels and respondents are asked to select their preferred option (Adamowicz, Boxall, Williams, & Louviere, 1995; Hanley, Mourato, & Wright, 2001; Louviere et al., 2000). The attribute levels of the alternatives, except the status quo or opt-out, are varied by the researcher, on the basis of an experimental design, over choice situations to provide the variation needed for estimating the underlying preference parameters. Burke, Harlam, Kahn, and Lodish (1992), Huber and Zwerina (1996), and List et al. (2006) provide evidence that experimental choice-based methodologies can provide accurate predictions of actual choice decisions.

In CEs, respondents are presented with a series of choice tasks consisting of two or more experimentally designed hypothetical alternatives described in terms of their attribute levels. Attributes included in the alternatives must be of relevance to respondents. The alternatives in each choice task may include a status quo or opt-out alternative to increase the realism of the tasks (Carson et al., 1994), enhance the theoretical validity of the welfare estimates and avoid the estimation of conditional demand (Kontoleon & Yabe, 2003), and improve the statistical efficiency of the estimated parameters (Louviere et al., 2000). To allow for the estimation of marginal WTP values for the attributes, a cost attribute is included in each alternative. By selecting the preferred alternative in each choice task, a respondent implicitly makes trade-offs between the attribute levels of alternatives. The series of choices made by respondents give rise to a panel of discrete choices.

Unlike the contingent valuation method (CVM), CEs allow the researcher to uncover respondents' preferences for the attributes of a scenario rather than a specific scenario as a whole, and the tradeoffs which respondents make between the attributes of the alternatives. Adamowicz et al. (1995) argue that the CE technique provides a richer description of the attribute trade-offs that individuals are willing to make compared to the CVM. As an alternative technique to the CVM, the CE approach: enables researchers to estimate multiple marginal WTP values or compensating surplus measures from a single experiment; requires a smaller sample since each respondent provides multiple responses; reduces strategic behaviour and "yea-saying" since respondents choose their preferred options from various choice sets and avoids an explicit elicitation of respondents' WTP. Furthermore, CEs provide a natural internal scope test because multiple elicitations are obtained from each respondent (Hanley et al., 2001; Holmes & Adamowicz, 2003; Willis, 2006). However, the drawbacks of the CE approach include placing a heavier cognitive burden on the respondents as they are required to evaluate larger or more complex choice sets, and the high level of complexity involved in the experimental design. Placing a larger cognitive burden on respondents may affect the quality of responses which in turn affects the validity and reliability of the results.

One of the major challenges of the CE approach involves the design of the CEs. Experimental design (ED) is the way in which the attribute levels of alternatives are set and structured into the choice sets (Bennett & Adamowicz, 2001). ED is complex, time consuming, and can heavily influence the outcomes (validity and reliability) and conclusions of the research (Hensher et al., 2005a; Johnson et al., 2013; Louviere et al., 2000; Louviere, Islam, Wasi, Street, & Burgess, 2008; Lusk & Norwood, 2005). Important decisions are made at the design stage, including, the number and levels of attributes to be included in the design, the number of alternatives, whether or not to include a status quo or opt-out alternative and the ED. A decision on the number and levels of attributes involves identifying and selecting relevant attributes, ascertaining their levels, and describing them in a clear manner to avoid ambiguity. Typically, literature review, expert opinion, and focus groups are used to address the issues highlighted above.

The choice of ED is important because in a multi-attribute valuation the efficiency of the estimates depends on how the attributes and levels are combined to form the alternatives and the choice sets (Ferrini & Scarpa, 2007; Hensher et al., 2005a; Louviere et al., 2000; Louviere et al., 2008). Furthermore, the selected ED should allow for the estimation of the independent influence of each attribute on choice and also maximize the power of the model to detect statistically significant relationships (i.e., maximize the *t*-ratios at any given sample size). A design is said to be efficient if it results in parameter estimates with small standard errors and a smaller sample size compared to others. Hence, the main objective of any ED is to maximize the statistical efficiency for a given model. Other objectives of ED include attribute level and utility balance. Burgess and Street (2003, 2005) and Street and Burgess (2004) provide a formal definition of statistical design efficiency for stated CEs and also discuss strategies for creating optimal designs.

The past twenty years has seen an increase in the number of studies advancing EDs (e.g., Bliemer, 2013; Bliemer & Rose, 2011; Ferrini & Scarpa, 2007; Kanninen, 2002; Kessels, Jones, Goos, & Vandebroek, 2009; Oppewal, Louviere, & Timmermans, 1994; Rose & Bliemer, 2009; Rose, Bliemer, Hensher, & Collins, 2008; Sandor & Wedel, 2001). All EDs are based on assumptions about the priors which can be zero, fixed non-zero values, or even distributions and specific model types, for example, MNL, mixed multinomial logit (MMNL), and nested logit (NL) (Johnson et al., 2013). Parameter priors are *a priori* parameter values which may include parameter estimates from similar previous studies, estimates from pilot surveys or even information on the expected signs of the parameters (Bliemer & Rose, 2011; Ferrini & Scarpa, 2007). For an overview of advances in EDs and the influence of EDs on results the reader may refer to Rose and Bliemer (2009) and Bliemer and Rose (2011) respectively.

There are no specific rules regarding which design approach a researcher should use. However, Ferrini and Scarpa (2007) evaluate EDs and advise that where good *a priori* information is lacking, which is typical in environmental valuation, the conventional factorial designs from linear models produce less biased estimates under misspecification than other designs that rely on broad priors. On the other hand Bliemer and Rose (2011) show that D-efficient designs result in lower standard errors in estimation thereby requiring smaller sample sizes, *ceteris paribus*, compared to orthogonal designs. Johnson et al. (2013) do not endorse any specific approach but provide a guide for choosing an approach that is appropriate for a particular study by summarizing the features of six approaches in terms of assumptions, accommodation of restrictions (e.g. implausible combinations), coding procedures, availability and cost of software.

Another challenge with the CEs approach concerns the treatment of AN-A and HB in model estimation. HB and AN-A are important issues that researchers need to address when conducting CEs. A discussion of these issues is provided in Chapter 4, section 4.2. In the next section we provide a theoretical foundation of discrete choice models and show how they will be applied in this research.

2.2.2 The discrete choice model

The random utility maximization (RUM) model proposed by McFadden (1974) provides the standard framework for modelling an individual's choice behaviour. RUM models combine random utility theory (RUT) and Lancaster's (1966) characteristic theory of consumer demand. RUT assumes that the utility (U_i) of an alternative i is additively separable into a systematic (deterministic or observed) component (V_i) and a random (stochastic or unobserved) component (ε_i) (Manski, 1977; Manski & Lerman, 1977; McFadden, 1974), whilst Lancaster's (1966) characteristics theory postulates that consumers do not derive satisfaction from goods themselves but from their attributes and attribute levels. Utility (U) is a latent variable representing true but unobservable indirect utility and the choices made by consumers reflect the underlying utilities.

Under the RUM framework, an individual n evaluates a set of J competing alternatives in a choice task (s) in terms of their attribute levels and selects the alternative that yields the highest expected utility. From the choices that individuals make in all choice tasks (S), researchers are able to estimate a $1 \times K$ row of taste intensities or utility coefficients β for a column of vector X of $K \times 1$ attributes of alternative i and individual n's SCDs included as interactions in the indirect utility function Vi of the alternative. Specifically, in the CE developed for this research, each respondent is presented with twelve choice tasks ($S = 12$). Each choice task consists of three alternatives ($J = 3$) which includes a status quo (respondent's current supplier) and two experimentally designed alternatives referred to in a generic sense as 'Supplier A' and 'Supplier B'. A panel choice data set with 12 levels is generated from respondents' choices. In the following sections we present the models that we use to analyze the choice responses to obtain a $1 \times K$ row of taste intensities or utility coefficients β for the attributes of interest. Marginal WTP estimates are then calculated from these coefficients.

2.2.3 Multinomial logit (MNL) model

The MNL model is used for estimating the probability of choosing a specific retail supplier from a set of available suppliers (alternatives) as a function of the attributes of the suppliers and individual characteristics (SDCs including attitudes). Introducing interactions of SCDs with design attribute levels in the MNL allows for the detection of the presence of observable or systematic heterogeneity in preferences for the attributes describing the suppliers. In this thesis the MNL model is applied as a base model in the analysis of choice to estimate consumer preferences for the attributes of the electricity services. Details of the attributes and levels used to describe the suppliers are provided in section 2.5.

The core elements of the MNL model applied in this thesis are; (1) a set of utility equations for alternative electricity suppliers; (2) a measurement equation relating the preference indicator to the utilities via a utility maximization equation; (3) a choice probability function; and (4) an appropriate likelihood function (Hensher et al., 2005a; Louviere et al., 2000; McFadden, 1974; Walker & Ben-Akiva, 2002).

Following standard practice in discrete choice modelling, the utility which a respondent n derives by selecting an electricity supplier i from a choice set c = (Your current supplier, Supplier A, Supplier B) in choice situation s may be expressed as:

$$U_{ins} = V_{ins} + \varepsilon_{ins} \tag{2-1}$$

The systematic component of utility V_{ins} may be estimated from the information which the researcher can observe and collect about the respondent's choices, and the characteristics of the electricity supplier and respondent (explanatory variables – X's). The component ε_{ins} is only known to the respondent, unobservable to the researcher, and represents the effect of all the factors that influence utility but are not captured in V_{ins} such as individual idiosyncrasies of tastes and omitted variables. Assuming that utility is a function of the explanatory variables (X's) describing electricity supplier i and the respondent n, and that utility is linear-in-parameters (Hensher et al., 2005a; Holmes & Adamowicz, 2003; Lancaster, 1966; Louviere et al., 2000), we rewrite equation (2-1) as:

$$U_{ins} = \sum_{k=1}^{K} \beta_k X_{ikns} + \varepsilon_{ins} \tag{2-2}$$

where X_{ikns} is the kth attribute of electricity supplier i or the kth characteristic of respondent n in choice situation s, β_k is the coefficient of the kth attribute, and ε_{ins} are independently and identically distributed (IID) type I extreme value (EV1) error terms, with zero mean and constant variance of $\pi^2/6$. The specification in equation (2-2) parameterises utility in 'preference-space'. The systematic component or relative utility in equation (2-2) may be written out as:

$$V_{ins} = \beta_{i0} + \beta_1 X_{i1ns} + \beta_2 X_{i2ns} + \ \dots\dots\dots\dots + \beta_K X_{iKns} \ , \tag{2-3a}$$

where β_{i0} is the alternative-specific constant which represents on average the influence of all unobserved sources of utility. The utility specification for the three alternative electricity suppliers offered to respondents in a choice task may be presented as:

$$V_n = \begin{cases} V_{SQn} = \beta_{SQ0} + \beta_1 X_{SQ1n} + \beta_2 X_{SQ2n} + \ \dots\dots.. + \beta_K X_{SQKn} \\ V_{An} = \qquad\qquad \beta_1 X_{A1n} + \beta_2 X_{A2n} + \ \dots\dots.\dots.\dots. + \beta_K X_{AKn} \\ V_{Bn} = \qquad\qquad \beta_1 X_{B1n} + \beta_2 X_{Bn} \dots\dots\dots\dots\dots.\dots... + \beta_K X_{BKn} \end{cases}, \qquad (2\text{-}3b)$$

When respondent *n* is presented with a choice among alternative electricity suppliers he/she will choose supplier *i* if and only if it yields utility greater than any other supplier *j* in choice set C;

$$V_{in} + \ \varepsilon_{in} > V_{jn} + \varepsilon_{jn}; \qquad \forall j \neq i \in C, \qquad (2\text{-}4)$$

Following McFadden (1974), we express the probability that supplier *i* is preferred to supplier *j* as the probability that the utility associated with supplier *i* is greater than the utility associated with supplier *j* as follows:

$$P(i|C) = P\big(V_{in} + \varepsilon_{in} > V_{jn} + \varepsilon_{jn}\big); \qquad \forall j \neq i \epsilon C \qquad (2\text{-}5)$$

Rearranging the terms in equation (2-5), the probability of choosing supplier *i* is expressed as:

$$P(i|C) = P\big(\varepsilon_{jn} - \varepsilon_{in}) < (V_{in} - V_{jn}\big); \quad \forall j \neq \ i \epsilon C \qquad (2\text{-}6)$$

The specific form of this probability function depends on the assumptions made about the distribution of the error term. For the MNL model the choice probability takes on a closed form and is specified with Gumbel error scale λ > 0 as (Train, 2009):

$$P_{ins} = \frac{\exp\big(\lambda(\beta' x_{ins})\big)}{\sum_{j=1}^{J} \exp\big(\lambda(\beta' x_{jns})\big)}, \qquad j = 1, 2, 3 \qquad (2\text{-}7)$$

The scale factor is inversely related to the variance of the error term and is usually assumed to be equal to 1 for CEs (Train, 2009). The scale factor cannot be estimated from a single dataset because of confounding with the vector of utility parameters (Swait & Louviere, 1993). However, this is not a problem in this thesis as the λ terms will cancel out when marginal WTP and MRS are estimated as ratios of the parameter estimates.

The log-likelihood function may be written as (Train, 2009):

$$\log L = \sum_{n=1}^{N} \sum_{j=1}^{J} \sum_{s=1}^{S} y_{ins} log\left(\frac{\exp(V_{ins})}{\sum_{j\epsilon C} \exp(V_{jns})}\right), \qquad (2\text{-}8)$$

where y_{jns} is a dummy variable (preference indicator), which takes the value of 1 if respondent *n* chooses supplier *i* in choice situation *s,* and zero otherwise.

The objective of estimating equation (2-8) is to obtain the parameter estimates that maximize the log likelihood function conditioned on the *X'*s (attributes of suppliers and SDCs) and the observed choices *y*. Since the choice probabilities in the MNL model take a closed form, the parameters are estimated by the maximum likelihood method using NLOGIT 5 software. The MNL model assumes homogeneity of preferences and the parameters estimated are the average taste intensities in the sampled population of electricity bill payers in New Zealand.

The MNL model assumes independence from irrelevant alternatives (IIA) which states that for any individual, the ratio of choice probabilities of any two suppliers in a choice set is not affected by the introduction or removal of other suppliers from the choice set, given that both suppliers have non-zero probability of choice (Louviere et al., 2000). This is a restrictive assumption which is often highlighted in non-market valuation literature as one of the main weakness of the MNL. A discussion of the power and limitations of the MNL model is provided in Train (2009). Less restrictive models that address some of the shortcomings of the MNL model are presented in the following sections.

2.2.4 Panel Latent class logit model

To account for the panel nature of the choice data set, we use a panel latent class (LC) choice model based on RUM to identify latent groups with similar preferences, and tease out taste intensities (parameters) and estimate marginal WTP estimates for the attributes of electricity services. The underlying theory of the LC model postulates that individual choice behaviour depends on observable attributes of electricity suppliers and characteristics of the individual, and on latent heterogeneity that varies with factors that are unobservable to the analyst (Greene & Hensher, 2003). The parameters of the LC model are modelled as having a discrete distribution with a small number of support points (Kamakura & Russell, 1989). In this application of the LC model we assume that the population consists of a finite number of preference classes (Q) with respect to the attributes of electricity services, where Q is exogenously defined and outside the space of estimable parameters. The application of the LC model in this thesis allows for the partitioning of retail electricity consumers into relatively homogeneous groups that differ substantially in their tastes for the attributes of electricity services.

The derivation of the LC logit model is based on a class-membership probability equation and a choice probability equation for a supplier in a choice set, both of which turn out to have a convenient logit formulation when two independent Gumbel-distributed error terms are assumed (Greene, 2008). The class membership probability equation explains the probabilistic assignment of respondents into Q classes whereas the choice probability equation explains a supplier's probability of selection among competing suppliers. The class membership probabilities for a given class are defined parametrically using a multinomial logit as the membership equation. The multinomial logit formulation of class membership probabilities meets the restriction that the probabilities take on positive values in the range 0-1 and sum to 1 (Boxall & Adamowicz, 2002). The parameters of the LC model are the share of the population in each preference class and the coefficients for each class.

Since the number of classes Q that are supported by the data is determined by the researcher without the imposition of any restrictive functional form on the distribution of the preference parameters, the LC model allows for a wider range of preference heterogeneity. Each class represents preferences that are clearly distinct from those of other classes. Latent class models have been used in previous studies to investigate preference heterogeneity in various contexts (e.g., Boxall & Adamowicz, 2002; Greene & Hensher, 2003; Milon & Scrogin, 2006; Morey et al., 2006; Morey et al., 2008; Nocella, Boecker, Hubbard, & Scarpa, 2012).

Based on RUM, we specify a class-specific utility function consisting of a deterministic component related to the attributes of the supplier ($\beta_q' X_{ikns}$) and a random component ($\varepsilon_{ins|q}$) as follows (Boxall & Adamowicz, 2002; Walker & Ben-Akiva, 2002):

$$U_{ins|q} = \beta_q' X_{ins} + \varepsilon_{ins|q} \ , \tag{2-9}$$

where $U_{ins|q}$ is the utility of supplier i to individual n in choice situation s conditional on class q membership, X_{ins} is a union of all attributes and characteristics that appear in all utility functions, $\varepsilon_{ins|q}$ is IID with Extreme Value

Type 1 (Gumbel-distributed) error component that captures unobserved heterogeneity for individual n and supplier i in choice situation s conditional on class q membership, and βq is a class-specific parameter vector to be estimated. An individual n is viewed as belonging to a latent class which is not revealed to the researcher. The probability of individual n choosing supplier i in choice situation s conditional on membership in class q (q = 1, 2, …, Q) is given by the MNL model (Boxall & Adamowicz, 2002; Kamakura & Russell, 1989):

$$P_{(nsi|q)} = \frac{\exp(\beta_q' X_{ins})}{\sum_{j=1}^{J} \exp(\beta_q' X_{jns})} \ , \tag{2-10}$$

where for convenience, the scale parameter of the Gumbel error distribution has been normalized to 1 and the other variables are as defined in equation (2-9).

The probability that an individual n is assigned to class q (q = 1, 2, …., Q) is expressed as an MNL model in which class membership is a function of class-specific constants identified by ensuring that they sum to zero (Heckman & Singer, 1984; Scarpa, Gilbride, et al., 2009) as follows:

$$P_n(class = q) = \frac{\exp(\alpha_q)}{\sum_q \exp(\alpha_q)}, \qquad \alpha_Q = 0 \tag{2-11}$$

where α denotes class-specific constants identified by ensuring they sum to zero, $0 \leq P_n(class = q) \leq 1$, and $\sum_{q=1}^{Q} \frac{\exp(\alpha_q)}{\sum_q \exp(\alpha_q)} = 1$. Equation (2-11) is the unconditional or prior probability of respondent n belonging to class q.

To obtain the unconditional probability that individual n chooses supplier i, in choice situation s, the law of total probability is applied by summing the conditional probabilities over the finite set of membership probabilities expressed in equation (2-11) (Boxall & Adamowicz, 2002; Kamakura & Russell, 1989):

$$P_{ni} = \sum_{q=1}^{Q} \left[\frac{\exp(\alpha_q)}{\sum_{q=1}^{Q} exp(\alpha_q)}\right] \left[\frac{\exp(\beta_q' X_{in})}{\sum_{j=1}^{J} exp(\beta_q' X_{jn})}\right], \text{ q =1, 2, ….. , Q; } \alpha_Q = 0 \tag{2-12}$$

where s has been omitted to avoid clutter.

The model represented in equation (2-12) permits class-specific constants and choice attribute data (X's) to simultaneously explain choice behaviour.

For a sequence of choices $y_n = \{y_{n1}, y_{n2}, \dots\dots, y_{nS}\}$ the log likelihood for the sample may be expressed as:

$$\ln L = \sum_{n=1}^{N}\sum_{s=1}^{S}\sum_{j=1}^{J} y_{nsj}\, ln\left[\sum_{q=1}^{Q}\frac{\exp(\alpha_q)}{\sum_{q=1}^{Q}\exp(\alpha_q)}\frac{exp(\beta_q' X_{ins})}{\sum_{j\in J} exp(\beta_q' X_{jns})}\right] \qquad (2\text{-}13)$$

where $y_{nsj} = 1$ if supplier *j* is selected in choice situation *s*, and zero otherwise.

We maximize the likelihood with respect to the *Q* structural parameter vector β_q and the *Q-1* latent class parameter vector α_q. Since the β_q's which include the coefficient of the cost attribute vary across classes, the LC model identifies heterogeneity in the consumers' values of the attributes of the alternatives, which would be obscured in a single average measure with the MNL. The LC choice model accounts for heterogeneity in the data by allowing for different population segments (latent classes) to express different preferences in making their choices. We include covariates in the class membership model to increase the accuracy of prediction of membership probabilities.

The number of latent classes cannot be determined *a priori* and there is no theory to guide the setting of the initial number of classes. Previous studies have relied on information criteria such as Akaike information criteria (AIC), AIC3, corrected AIC (crAIC), consistent AIC (CAIC) and Bayesian information criteria (BIC) to determine the number of classes (Morey et al., 2006; Morey et al., 2008; Nocella et al., 2012). Andrews and Currim (2003a), Morey et al. (2006), and Yang and Yang (2007) discuss the performance of these criteria and also provide formulae for their calculation.

The challenge in estimating LC models is the selection of the best model (the model that is closest to the true but unknown model) among a class of competing models based on suitable model selection criteria given the data set. The use of model fit statistics such as R^2 and the log-likelihood (*LL*) are not appropriate in the case of LC models since both R^2 and *LL* generally increase as the number of classes increases, which would result in over-fitting or over-parameterization of the model. The use of the log-likelihood ratio-test (LRT) statistic to determine the number of classes is also problematic because it does not allow the number of latent classes to be separated as its distribution is unknown and may not follow a χ^2 (McLachlan & Peel, 2000; Yang & Yang, 2007). For example, McLachlan and

Peel (2000) show that the LRT is not an appropriate test for determining the number of classes as the regularity conditions do not hold for the LRT statistic to have its usual asymptotic null distribution of chi-squared with degrees of freedom equal to the difference between the number of betas under the null and alternative hypotheses. On the other hand, the disadvantage of using information criteria is that they do not produce a number that quantifies the confidence in the results, such as a p-value.

For this study we use six widely applied information criteria listed below to select the most parsimonious best model among the competing LC models. The use of these criteria in this study allows us to compare their performance and to assess the suitability of each under different model specifications. For a summary of information criteria and how they can be related to each other, interested readers may refer to Yang and Yang (2007).

- Akaike Information Criterion (AIC) = $-2LL + 2k$
- AIC with a per-parameter penalty factor of 3 (AIC3) = $-2LL + 3k$
- Corrected AIC (crAIC) = $-2LL + k(2+2(k+1)(k+2)/(N-k-2))$
- Consistent AIC (CAIC)[6] = $-2LL + k[\ln(N)+1]$
- Bayesian Information Criterion (BIC) = $-2LL + k\ln(N)$
- Hannan-Quinn Information Criterion (HQC) = $-2LL + 2k\ln(\ln(N))$

The above information criteria are forms of penalized log likelihoods. The second term in each formula may be viewed as a penalty for over-parameterization since likelihood ratio tests inherently tend to favour full models in contrast to reduced models. The merits and demerits of the various model selection criteria are discussed in the literature and the general consensus is that there is no single criterion that is best in all study contexts. AIC and AIC3 have been criticised for not being asymptotically consistent since sample size is not directly included in their calculation and they would not select the "correct" model as N moves to infinity (Yang & Yang, 2007). CAIC, BIC and HQC achieve asymptotic

[6] CAIC for latent class models may be estimated from the following formula (Rose & Hensher, 2010): CAIC = $-2LL- (CK - (C – 1)H -1)(\ln(2N) + 1)$, where, C is the number of classes, K is the number of parameters in the class specific utility functions, H the number of parameters in the class allocation model and N is the number of respondents.

consistency by penalising over-parameterization by means of a logarithmic function of the sample size (*N*) whilst crAIC includes sample size (*N*) in the last term added to reduce bias when the sample size is small (Lin & Dayton, 1997; Yang & Yang, 2007). Although BIC and CAIC (which is equal to BIC + k) impose more severe penalties for over-parameterization and hence tend to select simpler models than those selected by the other criteria, their relative performance in selecting correct models is unpredictable (Lin & Dayton, 1997).

Simulation studies suggest that the accuracy of commonly used criteria for determining the number of latent classes or market segments depends on the distribution used to describe the data, the characteristics of the market and model specification (Andrews & Currim, 2003a, 2003b; Lin & Dayton, 1997; Yang & Yang, 2007). Andrews and Currim (2003b) use simulation to investigate the performance of seven segment retention criteria including AIC, AIC3, CAIC and BIC commonly used with finite mixture regression models and find that the AIC with a per-parameter penalty of 3, (AIC3), is the best criterion to use across a wide variety of model specifications and data configuration. They find the AIC3 to have the highest success rate in identifying the correct number of segments and producing very low parameter bias. CAIC and BIC were found to have a tendency of achieving lower over-fitting rates but lower success rates compared to the AIC3.

Yang and Yang (2007) compare various information criteria and find that HQC and AIC3 had the best average accuracy rates by sample size and latent class structure but needed a sample size of 600 to stay above the 90% accuracy rate. Their results show that increasing the number of classes, holding other factors constant, increases the difficulty for information criteria to find a proper solution, with BIC and CAIC showing higher sensitivity to large numbers of latent classes. However, adding covariates to the latent structures showed positive effects in correctly identifying the number of classes by all information criteria. Rose and Hensher (2010) suggest that CAIC is probably a better measure. Lin and Dayton (1997) also used simulation to compare AIC, BIC and CAIC in terms of their accuracy in selecting correct models as opposed to selecting models that are over- or under-parameterized. They find that BIC and CAIC are more accurate than the AIC when the true model is very simple or for relatively large sample sizes with somewhat more complicated models. AIC was found to have a tendency to over-fit. They suggest that BIC and CAIC would be satisfactory with relatively large sample sizes.

The decision on the number of classes or segments most appropriate for our data set was also informed by other factors such as the pattern of significant parameters and relative signs, ease of interpreting the results, percentage reduction in information criteria across subsequent models, and the need to avoid over-fitting the model. Heckman and Singer (1984) note that when the number of classes becomes larger than appropriate, the estimator is likely to break down. By this they mean that the model fails to find a maximum. This may occur where the number of observations in a class is small and/or if the model is misspecified resulting in large standard errors for some parameters. For example, in the models we estimate in later chapters, when the classes are increased from three to four the optimiser breaks down in at least one of the models. A five-class model produces some estimates but a lot of the parameters are insignificant and there are no apparent differences in preferences between two classes with all insignificant parameters.

2.2.5 The panel logit with continuous mixing (MXL)

The mixed logit model is highly flexible and can approximate any random utility model (McFadden & Train, 2000), as long as the researcher is able to specify the correct mixing distribution (Fiebig, Keane, Louviere, & Wasi, 2010) and the data are of adequate quality (Scarpa, Ferrini, & Willis, 2005). The mixed logit model allows for heterogeneity of preferences by assuming a continuous distribution of tastes in the population. Its advantage over the MNL model is that it allows for random taste variation among decision-makers, unrestricted substitution patterns between alternatives, and correlation in unobserved factors over time for each decision-maker (Train, 2009). The mixed logit model can be formulated using two behaviourally distinct specifications, random-parameters or error-components, which are mathematically equivalent, but provide different interpretations. For a detailed discussion of alternative specifications for the mixed logit model, interested readers may refer to Train (2009, pp. 137-141). The random-parameters specification is most widely used compared to the error-components and other specifications. Under the two mixed logit specifications referred to above, the utility functions of an alternative i for individual n in choice situation s is specified as, respectively:

$$U_{ins} = \alpha'_n X_{ins} + \varepsilon_{ins} \tag{2-14}$$

$$U_{ins} = \alpha' X_{ins} + \mu'_n Z_{ins} + \varepsilon_{ins}$$

where, α_n is a vector of taste intensities for individual n, α is a vector of fixed taste intensities, $\mu'_n Z_{ins}$ is the error-component, μ is a vector of random terms with zero mean, Z_{ins} is a vector of variables relating to alternative i, and X_{ins} and ε_{ins} are as defined in equation (2-9).

In view of the panel nature of our choice dataset and the presence of a status quo (SQ) option among alternatives in a choice set, a continuous mixing panel logit model with an error component is specified for this thesis, i.e. a panel random parameter logit model with error components (PRPL-EC) is specified (see, Scarpa et al., 2005). The error components specification allows flexible substitution patterns across the alternatives to be achieved through the relaxation of the IIA property (Train, 2009). In this study respondents are presented with choice sets consisting of a SQ or current supplier and two unlabeled alternative suppliers and asked to decide whether to remain with their current supplier or switch to one of the alternatives.

The selection of the error components specification is motivated by the hypothesis that alternatives offering changes from the SQ do not share the same preference structure as the SQ alternative (Scarpa et al., 2005). Evidence from psychology and experimental economics indicates that respondents facing new alternatives tend to disproportionately prefer the SQ (Samuelson & Zeckhauser, 1988). Furthermore, when making choices, respondents are faced with changing attribute levels of the non-SQ alternatives in different choice situations whereas the attribute levels of the SQ remain the same throughout. This increases the uncertainty of the utility of the non-SQ alternatives which induces correlations between these alternatives. Scarpa et al. (2005) suggest that the error component captures variance associated with the cognitive effort of evaluating the utility of alternatives whose attribute levels change across choice tasks. Examples of studies that have used the mixed logit model with error components specification in various contexts include Brownstone and Train (1999), Scarpa et al. (2005) and Thiene and Scarpa (2008).

A correlation structure that accommodates differences in correlations between the utilities of alternatives in each choice set can be incorporated in the RPL model by specifying an additional error component for the non-SQ alternatives (Train, 2009). Following Brownstone and Train (1999) and Train (2009) the utility which a respondent *n* derives from selecting supplier *i* from a choice set with three competing suppliers (*SQ*, *A*, and *B*) in choice situation *s* is specified as:

$$U_{ins} = \begin{cases} \alpha' X_{ins} + \alpha_{sq} + \varepsilon_{ins}, & if\ i = status\ quo\ alternative; \\ \alpha' X_{ins} + \mu_n' z_{ins} + \varepsilon_{ins}, & if\ i = Supplier\ A; \\ \alpha' X_{ins} + \mu_n' z_{ins} + \varepsilon_{ins}, & if\ i = Supplier\ B \end{cases} \tag{2-15}$$

where X_{ins} and Z_{ins} are vectors of observed variables relating to supplier *i*, α is a vector of fixed coefficients, μ is a vector of random terms with zero mean, α_{sq} is the alternative-specific constant for the SQ alternative, and ε_{ins} is IID extreme value. The terms in Z_{ins} are error components that define, along with ε_{ins}, the stochastic component of utility. The stochastic component of utility η_{ins} is equal to $\mu_n' z_{ins} + \varepsilon_{ins}$ which is correlated over alternatives depending on the specification of Z_{ins} (Train, 2009):

$$Cov(\mu_{in}, \mu_{jn}) = E\left[(\mu_n' Z_{in} + \varepsilon_{in})(\mu_n' Z_{jn} + \varepsilon_{jn})\right] = Z_{in}' W Z_{jn}, \tag{2-16}$$

where *W* is the covariance of μ_n. The non-SQ alternatives are modelled as sharing a common error component which is assumed to be normally distributed with zero mean and variance σ^2. The correlation between the non-SQ alternatives is revealed by a significant estimate of the standard deviation of the error component. The test is based on the null hypothesis that the error component is not there, hence no correlation exists between the utilities of the non-SQ alternatives.

Given the value of μ, the conditional choice probability is logit since the remaining error term is IID extreme value:

$$P_n(i|\mu) = \frac{\exp(\alpha' X_{ins} + \mu_{in})}{\sum_j \exp(\alpha' X_{jns} + \mu_{jn})} \quad , \qquad j = SQ, A, B \tag{2-17}$$

Since μ is not given, the unconditional probability is obtained by integrating the logit formula over all possible values of μ weighted by the density of μ as follows (Brownstone & Train, 1999):

$$P_n(i) = \int_{-\infty}^{+\infty} \frac{\exp(\alpha' X_{in} + \mu_{in})}{\sum_j \exp(\alpha' X_{jn} + \mu_{jn})} \phi(0, \sigma^2) d\mu, \qquad j = SQ, A, B \tag{2-18}$$

where $\phi(\cdot)$ is the normal density, and $\mu_{jn} = 0$ when $j = SQ$. It should be noted that the error component is the same for all choices made by the same individual and this avoids the restrictive assumption of independence in the error structures across choices by the same respondent. The above integral does not have a closed form solution and the choice probabilities are estimated through simulation using NLOGIT 5 software. The simulation involves taking draws of μ from its distribution and using these draws to evaluate the logit formula. This is repeated many times and an average for the choice probability is approximated as:

$$SP_{in} = \left(\frac{1}{R}\right) \sum_{r=1}^{R} L_{in}(\mu^r) \ , \tag{2 - 19}$$

where SP_{in} is the simulated probability that respondent n will choose supplier i, R is the number of replications or draws of μ, L_{in} is the conditional choice probability presented in equation (2-17), and μ^r is the r^{th} draw from the assumed distribution of μ. By construction, SP_{in} is an unbiased estimate of P_{in} and it is strictly positive for any R such that $ln(SP_{in})$ is always defined (Brownstone & Train, 1999; Train, 2009).

The joint probability of the sequence of choices is a product of the simulated probabilities. The log likelihood function $\Sigma_n \ln(P_{in})$ is approximated by the simulated log likelihood (*SLL*) function:

$$SLL = \sum_{n=1}^{N} \sum_{s=1}^{S} \sum_{j=1}^{J} d_{jn} \, lnSP_{jn} \tag{2-20}$$

where $d_{jn} = 1$ if respondent n chooses supplier j and zero otherwise

2.3 Conceptual model for integrating psychological constructs with stated choice

In this section we provide details of the latent class framework developed for the integration of psychological constructs with stated choice. The formulae for the choice probabilities and log likelihood functions are the same as those for the LC model presented in section 2.2.4 and will not be repeated in this section.

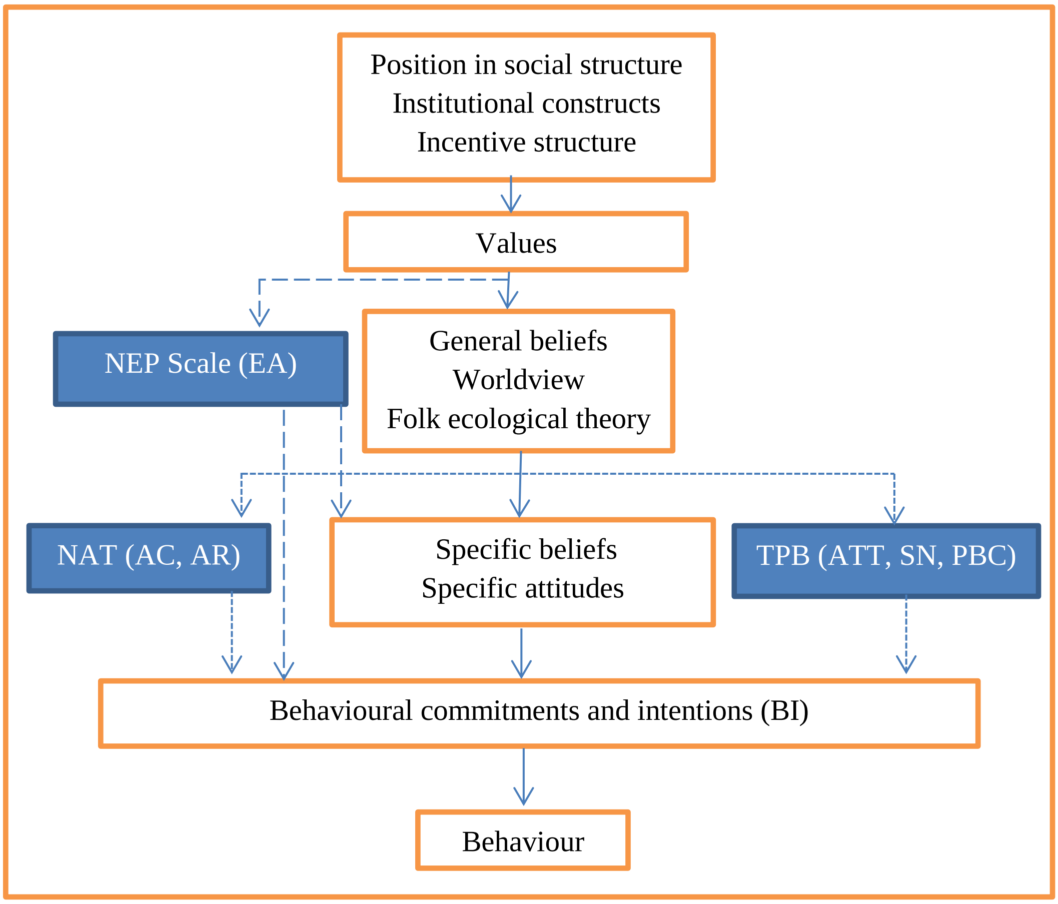
2.3.1 Background of the conceptual model

The conceptual framework developed in this research for integrating psychological constructs based on the New Ecological Paradigm (NEP) Scale, the theory of planned behavior (TPB) and the norm activation theory (NAT) with stated choice extends on the framework developed by Nocella et al. (2012) and incorporates some aspects of the causal model of environmental concern proposed by Stern, Dietz, and Guagnano (1995) and cognitive process for decision making by McFadden (1999). The NEP Scale, TPB and NAT are discussed in section 2.4.

Nocella et al. (2012) combine constructs based on the TPB with the theory of consumer demand to explain heterogeneity of preferences in a latent class framework. They hypothesize that psychological characteristics of individuals affect purchasing behaviour. Their model links the TPB constructs with stated choice by substituting behavioural intentions (BI) with a stated choice experiment, and the results indicate strong support for the inclusion of the TPB constructs in identifying heterogeneity of preferences. McFadden (1999) argues that the identification of groups of consumers with homogeneous preferences and corresponding behavioural intentions can be enhanced by measuring appropriate psychological constructs. McFadden also asserts that when psychological constructs are incorporated in economic models, choice behaviour becomes a decision process which is explained not only by economic and social factors but also by affect[7], attitudes, motives, and preferences.

[7] "Affect refers to the emotional state of the decision-maker and its impact on cognition of the decision task. Attitudes are defined as stable psychological tendencies to evaluate particular entities (outcomes or activities) with favour or disfavour. ……….Preferences are comparative judgements between entities….. Motives are drives directed toward perceived goals." (McFadden, 1999, p74)

Stern et al. (1995, p. 727) propose a theoretical model of environmental concern which places the NEP Scale in the context of social-psychological theory of attitude formation or attitude-behaviour relationships by embedding it in the model at the level of what they describe as “general beliefs, worldview and folk ecological theory” (see Figure 2-1).



(Adapted from Stern et al., 1995)

Figure 2-1: Schematic causal model of environmental concern

According to Stern et al. (1995), the major flow of causation is from top to bottom as indicated by the arrows in Figure 2-1. They argue that the NEP Scale, as a measure of generalized beliefs about the nature of human-environment interactions, constitutes a set of beliefs that influence attitudes, beliefs and behavioural intentions regarding specific environmental conditions. On the other hand TPB and NAT are placed at a lower level in the model and focus on the attitude-behaviour links but do not link specific environmental attitudes and beliefs they measure to broader worldviews and other variables higher up in the model. Thus, according to Stern el al.'s (1995) model of environmental concern, NEP Scale, TPB and NAT are hypothesized to influence behavioural intentions and ultimately behaviour. Although Schwartz (1977) did not provide a link between the NAT constructs and behavioural intentions, Stern et al (1995) and other studies, for example Wall et al. (2007), provide such a link

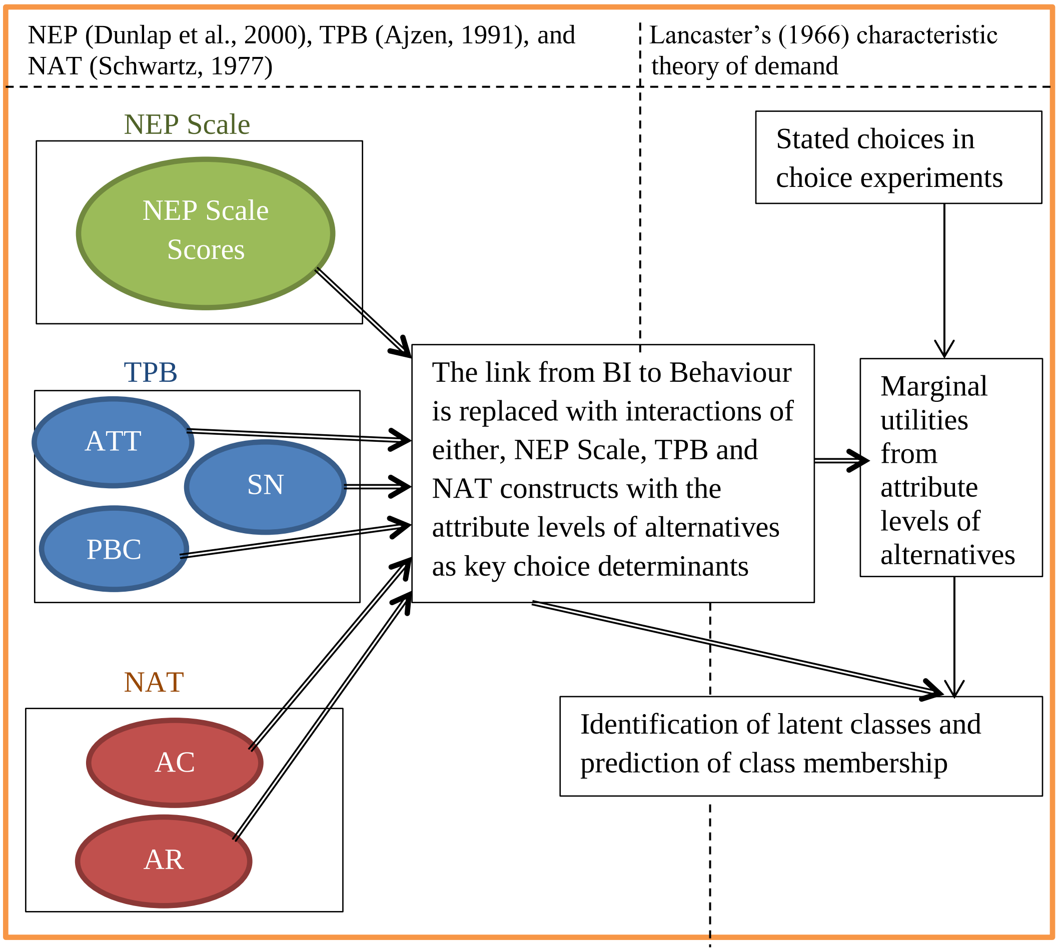
Stern et al.'s (1995) schematic causal model of environmental concern suggests that constructs developed from the NEP Scale, TPB and NAT influence behavioural intentions, hence the justification for their inclusion in our model of consumer choice. The argument for including psychological constructs based on more than one theory in a single model is supported in literature. For example, Wall, Devine-Wright, and Mill (2007) argue that combining NAT and TPB constructs accounts for a range of influences on BI that neither individual theory fully captures. Meyerhoff (2006) develops a composite attitude-behaviour model which includes three types of attitudes and recommends their inclusion in model estimation. This is supported by Liebe, Preisendoerfer, and Meyerhoff (2011) who conclude that studies using single theories omit crucial explanatory variables, and hence might be misleading. Furthermore, the NEP Scale, TPB and NAT focus on different aspects of social behaviour. NAT emphasizes on altruism whilst TPB stresses personal utility and captures behavioural control, and the NEP Scale captures the general beliefs about the relationship between humans and nature (Ajzen, 1991; Dunlap et al., 2000; Schwartz, 1977; Stern et al., 1995; Wall et al., 2007). We therefore postulate that the NEP Scale, TPB and NAT constructs influence electricity consumers' decisions to contribute financially towards the reduction of environmental impacts of electricity generation such as $C0_2$ emissions and also influence consumers' choice of electricity supplier.

2.3.2 The model

The model developed for this research allows for the individual or joint integration of the NEP Scale, TPB and NAT constructs with Lancaster's (1966) theory of consumer demand into a single model of consumer choice. The integration of the four models is achieved via the introduction of the interaction effects between the attributes of alternatives and the psychological constructs in the indirect utility of each alternative. This is based on the hypothesis that heterogeneity of preferences among electricity consumers can be better identified when the indirect utility functions of alternatives include interactions between the design attributes describing the alternatives and the NEP Scale, TPB and NAT constructs as shown in Figure 2-2. Alternatively, the constructs may be used individually in the class membership model and/or choice model. We also postulate based on Figure 2-1 that behavioural intention (BI) is a function of the NEP Scale, TPB and NAT constructs:

$$BI = f(EA, ATT, SN, PBC, AC, AR), \tag{2-21}$$

where EA is environmental attitude as measured using the NEP Scale, ATT, SN, and PBC are attitude, social norm and perceived behavioural control respectively based on TPB, and AC and AR are ‘awareness of the consequences’ of a behaviour, and ‘ascription of responsibility’ for the behaviour. These concepts are discussed in detail in section 2.4.



(Adapted from Nocella et al., (2012))

Figure 2-2: Conceptual framework integrating NEP Scale, TPB, NAT and stated choice analysis

The right-hand side of Figure (2-2) provides a schematic for the economic analysis of stated preferences in which econometric techniques are used to estimate the marginal utilities derived from specific attribute levels and, in the case of latent class analysis, the identification of consumer segments with homogeneous preferences. The constructs from the NEP Scale, TPB and NAT are represented by ovals inside boxes. The links between constructs have been omitted because our objective is not to investigate the relationships between them, but how these constructs influence choice behaviour. The double-lined arrows indicate how the four models may be combined into a single integrated choice NEP/TPB/NAT model via the introduction of interaction effects between the attributes of alternatives and the psychological constructs in the indirect utility of each alternative. BI, assumed to be causally antecedent to behaviour – “including the behavior paying money for a good” (Ajzen, Brown, & Rosenthal, 1996, p. 45), has been replaced with a stated choice experiment.

Different approaches to incorporating psychological constructs in discrete choice models have been adopted in previous studies. One approach takes responses to attitudinal questions as direct measures of attitude and uses them as explanatory variables in a latent class model. In this approach, class membership probability is a function of SDCs and responses to attitudinal questions. Studies that have used this approach include Boxall and Adamowicz (2002), Morey et al. (2006), Morey et al. (2008), and Breffle, Morey, and Thacher (2011). Boxall and Adamowicz (2002) assume that class membership probability is a function of responses to the attitudinal questions while Morey et al. (2006) argue that causality is in the opposite direction, i.e. responses to attitudinal questions are a function of one’s group membership.

In another approach, Morey et al. (2006) and Breffle et al. (2011) estimate latent class attitude (LCA) models with attitudinal data only, latent class choice (LCC) models with choice data only, and joint latent class (LCJ) models which use both sets of data to estimate the models simultaneously. In all these models there are no interaction terms between attitudinal responses and the attributes of the alternatives. However, attitudinal and choice responses are conditional on class membership, therefore the two are correlated and the joint estimation results in more consistent and efficient parameter estimates than the single models (Milon &

Scrogin, 2006). The direct incorporation of responses to attitudinal questions as explanatory variables implies that they are direct measures of the underlying attitudes. This may lead to measurement error and endogeneity bias as the responses may be correlated with the error terms (Ben-Akiva, Walker, Bernardino, Gopinath, & Morikawa, 2002; Walker & Ben-Akiva, 2002).

Cluster analysis which deterministically assigns individuals to groups based on their responses to attitudinal questions has also been used (e.g., Aldrich, Grimsrud, Thacher, & Kotchen, 2007). In such applications, a two stage approach is adopted. Cluster analysis is used in the first stage to determine the number of clusters or groups with similar attitudes. The second stage involves the estimation of a choice model for each group to obtain group-specific parameter estimates. Since each stage does not use all available information, the parameter estimates may not be consistent and/or efficient.

A recent approach to integrating psychological constructs or latent variables with stated choice is the estimation of hybrid choice models referred to in the literature as integrated choice and latent variable (ICLV) models. The ICLV model recognizes that responses to attitudinal questions are not direct measures of attitude but are driven by unobserved underlying attitudes that also drive the responses to choice questions (Ben-Akiva et al., 2002; Hess & Beharry-Borg, 2011; Walker, 2001). The ICLV model explicitly models the latent variables (LVs) that influence the choice process through structural equations relating responses to attitudinal questions to the LVs, thus modeling the behavioural process by which the LVs are formed. By simultaneously estimating the latent variable model and the choice model, the ICLV model uses all the information available and parameter estimates are consistent and efficient. The ICLV model differs from the LCJ models estimated by Morey et al. (2006), and Breffle et al. (2011) in that a latent variable model is jointly estimated with a choice model as opposed to jointly estimating a latent class model and a choice model. The ICLV model overcomes the problems associated with the approaches discussed above but it is difficult to estimate as its likelihood function includes complex multi-dimensional integrals. As the number of latent variables increases, the dimensions of the integrals increase and numerical integration method quickly becomes infeasible (Walker 2001).

Despite the advantages of the hybrid models, they are complex and difficult to estimate. While some previous studies suggest that ICLV models tend to result in significantly higher WTP estimates (e.g., Hess & Beharry-Borg, 2011), others have found no significant differences in WTP estimates and only small gains in model fit which do not justify the estimation of hybrid models (e.g., Klojgaard & Hess, 2014). Given the forgoing, we do not adopt this approach in this thesis but leave it for future research. Furthermore, the ICLV model does not identify latent preference classes or distributions of preferences as the LC and RPL models, respectively; hence it is not necessarily better than the latter models in addressing the research questions.

Although Nocella et al. (2012) adopt a latent class framework, their approach differs from previous studies by including interaction of psychological constructs with the attributes of the alternatives in the utility function and it also provides a theoretical framework for incorporating such constructs. This approach may be criticized for ignoring the argument that using responses to attitudinal questions as direct measures of the underlying attitudes results in measurement error and possible endogeneity bias. Despite the above shortcomings, we adopt a similar approach in this study. Our main focus is not on the selection of the best approach but to demonstrate, given a particular approach, how the choice of a version of the NEP Scale influences WTP estimates and how TPB and NAT constructs may help in explaining preference heterogeneity.

2.4 Measuring psychological constructs based on attitude-behaviour theories

In this section we discuss and present the psychological constructs (latent or internal variables) developed for use in this study to explain preference heterogeneity. The constructs are based on three established attitude-behaviour theories from the field of social psychology: the New Ecological Paradigm (NEP) Scale (Dunlap et al., 2000), the theory of planned behaviour (TPB) (Ajzen, 1988, 1991, 2005; Ajzen & Fishbein, 1980), and the norm activation theory (NAT) (Schwartz, 1977). NEP, TPB and NAT focus on different aspects of social behaviour. The NEP captures the generalized beliefs about the relationship between humans and nature whilst the TPB stresses personal utility and captures behavioural control, and the NAT emphasizes on altruism (Ajzen, 1991; Dunlap et al., 2000; Schwartz, 1977; Stern et al., 1995; Wall et al., 2007). The constructs were developed and applied in the context of consumer choice of electricity supplier

The selection of psychological constructs was based on literature review and the objectives of this thesis. The literature identifies two types of attitudes - general and specific attitudes (Meldrum, 2015; Meyerhoff, 2006). General attitudes relate to broad evaluative beliefs or opinions whilst specific attitudes relate to evaluative beliefs about the good or issue in question (Meldrum, 2015). We selected latent constructs which could explain consumer switching and/or demand for green electricity. For the latter, a suitable measure of environmental attitudes (EA) or environmental concern was the most appropriate. The NOAA panel (Arrow et al., 1993) and others (e.g., Spash, 1997) recommend the incorporation of general EA in economic valuation. The NEP Scale fits this category and has been used in previous economic valuation studies (e.g., Clark, Kotchen, & Moore, 2003; Cooper, Poe, & Bateman, 2004; Kotchen & Reiling, 2000). The literature also suggests that consumer switching behaviour may be explained by specific attitudes, which can be measured using the TPB and NAT constructs (e.g., Ajzen, 1988, 1991, 2001, 2005; Schwartz, 1977).

Since we model consumer switching using hypothetical scenarios, and the responses are assumed to represent intentions, the TPB and NAT constructs are appropriate for this study as they are linked to behavioural intentions (BI). Both theories postulate that BI is an antecedent of behaviour (i.e., switching and/or paying for green electricity). Furthermore, these theories are well-known and have also been widely used to explain and predict behaviour in the social psychology literature. In this study, the TPB constructs are "specific attitudes" since the questions we developed to measure these constructs relate specifically to switching behaviour. The NAT constructs are also "specific attitudes" and relate to WTP for green electricity. Some contingent valuation studies show that general attitudes tend to be poor predictors of WTP compared to specific attitudes (e.g., Cooper et al., 2004; Meldrum, 2015; Meyerhoff, 2006).

2.4.1 The New Ecological Paradigm (NEP) Scale

The New Ecological Paradigm (NEP) Scale is the most widely used measure of environmental attitude (Dunlap, 2008; Hawcroft & Milfont, 2010). The NEP Scale is a 5-point Likert-type scale consisting of 15 items or statements about the human-environment relationship. The scale was developed by Dunlap et al. (2000) as a revision and extension of the original 12-item New Environmental Paradigm (NEP) Scale to measure an individual's environmental concern or degree of endorsement of an ecological worldview. The original 12-item NEP Scale had become outdated and needed an extension to cover more facets of ecological worldview whilst achieving a better balance between pro- and anti-NEP statements. Dunlap et al. (2000) hypothesise the existence of five facets or dimensions of ecological worldview which focus on beliefs about: humanity's ability to upset the balance of nature (balance); the reality of limits to growth (limits); human domination of nature (anti-anthropocentrism); the idea that humans, unlike other species, are exempt from the constraints of nature (anti-exemptionalism); and the possibility of an eco-crisis (eco-crisis). Dunlap (2008, p. 9) argues that the NEP Scale is grounded in social-psychological theory because the NEP items measure "primitive beliefs about the relationship between human beings and their environment."

Dunlap et al. (2000) show that the items of the NEP Scale can be treated as an internally consistent summated rating scale and argue that the scale has been shown to be able to realistically differentiate between environmentalists and non-environmentalists. However, they admit that the dimensionality of the scale still needs to be investigated further especially across different populations. Dunlap (2008) points out that although the NEP Scale is viewed in various ways by researchers, who treat it as a measure of environmental concern, environmental values, and environmental attitude or environmental beliefs, he prefers ecological worldview because it measures the degree to which respondents view the world ecologically.

Each facet of ecological worldview is measured using three items which are interspersed with items measuring other facets. Table 2-1 presents the 15 items comprising the NEP Scale. Responses are recoded on a 5-point scale as "strongly agree" (SA), "mildly agree" (MA), "neither agree nor disagree" (NAND), "mildly disagree" (MD) and "strongly disagree" (SD) and are coded as 5, 4, 3, 2 and 1 respectively. Agreement with the eight odd-numbered items and disagreement with the seven even-numbered items indicates pro-NEP responses (Dunlap et al. 2000). The seven even-numbered items are reverse coded. An individual's score, which indicates the degree of endorsement of an ecological worldview, is the sum of the scores on the 15 items and has a range of 15 to 75 with higher scores indicating pro-NEP attitudes. Before the item scores are combined into a single summated scale, they are checked for internal consistency.

Table 2-1: The New Ecological Paradigm Scale items

Code	Statement
NEP1	1. We are approaching the limit of the number of people the earth can support.
NEP2	2. Humans have the right to modify the natural environment to suit their needs.
NEP3	3. When humans interfere with nature it often produces disastrous consequences.
NEP4	4. Human ingenuity will ensure that we do not make the earth unlivable.
NEP5	5. Humans are severely abusing the environment.
NEP6	6. The earth has plenty of natural resources if we just learn how to develop them.
NEP7	7. Plants and animals have as much right as humans to exist.
NEP8	8. The balance of nature is strong enough to cope with the impacts of modern industrial nations.
NEP9	9. Despite our special abilities humans are still subject to the laws of nature.
NEP10	10. The so-called 'ecological crisis' facing human kind has been greatly exaggerated.
NEP11	11. The earth is like a spaceship with very limited room and resources.
NEP12	12. Humans were meant to rule over the rest of nature.
NEP13	13. The balance of nature is very delicate and easily upset.
NEP14	14. Humans will eventually learn enough about how nature works to be able to control it.
NEP15	15. If things continue on their present course we will soon experience a major ecological catastrophe.

For this study we used the same wording and order for the statements as in Dunlap et al. (2000), and respondents were asked to indicate their responses on a clearly marked scale.

The NEP Scale statements were tested on a sample of 70 electricity bill payers as part of a pilot survey. Results of the pilot survey showed that respondents tended to have pro-NEP attitudes with respect to most items. This finding is consistent with results of previous studies using the NEP Scale (e.g., Aldrich et al., 2007; Dunlap et al., 2000; Ek & Soderholm, 2008). Following standard practice in previous studies, we tested for internal consistency of the NEP constructs using the corrected item-total correlation (r_{i-t}), Cronbach's coefficient alpha (α), and principal components analysis (PCA) (e.g., Clark et al., 2003; Dunlap et al., 2000; Kotchen & Reiling, 2000). Internal consistency describes the extent to which all 15 items of the NEP Scale measure the same concept or construct. The corrected item-total correlation is the correlation coefficient between each item's score and the sum of the scores of the other 14 items. A good candidate for inclusion in the final index should correlate well with the item-total score. Although there is no rule on the acceptable level of r_{i-t}, the literature suggests that a minimum value of 0.3 is acceptable. Cronbach's alpha is a coefficient of reliability used to test whether items are sufficiently inter-related to justify their combination in an index. Previous literature suggests that $\alpha \geq 0.70$ can be taken to indicate "acceptable" reliability (e.g., Clark et al., 2003). We provide a detailed discussion of the results of the pilot survey in Appendix 2.

2.4.2 The theory of planned behaviour (TPB): Application to consumer switching

The TPB postulates that a person's intention to perform a behaviour (BI) is the immediate determinant of any behaviour (Ajzen, 1988, 1991). Behavioural intention is assumed to be a function of three independent determinants: the individual's positive or negative evaluation of performing the behaviour in question [attitude towards the behaviour (ATT)]; the individual's perception of the social pressure exerted on him/her to perform or not perform the behaviour in question [subjective norm (SN)]; and, self-efficacy or the perceived ease or difficulty of performing the behaviour [the degree of perceived behavioural control (PBC)] (Ajzen, 1988, 1991, 2005; Ajzen & Fishbein, 1980). We express the relationship postulated in the TPB as follows:

$$BI = f(ATT, SN, PBC) \tag{2-22}$$

Based on the TPB an electricity consumer's intention to switch supplier (BI) is the immediate determinant of switching (i.e. behaviour). In the context of supplier choice, ATT measures a consumer's positive or negative evaluation of switching supplier; SN measures a consumer's perception of social pressure to switch or not to switch supplier; and PBC measures self-efficacy or the perceived ease or difficulty of switching supplier.

Ajzen and Fishbein (1980), Ajzen (1988), and Ajzen (2005) provide a detailed discussion of the TPB. We follow the procedure recommended by Ajzen and Fishbein (1980) and Ajzen (1988) in developing the questions used to measure the TPB constructs for this study as indicated below.

1. Define the behaviour of interest in terms of action and target
    - The action is "*switching*"
    - The target is "*electricity supplier*" or just "*supplier*"
2. Define the corresponding behavioural intention
    - The behavioural intention (BI) is "*intention to switch supplier*"
3. Define the corresponding attitude, social norm, and perceived behavioural control
    - Attitude (ATT) is "*attitude towards switching supplier*"
    - Social norm (SN) is "*social norm with respect to switching supplier*"
    - Perceived behavioural control (PBC) is "*perceived behavioural control with respect to switching supplier*"

Based on the above steps we constructed direct measures of ATT, SN, PBC and BI in the format suggested by Ajzen and Fishbein (1980, pp. 261-262) as follows:

- ATT: by using evaluative semantic differentials to obtain a direct measure of the same attitude (Ajzen, 2005; Ajzen et al., 1996; Ajzen & Fishbein, 1980; Fielding, McDonald, & Louis, 2008; King, 1975; Meyerhoff, 2006). A semantic differential scale is composed of polar opposite adjectives, e.g. good and bad, separated by a 7-point rating scale.
- SN: by asking respondents to judge how likely it is that most people who are important to them would approve or disapprove of their switching supplier (Ajzen, 2005).
- PBC: by asking respondents whether they believe that they are capable of switching electricity supplier and whether doing so is completely under their control (Ajzen, 2005).

- BI: by asking respondents how likely it is that they will switch supplier in the next 12 months (Ajzen, 2005).

Obtaining direct measures of the TPB constructs is attractive as it involves fewer questions and therefore a shorter questionnaire and also avoids the concern associated with the expectancy-value model or belief-based measures, whereby the assumed product (belief x evaluation) may misrepresent the cognitive process involved in attitude formation (Ajzen, 2001; Ajzen & Fishbein, 1980).

The wording of the statements or questions designed to directly assess the TPB constructs was developed by analogy with Ajzen and Fishbein (1980), Ajzen (2001, 2005) and King (1975). A sentence stem (or two statements) and two evaluative semantic differential scales, for example, “good – bad” and “rewarding – punishing” for the attitude (ATT) construct, were used to assess each TPB construct (see Table 2-2). The statements for each construct were interspersed among the statements for other constructs. The response categories are points on a 7-point bipolar Likert scale indicated as “extremely good”, “quite good”, “slightly good”, “neither good nor bad”, “slightly bad”, “quite bad” and “extremely bad” and are coded as 3, 2, 1, 0, -1, -2 and -3 respectively. For each construct an index (the average of the two scores e.g. ATT is the average of ATT1 and ATT2) is calculated as a measure for that construct. The index for each construct obtained from the pilot study is shown in Table 2-2. High positive scores indicate a higher possibility of switching whilst low and/or negative scores indicate a low possibility or likelihood.

Table 2-2: Description of the TPB constructs and average scores: pilot survey[1]

Variables	Sentence stem	Evaluative Semantic differential scale
Attitude [ATT = (ATT1 + ATT2)/2)] = **2.02**		
ATT1	For me switching to a supplier offering a better package of price and services would be:	good - bad
ATT2		rewarding - punishing
Social Norm [SN = (SN1 + SN2)/2] = **0.83**		
SN1	How likely is it that most people who are important to you think that you should switch to a supplier offering a better package of price and services?	likely - unlikely
SN2*	How likely or unlikely is it that most people who are important to you would approve if you switch to a supplier offering a better package of price and services?	likely - unlikely
Perceived behavioural control [PBC = (PBC1 + PBC2)/2] = **1.38**		
PBC1	I believe that I can switch to a supplier offering a better package of price and services if I want	Agree - disagree
PBC2	For me switching to a supplier offering a better package and services would be:	Easy - difficult
Behavioural intention [BI = (BI1 + BI2)/2] = **0.59**		
BI1	How likely or unlikely is it that you will switch to a supplier offering a better package of price services in the next 12 months?	likely - unlikely
BI2**	I intend to switch to a supplier offering a better package of price and services in the next 12 months	likely - unlikely

[1]N = 70 for the pilot survey. *The original statement and the corresponding evaluative semantic scale in the pilot survey were "How far do you think most people who are important to you would approve or disapprove of your switching to a supplier offering a better package of price and services: approve-disapprove." **The original statement in the pilot survey was "All things considered I would be willing to switch to a supplier offering a better package of price and services in the next 12 months."

As in the case of the NEP Scale discussed in the previous section, the TPB constructs were tested in the pilot survey which allowed us to address any issues before the final survey. Since only two statements were used for each construct it was not possible to carry out tests for internal consistency using item-total correlation, Cronbach's alpha and principal components analysis. Instead we performed a correlation analysis to assess the correlation between each pair of statements measuring the same construct. All the correlations were high and significant at the .05 level suggesting that each pair of statements could be combined into a single index. A detailed discussion of the pilot survey results is presented in Appendix 2.

2.4.3 Norm activation theory: Application to consumer switching

Schwartz's (1977) norm activation theory (NAT) was originally developed to explain altruistic behaviour. The theory postulates that personal norms (normative self-expectations experienced as feelings of obligations) are the immediate antecedent of altruistic behaviour. Personal norms are activated by awareness of a behaviour's consequences (AC) and beliefs about personal responsibility or ascription of responsibility (AR).

According to this theory, people who are aware of the consequences of choosing an electricity supplier offering a higher portfolio of renewables and who also have feelings of personal responsibility to choose such a supplier are more likely to do so compared to those who do not.

Two statements were used to assess respondents' "awareness of consequences" (AC) of switching supplier and another two statements were used to assess "ascription of responsibility" (AR). Responses were measured on a 5-point Likert scale with response categories "strongly agree" (SA), "somewhat agree" (SWA), "neither agree nor disagree" (NAND), "somewhat disagree" (SWD), and "strongly disagree" (SD). These were coded from 1 (SD) to 5 (SA).

The statements used to measure AC and AR in the final survey and a summary of the results of the pilot survey are presented in Table 2-3. Correlation between the AC statements was 0.285 whilst that of the AR statements was 0.704. Although both correlations were significant at the 5% level, the AC statements were refined in the final survey. A discussion of the pilot survey results is provided in Appendix 2.

Table 2-3: NAT constructs and distribution of response: pilot survey (N =70)

How far do you agree or disagree with the following statements		SA	SWA	NAND	SWD	SD
Awareness of the consequences of a behaviour (AC)						
AC1	I believe that switching to a supplier that produces electricity from renewable sources would be good for the environment.	23.94	47.89	25.35	4.23	2.82
AC2	My switching to a supplier that generates electricity from renewable sources will not make a difference to the environment.	4.23	22.54	26.76	40.85	5.63
Ascription of responsibility (AR)						
AR1	I feel morally obliged to switch to a supplier that generates most of its power from renewable sources.	4.23	30.99	40.85	14.08	9.86
AR2	I feel personally responsible for helping to reduce carbon dioxide emissions by switching to a supplier that generates electricity from clean energy sources	4.23	29.58	42.25	14.08	9.86

2.5 Experimental design and survey questionnaire development

The experimental design (ED) process is an important aspect of choice experiments. It involves a number of stages which include: identifying and defining the important attributes relevant to the research; selecting the type of experimental design to use in generating choice sets; model specifications; generating the design and deciding whether to use main effects only or include interaction effects; and including the choice sets in the survey questionnaire. Hensher et al. (2005a, p. 102) provide a summary of the ED process used to generate stated preference experiments.

2.5.1 Selection of decision-relevant attributes of electricity suppliers

Previous studies investigating consumer preferences for the attributes of electricity suppliers have relied on literature reviews, focus groups, expert advice and pilot surveys in identifying and defining important attributes and their levels. For this research we relied primarily on three New Zealand national surveys on consumer switching and focus groups for the identification of important attributes. The three surveys, by the Electricity Commission (2008) and Electricity Authority (2011a, 2012a) were conducted by a professional market research company on behalf of the Electricity Authority. The surveys were conducted at a national level with sample sizes of 1000 respondents who were responsible for paying the electricity bill or had a say in choosing their electricity supplier. All the surveys included focus group interviews and discussions conducted by trained staff. Results from these studies have been adopted by the Electricity Authority in its policy on consumer switching, which provides reasonable grounds for their acceptability in this research.

The above studies identified 15 incentives used by retailers to attract customers. Respondents in the national studies were asked to rate each incentive for switching on a 11-point scale with endpoints marked as 0 (not at all important) and 10 (a very important). The ratings provided a ranking of the incentives for switching at a national level. To explore if the inclusion of any additional incentives or reasons for switching was warranted, we conducted a Delphi type focus group consisting of electricity bill payers.

For our first focus group, 10 respondents were intercepted at random and interviewed by the researcher whilst they were waiting to collect their children from school. Each participant was given a questionnaire in which they were asked to list the reasons for choosing their current supplier, after which they were asked to rate them on a 11-point scale as in the national surveys. Respondents were then provided with the 15 incentives identified in the national surveys and asked to provide their own rating, after which they were shown the ratings from the national survey and asked if they would want to adjust their ratings given the national results. This procedure is similar to the Delphi method in that the focus group members did not meet but got an opportunity to react to the responses of the participants in the national survey. The advantage of this approach is that it costs less and avoids the influence of dominant individuals in the group. The ratings and rankings from the focus group were similar to those of the national surveys and no important additional reasons were identified. The final attributes used in this research were therefore drawn from the 15 incentives identified in the national surveys.

To avoid a large ED we selected seven attributes from the list of 15 incentives based on a minimum rating of 6. In addition to these we included supplier type as an additional attribute to allow for investigation of how different types of supplier, particularly new entrants, influence choice. The selected attributes, their levels and design codes are presented in Table 2-4. The attribute ranges were based on extensive searches of the electricity suppliers' websites and the Powerswitch website. The attributes are quantified based on criteria similar to recent studies on consumer preferences for the attributes of electricity suppliers. For example, the share of generation from renewables was measured as a percentage (e.g., Amador et al., 2013; Bollino, 2009; Borchers, Duke, & Parsons, 2007; Goett et al., 2000; Kaenzig et al., 2013), cost was measured as monthly power bill (e.g., Amador et al., 2013; Bollino, 2009; Kaenzig et al., 2013), and discount as a percentage (Goett et al., 2000).

In generating all the designs used in this research we considered the coding scheme recommended by Hensher et al. (2005a) and used attribute-level labels for all quantitative attributes and dummy codes for qualitative attributes. Hensher et al. (2005a) suggest that an appealing feature of using attribute-level labels directly when dealing with quantitative attributes is that one can meaningfully predict over the entire range of attribute-level labels from models estimated specified with such attributes.

Table 2-4: Attributes, attribute levels and the design codes used in the ED

Attributes	Description	Levels	Pivot design codes
Time	Average time for telephone calls to be answered by a customer service representative	0, 5,10, 15 (minutes)	-5, 0, -5, -10
Fixed	Length of time over which prices are guaranteed	0, 12, 24, 36 (months)	0, +12, +24, +36
Discount	Discount for paying electricity bill on time including online prompt payments	0%, 10%, 20%, 30%	-10, 0, +10, +20
Rewards	Loyalty rewards such as Fly Buys, Brownie points, prize draws, and annual account credits (excludes annual network dividends)	No (0) Yes (1)	-1 0
Renewables	Proportion of electricity generated from wind, hydro, geothermal, bioenergy and solar.	25%, 50%, 75%, 100%	-25, 0, +25, +50
Ownership	%NZ ownership of supplier	25%, 50%, 75%, 100%	-25, 0, +25, +50
Supplier type	Type of supplier (dummy coded)	New electricity company	1
		New non-electricity company	2
		Well-known electricity company	0
		Well-known non-electricity company	3
Bill	Average monthly electricity bill before GST, levy and discounts.	$150, $200, $250, $300	-100, -50, +0, +50

The attribute-level range for *Time* was based on timed calls that were made by the researcher to electricity suppliers to determine how long it took to talk to a customer representative. Some calls were answered immediately while some took as long as 15 minutes, so the range was set as 0-15 minutes and split into four levels. This was further refined by taking into account responses from the pilot survey where each respondent evaluated their current supplier on the basis of all the attributes used in the experimental design. The length of time over which prices were fixed (*Fixed*) was based on the various pricing plans offered by suppliers which ranged from 0-36 months. This range was split into four levels representing actual levels available in the market.

Discounts (*Discount*) available in the market ranged from 0 to 22% but we raised the upper limit to 30% to provide a range that could be split into four levels that are equidistant in spacing, and also provide an opportunity to stretch the range beyond what is currently available in the market but is still within reasonable bounds. Loyalty rewards (*Rewards*) were assessed on the basis of whether a supplier offered these or not, so the variable took on two levels; 0 or 1. Electricity generation from renewable sources (*Renewables*) ranged from a low of 24.7% by Genesis Energy to 100% by Meridian Energy and TrustPower. The range for *Renewables* was therefore set at 25-100%. The lowest level for local ownership (*Ownership*) that could be established was 48% for Contact Energy (52% owned by an Australian company) and the highest was 100% for Meridian and Genesis before their partial privatisation. For suppliers listed on the stock exchange, it is difficult to ascertain the levels of local ownership from publicly available information. The range for *Ownership* was set at 25-100%, which includes all the levels that were identified.

For supplier type (*Supplier type*) we considered the possibility of existing well-known non-electricity companies diversifying into electricity retailing, and new companies (not well-known) entering the market. We set four levels for *Supplier type* to include the incumbent – 'well-known electricity supplier'. The range for monthly power bill (*Bill*) was based on the annual estimates from the "Provider cost table" available on the Consumer Powerswitch website. The table provides annual estimates for small, medium and large households based on prices from each retailer.

2.5.2 Experimental design for pilot survey

A major challenge with the CEs technique is the experimental design (ED) of the choice sets used to generate choice datasets, which is fundamental in the development of stated choice surveys. ED is the way in which the attribute levels of alternatives are set and structured into the choice sets (Bennett & Adamowicz, 2001). The ED process is complex, time consuming, and can heavily influence the outcomes (validity and reliability) and conclusions of the research (Hensher et al., 2005a; Johnson et al., 2013; Louviere et al., 2000; Louviere et al., 2008; Lusk & Norwood, 2005). The choice of ED is important because in a multi-attribute valuation the efficiency of the estimates depends on how the attributes and levels are combined to form the alternatives and the choice sets (Ferrini & Scarpa, 2007; Hensher et al., 2005a; Louviere et al., 2000; Louviere et al., 2008).

The selected ED should allow for estimation of the independent influence of each attribute on choice and also maximize the power of the model to detect statistically significant relationships for a given sample size. An efficient design produces parameter estimates with small standard errors from a smaller sample size compared to others. Hence, the objective of any ED is to maximize the statistical efficiency for a given model. Burgess and Streets (2003, 2005) and Street and Burgess (2004) provide a formal definition of statistical design efficiency for stated choice experiments and also discuss strategies for creating optimal designs. Louviere et al. (2000) provide a detailed discussion of the theoretical aspects of experimental designs.

A sequential orthogonal design with three unlabelled alternatives was developed as a starting design using NGENE 1.1.0 software. Sequential orthogonal designs do not require any prior information about the parameters of the model. This design strategy has been criticised for its failure to utilize information that may be available to the researcher, such as estimates of betas from related studies (Ferrini & Scarpa, 2007; Huber & Zwerina, 1996; Scarpa & Rose, 2008), and assumptions about the signs of the betas e.g. negative sign on the cost coefficient or positive (negative) signs on betas for desired (undesired) attributes (Ferrini & Scarpa, 2007). Furthermore, using a design that assumes zero values for all the betas may be unrealistic given that the attributes used in the experimental design are those identified as important to consumers in choosing their preferred electricity supplier. However, we do not view this as a major issue since this was the first stage of ED.

The initial design consisted of 16 choice tasks which were administered on a convenience sample of 6 students providing a total of 96 responses. A base MNL model was fitted to the data. All the coefficients had the expected signs. Only *Discount*, *Ownership* and *Bill* were significant at the 5% level. The parameter estimates from the first stage were used in a D-efficient homogeneous pivot design for an MNL model. A pivot design with specified levels for the reference alternative was selected as opposed to a 'no choice' option as it most closely approximated the choice setting experienced by individuals in real retail electricity markets. In a homogeneous pivot design each respondents faces the same reference alternative or status quo (SQ) (ChoiceMetrics, 2012; Rose et al., 2008).

Although a supplier's customers on the same electricity plan face similar attribute levels except *Bill* which depends on the unit price and power consumption level, perceptions of these levels may vary among customers. With 18 electricity suppliers in the retail electricity market in New Zealand a heterogeneous pivot design would have entailed designs for 18 sub-groups using attribute levels specific to each supplier. To avoid multiple designs, a homogeneous pivot design was generated using the average attributes for all suppliers as recommended in the literature (ChoiceMetrics, 2012; Louviere et al., 2000). The MNL efficiency measures are provided in Table 2-5 and an example of the choice card is provided in Figure 2-3.

Table 2-5: MNL efficiency measures for ED for the pilot survey

Measure	Value
D_p-error	0.0563
A_p-error	2.7130
B estimate	74.3971 (this falls in the range of optimal values (70-90) for utility balance
S estimate	360 (for *Renewable*: coefficient was insignificant).

In the scenarios that follow please only consider the information provided in deciding whether to switch supplier or not. Assume that any information not provided is the same for the three suppliers. Which supplier would you prefer?

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	15 minutes	15 minutes	0 minutes
Fixed rate guarantee	0 months	36 months	0 months
Prompt payment discount	10%	0%	20%
Loyalty rewards	Yes	No	Yes
Electricity supplied from Renewable sources	50%	100%	75%
NZ ownership	100%	100%	50%
Supplier type	Well-known electricity company	New electricity company	Well-known non-electricity company
Average monthly electricity bill	$250 ($225 after discount)	$250	$200 ($160 after discount)
Which supplier would you prefer?	○	○	○

Figure 2-3: Stated choice scenario and example of a choice task.

The design consisted of 12 choice tasks and was tested in May 2013 on a sample of 70 electricity bill payers sampled from an online panel managed by a marketing company. The sampling was stratified based on quotas for gender, age groups, and income groups built into the 'survey flow' to ensure that a representative sample was obtained. The pilot sample of 70 respondents provided 840 responses that were used to estimate MNL, LC, and RPL-EC models presented in Table 2-6.

Although experimental designs are generally expected to reduce multicolinearity among the attribute levels in stated CEs, we checked for collinearity before model estimation for both the pilot and final surveys. None of the correlations were greater than the frequently used cut-off point of 0.8 (see, Hensher et al., 2005a), suggesting that orthogonality may not have been lost in the data. Collinearity in SP data may be induced by missing SP observations and/or different numbers of respondents presented with different blocks of the ED (Hensher et al., 2005a). In both the pilot and final surveys, all respondents were presented with the same choice tasks since the ED was not blocked, and the online surveys were only terminated when the target sample sizes of fully completed questionnaires were achieved.

Table 2-6: Regression results for the pilot survey (z values are in parentheses)

Variables	MNL model	LC model		RPL-EC model	
		Class 1	Class 2	parameters	SD*
ASCSQ	0.4336^{b}	0.1087	1.2017^{c}	0.4403^{a}	
	(2.06)	(0.26)	(3.40)	(1.80)	
Time (minutes)	-0.0239^{a}	-0.0227	-0.0307	-0.0261^{b}	0.0377^{a}
	(-1.91)	(-0.97)	(-1.56)	(-1.80)	(1.68)
Fixed (months)	-0.0089	-0.0028	-0.0093	-0.0115	0.0322^{c}
	(-1.57)	(-0.27)	(-1.05)	(-1.50)	(3.96)
Discount	0.0378^{c}	0.0109	0.0517^{c}	0.0423^{c}	0.0336^{c}
	(4.75)	(0.58)	(4.38)	(4.27)	(2.60)
Rewards	0.2434	0.5593	0.6559^{b}	0.2573	0.976^{c}
	(1.33)	(1.60)	(2.42)	(1.00)	(3.51)
Renewable	0.0099^{c}	0.0045	0.0205^{c}	0.0114^{c}	
	(3.43)	(0.77)	(4.60)	(3.53)	
Ownership	0.0144^{c}	0.0185^{c}	0.0126^{c}	0.0153^{c}	
	(4.90)	(3.74)	(2.60)	(4.74)	
New electricity company	-0.5961^{b}	0.2275	-1.2395^{c}	-0.5711^{b}	
	(-2.48)	(0.45)	(-3.33)	(-2.08)	
New non-electricity company	-0.6760^{c}	-0.0357	-1.3336^{c}	-0.8014^{c}	
	(-2.71)	(-0.09)	(-3.08)	(-2.82)	
Well-known non-electricity company	-1.0210^{b}	-2.4548^{b}	-0.9195^{a}	-1.3299^{b}	
	(-2.24)	(-2.12)	(-1.69)	(-2.56)	
Bill	-0.0140^{c}	-0.0323^{c}	-0.0079^{c}	-0.0163^{c}	
	(-17.42)	(-9.55)	(-6.83)	(-15.05)	
Error Component				0.0	-0.1909
					(-1.23)
Estimated Latent Class Probabilities		0.6381^{c}	0.3619^{c}		
		(10.69)	(6.065)		
Model Fit					
Pseudo R^2	0.39	0.49		0.406	
χ^2 [p-value]	592.35 (11 d.f.)	755.30 (23 d.f.)		624.79 (16 d.f.)	
	[.0001]	[.0001]		[.0001]	
LL(β)	-466.24	-391.38		-456.63	
AIC	962.7	828.8		945.3	

^{c}, ^{b}, ^{a} Denote significance at the .01, .05, and .1 level, respectively. *Standard deviation

2.5.3 Experimental design for the final survey

Based on the results from the pilot survey a Bayesian D-efficient homogeneous pivot design for an MNL model was generated for the final survey. Setting realistic levels for the pivot or reference alternative is very important. We relied on levels reported by respondents in the pilot survey and information on generators/retailers' actual output and market shares in 2012 to set the levels for the reference alternative. The level for *Renewable* was set at 50% because the two suppliers accounting for nearly 50% of the retail electricity market, Contact Energy and Genesis Energy, generated only 48.6% and 32% of their electricity from renewable sources in 2012 (MBIE, 2013). In the pilot survey 51% of respondents were customers of Contact Energy and Genesis Energy. However, 74% of respondents were not sure about the proportion of electricity generated from renewables by their supplier. The selected level of 50% reflects the average market condition and may likely be perceived as realistic.

Genesis was the only supplier that was 100% state owned but there were plans to sell 49% to the general public. Contact Energy is 52% owned by an Australian company Origin Energy; 48.22% of Mighty River Power is listed on the stock exchange; TrustPower is listed on the stock exchange with 50.7% of its shares held by Infratil Ltd, an NZ-based public company; recently 49% of Meridian Energy was sold to the public and the company was listed on the stock exchange. Based on this information, an average level of 50% for *Ownership* seemed to be reasonable. The level for *Bill* was set at $250 as in the pilot survey. The sample median power bill in the pilot survey was $200 but it is not clear whether respondents were reporting the net bill after the discount or the gross bill before the discount.

The level for *Discount* rate was set at 10% as 47% of the sampled respondents indicated that their current supplier provided this level of discount. Half the sample indicated that their supplier offered loyalty rewards. The level selected for *Supplier type* is 'Well-known Electricity Company' as 87% of respondents indicated this level for their current supplier. About 74% of respondents were not on any fixed rate plan, and 83% indicated 5 minutes or less call waiting time, so the levels for *Fixed* and *Time* were set at zero and 5 minutes, respectively. The selected levels for the SQ or reference alternative turned out to be the same as in the pilot survey.

Although the LC model is our main model for the analysis of responses to the stated choice experiments, the ED generated was for an MNL model. Design strategies specifically for LC models are not available and NGENE cannot yet generate efficient designs for LC models (Bliemer, 2013). However, previous studies employing the LC model have used EDs for MNL models and experience from empirical applications is that designs for MNL models perform quite well (Rose, 2013). Conceptually the problem with using designs for MNL models for

LC models is that the analyst may run out of degrees of freedom as the number of parameters increases rapidly with the number of classes.

Our design consists of seven attributes with four levels each and one attribute with two levels, giving a total of 4^7x2 = 32,768 treatments, which is too much for any individual to handle. A fractional factorial design was employed to reduce the number of treatments to manageable levels. For fractional factorial designs, a value for the "*rows*" property for the experimental design must be set. This requires the determination of the degrees of freedom required for the ED, which depends on the utility specification (Hensher et al., 2005a). The value for the "*rows*" property or the number of choice situations in the experimental design must be equal to or greater than the degrees of freedom. Hensher et al. (2005a, p. 122) define the degrees of freedom for an experimental design as "the number of observations in a sample minus the number of independent (linear) constraints [i.e. the β's to be estimated] placed upon it during the modelling process."

For main effects-only MNL models, the degrees of freedom required for the ED are determined as the number of parameters to be estimated over all alternatives excluding the constant terms, plus one additional degree of freedom for the random error component of the model (Hensher et al., 2005a). The number of parameters to be estimated in our MNL model, excluding constants, is 10, hence a minimum of 11 degrees of freedom were required for the design. However, when the value for the "*rows*" property was set at 11, NGENE warned that one or more attributes would not have level balance with the number of rows specified. Setting the number of rows for the ED at 12 overcame this problem.

Although some of the models to be estimated include interactions of design attributes with psychological constructs and SDCs, these interaction effects were not included in the ED for practical and financial reasons. Including these interaction effects would have entailed many designs, ideally one for each respondent, using a two-stage approach where information on each individual's scores for psychological constructs and SDC are obtained in the first stage and a specific design generated taking into account this information. Although such an approach is possible, it is expensive, time-consuming, and beyond the scope of this study. Despite the exclusion of interaction effects, Hensher et al. (2005a) suggest that the analyst would still be able to estimate some of the interaction effects of interest although this would come at a cost in terms of lost information.

The parameter estimates from the pilot survey were used as priors in a Bayesian D-efficient main effects design consisting of seven attributes with four levels each and one attribute with two levels as in the pilot survey. Bayesian efficient designs use random priors described by random distributions to account for uncertainty about the true parameter values. Ferrini and Scarpa (2007) contend that Bayesian efficient designs are less sensitive to misspecification of the priors compared to designs which used fixed priors. To generate a Bayesian efficient design, simulations are required for evaluating the design over the parameter distributions. This is achieved by taking draws from the parameter distributions. Following Bliemer and Rose (2011) we generated a Bayesian D-efficient design using priors drawn from Bayesian normal distributions β $N(\mu,\sigma^2)$ where the means (μ) were assumed to be the parameter estimates from the pilot survey, and the standard deviations (σ) the standard errors of the parameter. The number of draws was set at 350 and was taken using an intelligent sequence called Halton Sequences.

An experimental design is efficient if it yields data with minimum correlation that enables estimation of the parameters with the lowest possible standard errors. The most widely used efficiency measure is the *D*-error, which takes the determinant of the asymptotic variance-covariance (AVC) matrix of the parameter estimates assuming only a single respondent. A design with the lowest *D*-error is called *D*-optimal and a design which has a sufficiently low *D*-error is called a D-efficient design. Finding an efficient design given a feasible set of attribute levels, a number of choice situations, and prior parameter values (or probability distributions), involves determining a level balanced design that minimizes the efficiency error.

The efficiency measures and probabilities for the experimental design are reported in Tables 2-7 to 2-10. The results indicate considerable improvement in efficiency in terms of *D*-error, *A*-error, *B*-estimate and *S*-estimate compared to the ED for the pilot survey. For example, the *D*-error and minimum sample size were reduced by 82% and 61% respectively in the final ED. Utility balance of 76.34 is in the recommended range (ChoiceMetrics, 2012). This highlights the benefits of adopting a sequential updating Bayesian design approach.

Table 2-7: MNL Bayesian experimental design efficiency measures

Efficiency measure	Fixed	Bayesian Mean
D_b-error	0.010925	0.011492
A_b-error	0.607957	0.640720
B_b-estimate	76.347688	70.03800
S_b-estimate	42	

Table 2-8: MNL probabilities

Choice situation	Your Current Supplier	Supplier A	Supplier B
1	0.301005	0.342824	0.35617
2	0.304624	0.294842	0.400534
3	0.320927	0.351339	0.327734
4	0.752135	0.124689	0.123176
5	0.370232	0.316948	0.312820
6	0.30223	0.193160	0.504611
7	0.826006	0.097969	0.076025
8	0.856243	0.055814	0.087943
9	0.343993	0.414164	0.241844
10	0.305436	0.429426	0.265138
11	0.30381	0.408978	0.287212
12	0.295387	0.358897	0.345716

Table 2-9: Minimum sample estimates for individual priors

	Time	Fixed	Disc	Rew	Ren	Own	D0	D1	D2	Bill
Prior	-0.24	-0.01	0.04	0.24	0.01	0.01	-0.59	-0.67	-1.02	-0.01
Sp-estimate	29.7	38.6	4.6	41.6	7.9	5.2	14.9	16.0	7.9	2.2

D0, D1, and D2 are dummy variable levels for *Supplier type* indicating ‘New Electricity Company’, ‘New Non-electricity Company’ and ‘Well-known Non-electricity Company’, respectively. Disc, Rew, Ren and Own are *Discount, Rewards, Renewable, Renewable* and *Ownership*, respectively.

Table 2-10: MNL D-efficient design summary of iteration history

Evaluation	Time	Mean Bayesian MNL D-error	Invalid designs	Improvement
1	12:55:25 PM, 20/01/14	0.023139	0	-
103	12:55:29 PM, 20/01/14	0.017599	0	0.005540
87,788	1:52:37 PM, 20/01/14	0.011492	0	0.006107
833,394	3:41:05 AM, 21/01/14 (stopped)	0.011492	0	Nil

2.5.4 Simulation of experimental design for the final survey

The ED described in the previous section was simulated in Microsoft Excel. The objective was to explore whether the design was capable of generating choice response data that could result in significant parameter estimates with expected signs for a financially feasible sample of 200 respondents. The minimum sample required for all parameters to be statistically significant was 42 for an MNL model (see Table 2-9). However, the estimation of LC models would require larger sample sizes due to the proliferation of parameters as the number of classes increase.

The design was simulated using a sample of 200 virtual respondents. Each virtual respondent faced a single replication of the ED which consisted of 12 choice tasks. Based on the priors used in the ED, the observed utility ($\beta' X_{ins}$) for all alternatives was computed. A random error term (ε_{ins}) is required to estimate each U_{ins} but this is not observable to the researcher. To estimate ε_{ins} for each data point, we took random draws (η_{ins}) from a standard normal distribution, which is equivalent to taking draws directly from a cumulative density $F(\varepsilon_{ins}) = \eta_{ins}$, and computed the errors as: $\varepsilon_{ins} = -\ln(-\ln(\eta_{ins}))$ which is obtained by taking the double natural log of the cumulative density $F(\varepsilon) = e^{-e^{-\varepsilon}}$ (Train, 2009). The estimated random error terms were then added to the observed components of utility. We then assumed that each virtual respondent chose the alternative with the highest utility. This provided simulated choices for the data set.

An MNL and LC model were estimated from the data, which included simulated choices for the 200 virtual respondents. The results are presented in Table 2-11. All the parameters for the MNL model were significant at the 0.01 level and had the expected signs suggesting that the sample size of 200 was adequate and that the design was capable of generating responses that would allow for the estimation of the independent influence of each attribute on choice. LC models with two and three preference classes were estimated but the probability of the third class was statistically insignificant. The results suggested that the design could generate responses that would allow us to estimate LC models. The simulation results provided a degree of confidence that the choice data that would be generated by the ED would be adequate to achieve the objectives of the research.

Table 2-11: Experimental design simulation results

Variables	MNL model		LC model			
			Class 1		Class 2	
	Parameter	| z |	Parameter	| z |	Parameter	| z |
ASCSQ	0.4637[c]	5.50	0.3835	1.47	0.5531[c]	3.47
Time (minutes)	-0.0201[c]	4.25	-0.0093	0.52	-0.0248[c]	2.96
Fixed Term (Months)	-0.0064[c]	3.21	0.0014	0.24	-0.0098[b]	2.42
Discount	0.0394[c]	13.21	0.0258[c]	2.71	0.0463[c]	7.32
Rewards	0.1999[c]	3.51	0.5823[a]	1.82	0.0368	0.31
Renewable	0.0100[c]	9.84	0.0205[c]	3.15	0.0052[a]	1.91
Ownership	0.0125[c]	10.40	0.0146[c]	3.41	0.0112[c]	4.67
New electricity company	-0.6725[c]	8.05	-1.0274[c]	2.82	-0.5263[c]	3.51
New non-electricity company	-0.7483[c]	7.68	-1.1390[c]	3.18	-0.56299[c]	3.10
Well-known non-electricity company	-1.1505[c]	10.99	-1.4645[c]	4.30	-1.0052[c]	5.51
Monthly Power Bill	-0.0143[c]	18.88	-0.0146[c]	6.36	-0.0143[c]	10.97
Class probabilities			0.371	1.81	0.629	3.06
Model Fit						
Pseudo R^2					0.13	
χ^2					690.14762	
LL(β)	-2298.77733				-2291.59568	
AIC					4629.2	

[c], [b], [a] Significant at .01, .05, and .1, respectively

2.5.5 Survey questionnaire

Data required for this research was generated using an online survey administered to an online panel of domestic electricity bill payers in New Zealand in January 2014. The survey questionnaire was developed and programmed using Qualtrics, a software package provided by Qualtrics.com. The online panel was provided by a market research company called Research Now Pty Ltd. An online survey was preferred to a mail survey based on cost considerations and a literature review on online surveys discussed below.

With a target of 200 completed responses and a typical response rate of 20% for mail surveys, a sample size of 1000 would have been required. A mail survey consisting of an initial mail-out of 1000 questionnaires, 800 reminder/thank you post cards, 800 first follow-up letters, and 500 second follow-up letters with survey questionnaire and return envelope would have cost a minimum cost of $5170. On the other hand the cost of 200 completed responses from an online panel provided by a marketing company was $1900 (plus GST) for a 15-25 minute survey questionnaire, which was within the budget.

The advantages of using online surveys to collect data often cited in the literature include the speed of distribution, reduced cost, reduced errors in compiling the data from the responses, interactivity, and the possibility of randomizing and customizing the questions (Fleming & Bowden, 2009; MacKerron, 2011). The use of online panels allows the target sample size to be achieved relatively quickly; in our case the target was achieved over night. A growing number of studies using online surveys show that reliable data may be collected through such surveys (Börjesson & Algers, 2011; Lindhjem & Navrud, 2011; MacKerron, 2011; Tonsor & Shupp, 2011). However, the main drawback for online surveys is an incomplete and biased sample frame as panel members are originally recruited through non-probabilistic methods and individuals who have no access to the internet are excluded. An increase in internet penetration rates over the past few years has reduced the proportion of people with no internet access. With an internet penetration rate of 84.5%, New Zealand is ranked 12th in the world (Internet World Stats, 2012), which may justify the use of the online survey for this study. However, despite the high internet penetration rate in New Zealand, some population segments, especially low income groups in rural or remote areas, may still not have access to the internet.

A review of literature on the possible survey mode effects of internet based surveys lends support to the decision to use an online survey for this research. Denscombe (2006) investigates survey mode effects using “near-identical” web-based and paper survey questionnaires administered to “near-identical” groups in the context of voluntary risk-taking and health-related behaviour of young people in the UK. The study finds very little evidence of survey mode effects in terms of completion rates and data content. In contrast, Dolnicar, Laesser, and Matus (2009) compare an online and a paper (mail) survey on tourism and find significant differences in responses to tourism-related questions. Respondents in this study were asked to choose their preferred survey format, which may have resulted in self-selection bias with younger and more educated respondents opting for the web-based survey. It is not surprising that the results of the two survey modes are statistically different since socio-demographic characteristics (SDCs) were not controlled for in the surveys. Fleming and Bowden (2009) also compare results from a web-based and a mail survey on tourism but find no statistical differences in SDCs, response rates, and consumer surplus estimates. Respondents for the two survey modes were recruited onsite, hence the profiles and preferences of respondents in the two samples are likely to be similar, in contrast to the study by Dolnicar et al. (2009) where recruitment was off-site (i.e. at respondents’ residences). It would appear that if representative samples are used in both web-based and mail surveys, survey mode effects may be reduced or eliminated.

The survey questionnaire developed for this study consisted of an introduction and questions arranged into seven blocks or sections. An example of a completed final survey questionnaire is provided in Appendix 1. The introduction explained the purpose of the survey and solicited participation. Respondents were advised that participation was voluntary and that anonymity would be maintained. This was followed by three screening questions which asked if respondents consented to participating, were at least 18 years old, and whether they were responsible for paying the electricity bill or had a say in choosing their electricity supplier. Respondents providing a ‘NO’ response to any one of these questions were automatically screened out. The next section consisted of questions on age, gender and income, which were used to set quotas to ensure that a representative sample was achieved. The quotas reflected the population breakdown based on the 2006 Census. The quota for gender was 49% males (51% females). Table 2-12 presents the quotas used for age and income. Additional questions on socio-demographic characteristics followed the questions used to set the quotas.

Table 2-12: Quotas used for age and income groups

Age		Personal Income	
Age group	Quota	Income group	Quota
19 and Under	9%	≤ \$15 000	34%
20-24	9%	\$15 001 - \$30 000	24%
25-29	8%	\$30 001 - \$40 000	14%
30-34	9%	\$40 001 - \$50 000	9%
35-39	10%	\$50 001 - \$70 000	10%
40-44	10%	\$70 001 - \$100 000	4%
45-49	9%	≥ \$100 000	4%
50-54	8%		
55-59	7%		
60-64	6%		
65+	16%		

The third section included questions soliciting information on respondents' switching behaviour, reasons for switching or not switching, and their current supplier. This was followed by a section consisting of attitudinal questions. These included the NEP Scale statements and questions measuring constructs based on the TPB and NAT. The fifth section included questions that asked respondents to evaluate their current supplier in terms of the attributes used in the ED by indicating the levels perceived to apply to their supplier. The next section introduced respondents to the choice tasks. The design attributes were defined and an example of a completed choice task was provided. To ensure that respondents did not skip this section, the page was timed and the 'next button' was disabled for 25 seconds. The next section presented the twelve choice tasks. The final section of the survey questionnaire included debriefing questions. Respondents were asked to indicate the attributes they ignored in making their choices, if any. Likert-type scales were used to rate how certain respondents were in their choices, their understanding of the choice tasks, and how easy it was to make choices.

The online survey questionnaire was first tested on a convenience sample of 10 friends and relatives on my e-mail contacts list to identify any possible glitches in the survey-flow. A survey link was also sent to Research Now Pty Ltd, who tested the survey for the screen-out and quota questions. A second pilot test was conducted on a sample of 70 respondents from the online panel of electricity bill payers. The second pilot proceeded smoothly, which led to the final launch of the survey.

2.5.6 Choice data

The data set used in this research is constructed from responses obtained from an online survey described in the previous section. In total 477 respondents started the survey; 38 (8%) dropped out at various stages of the survey questionnaire and /or were timed out once the target sample was achieved, 76 (16%) were screened out because they were not responsible for paying the electricity bill or did not have a say in choosing their electricity supplier, and 138 (29%) were screened out because the quotas set for gender, age group and income had already been met. Of the dropouts, only one respondent went as far as completing three choice tasks. A total of 224 completed and useable responses were achieved.

A panel data set was constructed from the 224 completed survey questionnaires. The data was formatted for NLOGIT 5 software. Each observation is represented by a block consisting of three rows, one for each alternative in a choice set. Since each respondent faced twelve choice tasks, the data set consists of 2688 (12 x 224) blocks or observations with each respondent being represented by 36 rows of data, resulting in a dataset with 8064 rows. All categorical levels were coded using dummy codes. This data set is used in model estimation in chapters 4 to 6.

2.5.7 Summary

In this chapter we have formally stated the standard discrete choice models (MNL, LC, RPL-EC) that are applied in this research. An extension of the LC model developed specifically to integrate psychological constructs with stated choice is also described. We have provided an overview of stated choice experiments highlighting the state-of-the-art. The main hypotheses tested in this thesis are stated. The models described in this chapter are used as the main tools in the analysis of data in chapters 4 to 6.

Chapter 3. The New Zealand electricity market

3.1 Introduction

The objective of this chapter is to provide a context for this research. We provide an overview of the electricity markets in New Zealand to highlight aspects of the markets that are relevant to this thesis. A discussion of the current debate on whether market reforms have worked in creating efficient and competitive wholesale and retail markets is provided towards the end of the chapter.

3.2 The New Zealand electricity market (NZEM)

The Electricity Authority (EA) is an independent Crown entity established under the Electricity Industry Act 2010 to provide regulatory oversight of the electricity sector. Its statutory objective is to promote competition, reliable supply, and efficiency in the electricity industry for the long-term benefit of consumers (Electricity Authority, 2011b). The New Zealand electricity market is a stand-alone closed market with no means of importing or exporting electricity. Therefore, generation and investment in new capacity are driven by local demand conditions. Any supply shortages result in demand rationing and/or price spikes.

Electricity generation in NZ is dominated by hydro which accounted for 57.6% of total generation in 2011 (Ministry of Economic Development, 2011c). However, generation from hydro is highly dependent on hydro storage levels and inflows into rivers and lakes with, a total storage capacity sufficient to cover demand for only seven weeks (Ministry of Economic Development, 2012). Generation is highly vulnerable to weather conditions. For example, in the dry winter periods (March-June) in 2001, 2003 and 2008, hydro storage levels were critically low and public awareness campaigns were used to reduce demand by encouraging consumers to conserve electricity. In 2003, the Whirinaki 155 MW oil-fired power plant was built specifically to provide reserve generation during dry periods and to cover major breakdowns in other generation plants (MBIE, 2010). The isolation of the NZ electricity market and the heavy reliance on hydro generation, which is affected by weather conditions and storage levels, pose serious challenges for the

Electricity Authority in fulfilling its mandate of ensuring security and reliability of supply and delivery of electricity to consumers at least cost.

According to MBIE (2015), net electricity generation in 2014 was 42,231 GWh or 152 Pj. Demand for electricity for the same period was 39,210 GWh. Residential electricity demand accounted for 32.1% (12,374 GWh) of total annual demand. Residential connections as at March 2011 were 1,683,089, accounting for 87.2% of total nationwide connections (Ministry of Economic Development, 2012).

3.3 Reasons for deregulating the electricity markets

The current deregulated electricity market in New Zealand is the result of a series of reforms which started in the mid-1980s. Before the reforms, electricity generation and transmission were operated as a state-owned monopoly, whilst distribution and retail were under publicly owned territorial monopoly franchises (Bertram, 2006). Investment and pricing decisions were influenced by political factors and the electricity supply system was operated with social rather than commercial goals. According to (MBIE, 2010), the market was characterized by inefficiency, lack of customer choice and cross-subsidies[8]. The electricity reforms were part of economy-wide reforms triggered by increasing concern about New Zealand's overall economic performance. At the same time, a wave of electricity market reforms was sweeping across many countries including the USA, Australia, and the UK.

The main objective of the reforms was to stimulate economic growth through efficient resource use, driven by clearer price signals, and where possible, by competitive markets (MBIE, 2010). Specifically, the electricity reforms were aimed at establishing competitive and efficient wholesale and retail electricity markets, and regulating monopoly in transmission and distribution for the long-term benefit of electricity consumers. Competition was expected to drive a search for greater production and service delivery efficiency, drive average prices down, and remove the regulator's role of setting the prices. Consumer switching and/or a high propensity to switch were expected to exert pressure on retailers to offer competitive prices.

[8] Prices were set to recover costs, with price discrimination in favour of domestic consumers (low price) relative to commercial customers (high price) and industrial customers (in between).

Over the past 28 years, the electricity reforms have resulted in the partial privatization of the electricity sector, and the establishment of “workably competitive” wholesale and retail markets. According to Hansen (2014), a market is “workably competitive” if it ensures that prices broadly reflect cost of supply, drives costs towards efficient levels, spurs innovation and allows customers greater freedom to choose among competing retailers. The issue of whether the reforms so far have achieved efficiency in the wholesale and retail markets has been the subject of heated debate. We discuss this issue later in section 3.7. A list of key dates in the development of the electricity sector in New Zealand is provided in Appendix 3. Bertram (2006), Electricity Authority (nd), Rowlands et al. (2004) and MED (2010) provide details of the reforms.

3.4 Current market structure

A summary of the current electricity sector in New Zealand is presented in Figure 3-1. Participation in the electricity markets is governed by the Electricity Industry Participation Code 2010 (Code) which specifies the duties and responsibilities that apply to industry participants including the Electricity Authority. Key players other than the Electricity Authority include generators, a system operator (Transpower), an independent market operator (NZX Energy), lines or distribution network companies, retailers, and large consumers. The Code allows for buying and selling wholesale electricity through a compulsory pool or power exchange. Generators offer to sell while retailers bid to buy electricity to on-sell to consumers, and some large industrial consumers bid to buy electricity for their own use. The main components of the electricity industry activities governed under the Code that are relevant to this research are: generation, transmission, distribution and retail. We will show later how retail is linked to the other activities, and thus their relevance.

The Electricity Industry Act 2010, which replaced the Industry Reform Act 1998, provides for a monopoly of transmission and requires full ownership separation of distribution (lines) businesses from retail and generation businesses. Transmission is a natural monopoly and is provided by Transpower – a state owned enterprise which owns and operates the national grid or high voltage transmission lines. The separation of ownership of distribution from retail and generation is meant to promote competition in the retail and generation activities and to prevent cross-subsidization of generation and retailing from lines customers.

Today the wholesale electricity market is an oligopoly in which five major generators dominate the market. During the period 2003-2014, Meridian Energy, Contact Energy, Mighty River Power, Genesis and TrustPower jointly accounted for 92-96% of total generation (Bertram, 2014), with eight smaller grid-connected generators and other smaller distributed generators accounting for the balance. There are 22 retail brands and consumers are free to choose their preferred supplier from the 8 to 18 retail brands available depending on the region (Electricity Authority, 2013b). However, the electricity market is characterized by a high degree of vertical integration, with the five major generators (often referred to as 'gentailers' or the 'Big 5') dominating 95% of the retail market. The retail market structure thus leans towards oligopoly despite the existence of many small or fringe retailers, who account for only 5% of the market. This, according to some commentators, reduces the competitiveness of the market.

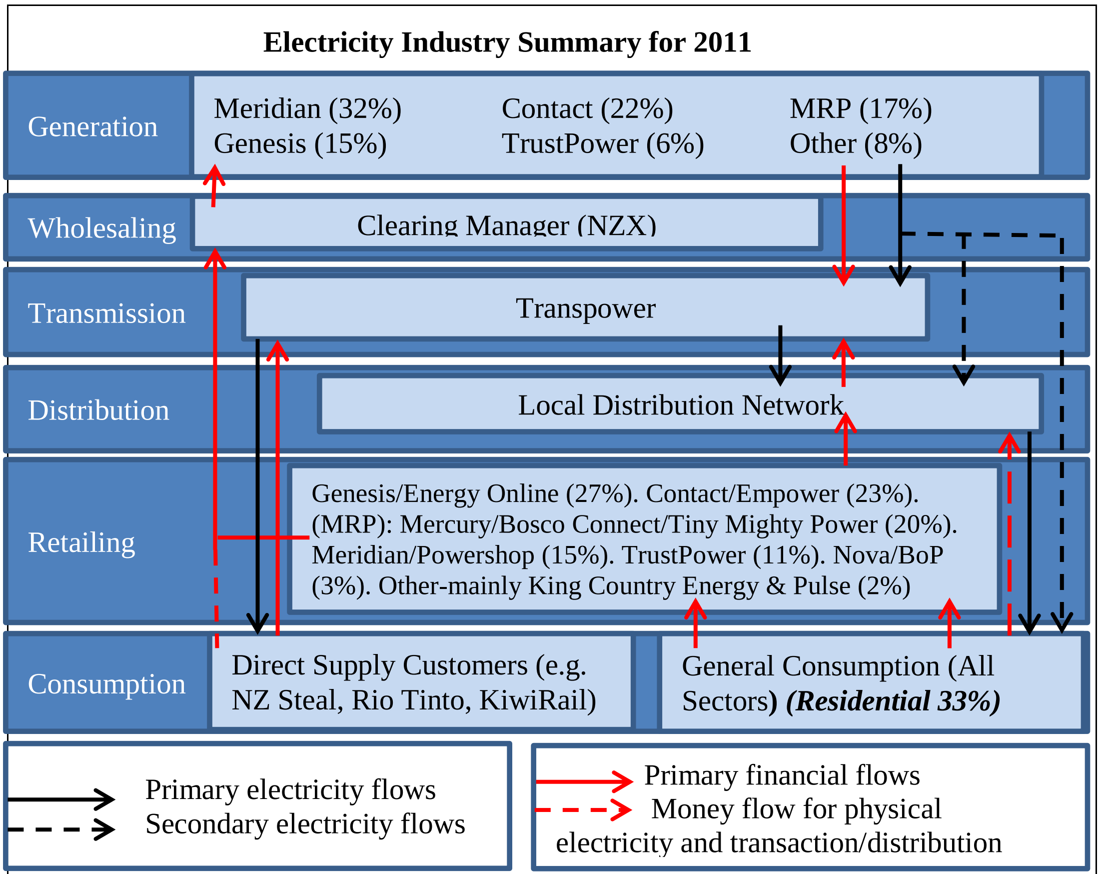


Figure 3-1: A schematic of the NZ electricity industry (Source: NZ Energy Data File 2012)

Although there are no regulatory barriers to entry into the wholesale market, the high cost of new generation plants and the length of time required for feasibility studies, resource consent, and construction of the plant may prevent new entrants into the wholesale market for considerable lengths of time. The captive residential customer base in the retail markets limits the extent to which new entrants may penetrate the market. For example, the Electricity Authority (2012a, p. 4) observes that "consumer inertia is still strongly in play." From March 2010 to March 2012 about 47.5% of respondents were not happy with the 'value for money' from their current retailers yet the average switching rate was only 15% per year, indicating that the majority of unsatisfied customers did not switch despite the nation-wide campaign promoting switching.

Bertram (2014) argues that vertical integration of generation and retail in the NZ electricity markets offers large synergies to the Big 5 because they can match generation with their customer base, allowing them to conduct most of their wholesale transactions in-house rather than in the open market. This reduces the Big 5's exposure to the wholesale spot market price compared to small retailers and new entrants who do not own generation plant and have to buy their hedges from a market serviced by the Big 5. These conditions may not be conducive to the development of a competitive and efficient market especially if the Big 5 are able to collude or withhold available supply from the market.

NZX Ltd is currently contracted as an independent market operator providing functions such as the management of reconciliation, pricing, clearing and wholesale information trading system (WITS). Transpower, as owner and operator of the transmission system, is responsible for the scheduling and dispatch of generation. Electricity is supplied to consumers by 29 distribution companies and 105 embedded networks (Electricity Authority, 2011b). To overcome the limited investment opportunities in competing distribution infrastructure, local distribution networks are owned either by trusts that return profits to their consumers, or companies under Commerce Commission price control but allowing for a reasonable rate of return on assets (Electricity Authority, 2011b).

Bertram (2014) argues that distribution companies have been able to justify increases in charges based on upwards asset revaluations which reduce the rate of return on assets or equity and therefore allow for increases in prices or revenues to bring the rate of return back to a reasonable level. The increase in charges is passed on to the consumers. This is seen as a loophole in the system and such behaviour is viewed by Bertram (2014) as violating the regulatory compact. A regulatory compact is a social contract and represents a combination of constitutional rights, laws and regulations, franchise agreements, regulatory commission rules and policy statements. A regulatory compact may be defined as follows: first, in return for a monopoly franchise the distribution company accepts an obligation to serve all consumers in the locality; and second, in return for agreeing to commit capital to the business, distributors are assured a fair opportunity to earn a reasonable return on that capital.

3.5 Retail electricity prices

Retailers sell electricity purchased from the wholesale market to residential, commercial and industrial consumers. Details of how the wholesale spot market price is determined are provided in Appendix 3-1. The retail price for residential consumers covers the total cost of supply which includes the following components: wholesale price, transmission, distribution, metering, market services, market governance, retail, and GST (see Figure 3-2). Commercial and industrial consumers do not pay GST and currently face lower retail prices than residential consumers. Although retail prices differ by consumer type they also differ by location or grid-exit point (node), reflecting the total cost of supplying electricity to the consumer's installation control point (ICP), the metered point for transacting the delivery of electricity between the distribution network and the retailer.

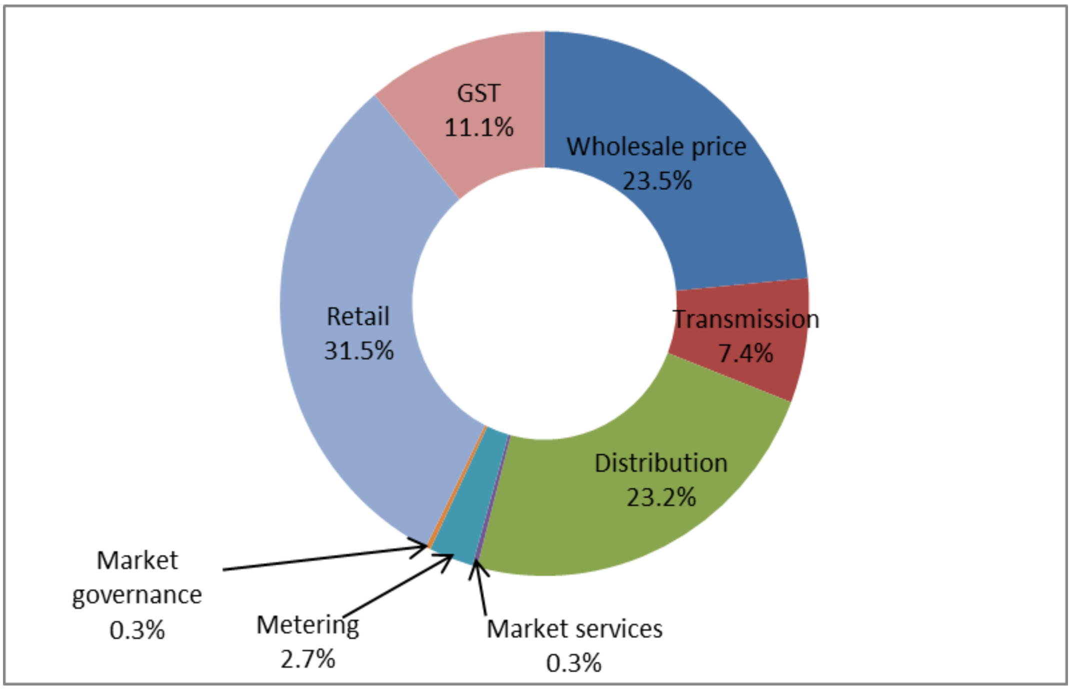
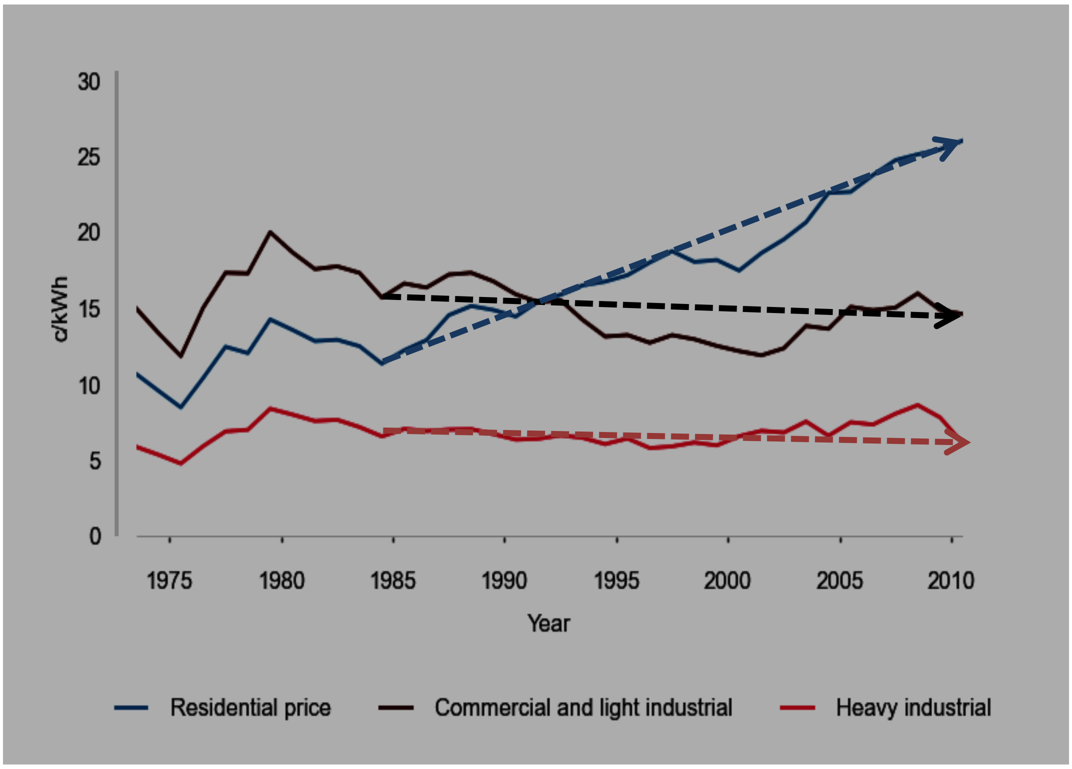


Figure 3-2: Components of the residential retail price in 2010 (Source: NZX Ltd, 2014)

In Figure 3-3 we present real annual average retail prices by consumer type (based on 2013 prices) for the period 1975 – 2010. Figure 3.3 shows that since 1985, residential retail prices have risen sharply in real terms whilst retail prices for commercial and industrial consumers have fallen. A number of explanations have been suggested for the observed trends in retail prices. One explanation is that with the onset of market reforms in the mid-1980s the removal of cross-subsidization from commercial to residential consumers resulted in price corrections leading to increases in residential retail prices and a fall in retail prices for commercial consumers. Increased competition for commercial customers also exerted downward pressure on commercial retail prices leading to lower prices.

Another explanation given for the increase in residential retail prices is the introduction of a 10% GST on residential retail prices in 1988 which was subsequently raised to 12.5%, adding 5.4% to the price rise that year (Evans & Meade, 2005). A possible third explanation for the sharp rise in residential retail price is the inelastic demand curve for residential consumers and the fact that consumption is mainly concentrated during peak periods when prices are highest. However, residential consumption has been flat over the past decades, only increasing at an annual average of less than 0.1%.



(Source: Hansen (2014))

Figure 3-3: Real retail electricity prices by consumer category (NZ$$_{2013}$)

3.6 Promoting consumer switching in NZ retail electricity markets

The introduction of retail competition in 1998 was meant to increase consumer choice and encourage innovation in service delivery, which would lead to lower retail prices. A decade later, a review of the performance of the markets revealed that switching levels had not met expectations and had been insufficient to induce competitive behaviour among retailers (Electricity Authority, 2010). Retail prices, particularly residential, had increased rapidly contrary to expectation (see Figure 3-3 in previous section). To promote consumer switching, the government adopted a programme that addressed some of the major barriers to switching identified in the literature on consumer switching (e.g., Gamble et al., 2007, 2009; Gärling et al., 2008; Giulietti et al., 2005; Rowlands et al., 2004). The barriers include, lack of information, perceived search costs, perceived low economic benefits from switching, and loyalty to the incumbent. The campaign used to promote switching is discussed further in the next chapter.

A key rationale for the programme promoting consumer switching is that increased switching activity or increased propensity to switch alters the demand curve facing each retailer. With increased propensity to switch, the authorities argue that each retailer faces a more elastic demand curve in the short term and can attract customers if it lowers its price or lose customers if it prices above its competitors. An elastic demand curve provides incentives to lower retail prices and drives a search for increased efficiency and risk management strategies to mitigate price swings in the wholesale market. Lower retail prices and increased efficiency in the retail electricity market provide less ability for generators with market power to increase wholesale prices (NZX Ltd, 2014). The critical aspects of an efficient retail electricity market are: that consumers should be able to make choices about how much electricity they want to consume at a given price, and the market should promote least-cost production in electricity generation and delivery to consumers. A competitive retail market is therefore crucial for achieving a competitive wholesale market. The link between an efficient retail electricity market and the wholesale market is further obviated, in the case of NZ, by the vertical integration of generation and retail, where the main generators are the main retailers so that the behaviour of the same players influences both markets.

3.7 Debate on the competitiveness of the New Zealand electricity market

The electricity market in New Zealand continues to evolve as governments seek to improve competition and efficiency to achieve lower power bills for New Zealanders. However, concerns have been raised over the sharp rise in retail prices especially for residential consumers. For example, Statistics NZ figures show that despite weak demand, electricity prices rose 3% in 2013, nearly double the 1.6% rate of inflation. For the year ended March 2014, average residential electricity prices were 2.3% higher compared to the previous year. In April 2014, further retail price hikes were justified by retailers and lines companies as reflecting increases in operating costs. However, Statistics NZ’s producer price index shows that input costs for the sector have fallen in the last two years. As a result of the sharp rise in retail prices over the years, some commentators have questioned the competitiveness of the current market structure and the effectiveness of the regulations in ensuring lower prices. On the other hand, proponents of the current market structure still argue that high prices don't necessarily indicate the exercise of market power. Instead they suggest that the observed price increases may be due to other factors such as constraints in the transmission system, increasing cost of production and new capital, depletion of Maui gas fields and low hydro storage levels, which some critics fail to recognize.

A single buyer model proposed by the Labour-Greens coalition during the 2014 election campaign promised to reduce retail prices by 10-14%. The coalition argues that the current market structure is inefficient and uncompetitive as it allows the major power companies to exercise market power and charge unjustifiably high prices. They suggest that generators should be paid according to their offer schedules, which would provide incentives for the true revelation of marginal cost and elimination of any possible collusion[9]. Under the proposed single buyer model, NZ Power, a state owned company, would buy all electricity offered in the wholesale market, offer same the terms to all retailers, enter into long term contracts with generators and retailers to ensure stable prices, and hold tenders for the provision of new capacity (Bertram, 2014). The single buyer model, it is argued, would result in reductions of 10-14% in annual power bills.

Opponents of the single buyer model argue that the model would install a monopsony arrangement on the buy-side of the market after the industry has worked hard to minimise the monopoly that had characterised the supply side of the industry for many years. Furthermore, the single buyer model would not facilitate transparent pricing in the market. Instead it would encourage contracting arrangements similar to transfer pricing between generators and their retailers. Layton (2013) and Evans (2013) argue that adopting this model would be tantamount to returning to central planning which has failed in the past and would lead to higher prices. They suggest that the single buyer model is based on conclusions drawn from inadequate research that assumes, among other things, that dams have been paid for, and fails to recognize that water is not free since it has an opportunity cost.

Some New Zealand studies indicate that under the current market structure and regulations, the four largest players in the market (Meridian, Contact, Genesis and

[9] Currently, generators are paid at the cost of the marginal plant irrespective of their bids for the previous plants.

Mighty River Power) have, in the past, been able to exercise market power leading to higher wholesale and retail prices (see, Bertram, 2014; Browne, Poletti, & Young, 2012; Wolak, 2009). For example, the Wolak Report concludes that generators exercised market power in the wholesale spot market especially in dry years and, over the period 2001 – 2007, overcharged consumers by a cumulative total of NZ$4.3 billion (Wolak, 2009). Proponents of the current market structure have criticized Wolak's findings and argue that the results are based on wrong assumptions of the market structure used in the analysis and the benchmark for competitive prices used in the estimation of the overcharging (Electricity Technical Advisory Group, 2009; Evans & Guthrie, 2012; Hogan & Jackson, 2012). Browne et al. (2012) use an alternative method to Wolak (2009) which addresses some of the criticisms of the latter and finds evidence of the exercise of market power by the major power companies which resulted in overcharging of $2.6 billion in 2006 and 2008.

The Electricity Authority argue that the current electricity market is a "workably competitive" market in which prices broadly reflect the cost of supply (Hansen, 2014; Layton, 2014). They state that the reforms from 2009 have reduced the ability of generators to exercise market power from 18% to only 2% of the time and small retailers have expanded rapidly, resulting in significant decline in retail concentration[10]. Furthermore, competition for customers has increased and more residential customers have reported having been approached by retailers enticing them to switch on more than two instances in the past three years. They also argue that since the spot price is based on the market clearing price, there is transparency in price discovery in the market; that is, the current wholesale market provides incentives for generators and retailers to reveal their true preferences and profits earned on low cost plants provide incentives for efficiency and promote investment. All this would be lost to the detriment of consumers if a single buyer model is adopted. However, they acknowledge that more still needs to be done to address concerns about the competitiveness of the retail market.

[10] Retail market concentration measured using the Herfindahl-Hirschman Index (HHI) was between 0.4 and 1 in 2004 but by 2013 it had declined to between 0.2 and 0.6

3.7.1 Study contribution to the debate

The Electricity Authority (2010, p. 4) contends that "The benchmark for successful retail electricity market competition therefore requires that price differences between retailers reflect brand value and service factors (which are likely to be small for electricity retailing)." Defeuilley (2009) argues that the homogeneous nature of electricity makes it difficult to differentiate and the potential to create value-added services is therefore limited. This implies that only small price differences are expected within retail markets, and therefore, an examination of changes in price differences over time may provide an indication of whether the markets are becoming more competitive or not.

An important assumption of the introduction of competition in retail electricity markets is that innovative new entrants undercut incumbent prices and also offer better services (Defeuilley, 2009; Electricity Authority, 2010; Littlechild, 2009). This would exert downwards pressure on prices as incumbents are forced to innovate and reduce prices to retain market share. The expectation is that, in the short run, prices should fall towards new entrants' prices. However, evidence from some countries suggests that these expectations may not have been met. For example, Defeuilley (2009) argues that in many cases new entrants in the British retail markets failed to be innovative, did not offer consumers anything new or better than incumbents, and failed to capture significant market share. He notes that in most European countries incumbents' market shares lie between 85 and 95%. This is supported by a review of retail electricity markets in Great Britain which revealed that the six traditional power companies control 99% of the market and all new entrants were insignificant (see, Giulietti, Grossi, & Waterson, 2010). Insignificant market shares held by new entrants, increasing retail prices, and price differences ranging between 12-17% cast doubts on the competitiveness of the retail markets (see, Defeuilley, 2009; Giulietti et al., 2010). It is therefore interesting to see how New Zealand compares to these markets.

We assess the competitiveness of a number of retail electricity markets across New Zealand based on the assumption that new entrants undercut incumbents and that prices fall towards new entrants' prices. Specifically we look for evidence that new entrants' prices are the lowest at entry or any other time, and for evidence of a reduction in price differences between highest- and lowest-priced retailers. The data used is compiled from price trend graphs available from the Consumer NZ website[11]. The price trends graphs provide data on average annual expenditure on electricity consumption for a medium sized household from July, 2012 to July, 2015 for each regional market. The price trends graphs use prices for the most common electricity plan type. We calculate percentage differences in price between the highest and lowest priced retailer in each region in July each year, and also note the behaviour of new entrants in terms of where their prices lie in the market.

The percentage differences in prices in selected regions are presented in Figure 3-4. All but one market included in our analysis recorded a sharp decline in price difference from 2012 to 2013. This reduction in price differences is due to increases in the lowest prices rather than a decline in the highest prices and does not reflect an improvement in competitiveness. The opposite is expected in a competitive market. In the majority of cases, the differences in prices increase from July 2013 to July 2015 which may indicate non-competitive behaviour by retailers. In some instances the increase in price differences is due to new entrants providing the lowest prices whilst traditional incumbents do not appear to respond to these lower prices. For example, in Northland, Nova Energy (a non-traditional retailer) was the cheapest and did not change its price from July 2014 to July 2015, but the most expensive retailer, TrustPower, increased its price during the same period. At the same time other entrants' prices (Pulse Energy and Energy Online) were wedged between those of traditional retailers.

Only one new entrant, Fick Electric, appears to have consistently behaved as expected by offering the lowest price on entry into the market. Other new entrants or non-traditional retailers price in the middle of the pack, contrary to expectation. In the Waikato region, a non-traditional retailer, Nova Energy was the most expensive retailer in July 2015. This unexpected behaviour by most new entrants does not put pressure on incumbent traditional retailers to lower their prices. In the main we find that where price differences decline it is due to the lowest price creeping towards higher prices, and where price differences increase due to the entry of lower-priced retailers, there is no apparent immediate counteraction by the incumbents.

---

[11] https://www.powerswitch.org.nz/powerswitch/price-trends

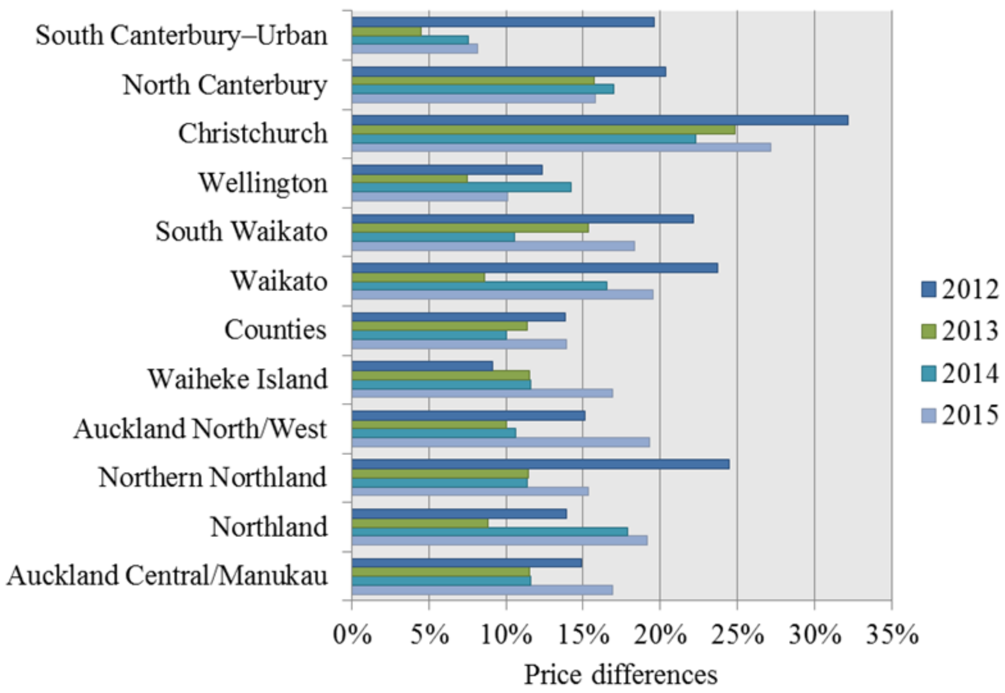


Figure 3-4: Price differences between highest- and lowest-priced regional retailers

Based on the benchmark for successful retail electricity market competition suggested by the Electricity Authority (2010), the large price differences in all the markets included in our analysis suggest that, in the main, retailers are not behaving competitively. Although the number of new entrants has increased, the five traditional retailers still control more than 90% of the market. The price differences observed in these markets are at least of the same magnitude as those observed in some European countries where such differences have cast doubt on the competitiveness of the retail markets (see, Defeuilley, 2009; Giulietti et al., 2010).

However, what is still lacking in the current debate is defensible empirical evidence indicating retail prices would have been higher if reforms were not introduced in the electricity markets. Since the focus of this thesis is not on whether or not the reforms have worked so far, we leave this question for possible future research. A problem that may be encountered with an analysis of this kind would be the lack of data on retail prices that have been measured in a consistent manner since the beginning of the reforms. For example, MBIE now uses "sales-based electricity cost" to estimate residential retail prices and a revision has been made back to 2009 data; similar data prior to this period is not currently available[12].

3.8 Electricity as a product

Compared to other products, electricity is unique in the sense that it is homogeneous, cannot be stored on a significant scale given current technologies, its supply and demand are instantaneous, and demand is highly volatile (Evans & Guthrie, 2012; Evans & Meade, 2005). Actual demand for electricity at any instant is difficult to predict as it is a combined effect of instantaneous decisions of multiple users. In a gross pool system, once electricity has been generated and dispatched to the grid, individual electricity consumers have no information about the actual source of generation for the units they consume. However, at the retail level, consumers may view electricity as a differentiated product if retailers offer different levels of non-price attributes of electricity services described in section 2.5 of Chapter 2.

3.9 Summary

In this chapter, we have provided an overview of the New Zealand electricity markets. We highlighted the main objective for the reforms as the creation of efficient and competitive markets for the long-term benefit of New Zealanders. The important role of consumer switching in achieving the objective of the reforms was explained, and how price played a central role in the campaign used to promote switching was emphasized. The reason for the authorities' belief that the law of one price would apply in the retail markets was that consumers perceive all suppliers to be the same except for the price, because of the homogeneous nature of the product. The implication of this belief is that consumers in any one particular retail market would switch to the cheapest available supplier, which would force retailers to reduce costs and offer competitive prices. We also identified the major players in the markets and how the market structure works in determining market prices. A summary of the current debate on the success of the reforms was given and we highlighted the main differences from the two main camps. The authorities argue that the market is workably competitive because prices broadly reflect the cost of supply, but

[12] Sales-based cost is estimated by dividing the dollar value of residential electricity sales by the number of kilowatt-hours sold to residential consumers.

concede that more still needs to be done particularly in the retail markets. The opponents argue that the major players are manipulating the market and have been able to overcharge consumers by billions of dollars. They advocate for a single buyer model and some changes in the regulations concerning asset revaluations and wholesale prices based on ‘pay-as- bid’.

Our findings from an analysis of price differences and the behaviour of new entrants from 2012 to 2015 cast doubt on the competitiveness of the retail electricity markets in New Zealand. We have also suggested an area for future research, which may provide some empirical evidence that is currently lacking.

In the next chapter, we use the multinomial logit (MNL), random parameter logit with error components (RPL-EC), and latent class (LC) models to analyze choice data in order to determine whether non-price attributes matter. This is expected to shed light on whether the belief that the law of one price should apply is justifiable.

Chapter 4. Consumer switching: Is price all that matters?

4.1 Introduction

In this chapter we assess whether consumers perceive all electricity retailers to be the same except for the price (*Question 1*). Our main objective is to gain a better understanding of switching behaviour in retail electricity markets in New Zealand by identifying important determinants of switching and estimating the value of non-price attributes using the random utility models described in Chapter 2. We start by providing a brief background and stating the research question. This is followed by a brief discussion of the 'What's My Number' (WMN) campaign that has been used to promote consumer switching in New Zealand. An overview of the local and international literature on consumer switching and valuation of the attributes of electricity services is provided to highlight the gaps in the literature. We then discuss the contribution of this chapter and show where it fits within the current literature. Finally we present results from an analysis investigating the factors that influence consumer switching in the residential retail electricity markets in New Zealand.

Deregulated electricity markets offer consumers freedom to choose their retailer and provide opportunities to regularly review current retailers and switch suppliers when better offers are available. Opening formerly regulated retail markets to competition allows new entrants into the market, which increases supplier options available to consumers. Currently, New Zealand consumers are free to choose among 8 to 18 retail brands available depending on their region (Electricity Authority, 2013c). Consumers benefit from increased choice through improved conditions of supply and lower power bills by switching to cheaper retailers. On the other hand, switching to cheaper retailers exerts downward pressure on retail prices as retailers compete for customers. To retain or increase market shares in markets characterized by high mobility of customers, retailers are expected to offer lower prices, search for innovative ways to reduce costs and offer customers new value-added services.

Consumer switching has been touted as one of the key drivers for achieving efficient and competitive retail electricity markets. The idea that customers may perceive all supplier deals to be the same, except for price (since electricity is a homogeneous product) leads to an expectation of price convergence within regional markets (e.g., Defeuilley, 2009; Electricity Authority, 2010). The expectation of price convergence seems to rely on the assumption of low information search cost, low transaction (switching) costs, an easy switching process, and consumers actually switching to cheaper retailers. As a consequence, the promotion of switching has seen the setting up of independent price-comparison websites in various jurisdictions[13]. Significant price differences are, therefore, expected to induce switching to lower-priced retailers.

Evidence from previous studies indicates that a majority of customers rarely search for alternative retailers and that substantial price differences exist within retail markets (e.g., Brennan, 2007; Defeuilley, 2009; Electricity Authority, 2011a, 2012a, 2013b; Hortaçsu, Madanizadeh, & Puller, 2015). Defeuilley (2009) argues that the proportion of active switchers is fairly small in many countries and the expected results of introducing retail competition do not always materialize. He attributes low switching rates in the British electricity markets to risk aversion, and behavioural biases encouraging customers to stick with the "status quo." The low switching rates have allowed incumbent retailers in most European countries to continue dominating 85-95 percent of the markets. Littlechild (2009) argues that the observed persistent price dispersion in retail markets should not be taken as evidence that market prices generally are not tending to the costs of new entry, but should be seen as a feature of any competitive market in the real world.

In this chapter we challenge the perception that "only price matters" and hypothesize that non-price attributes of electricity services are also important determinants of switching and that preferences for non-price attributes may, in part, explain the price dispersion currently observed in retail electricity markets in New Zealand. Therefore, the following set of questions is addressed.

> *Question 1: Do consumers perceive all electricity retailers to be the same except for the price?*

[13] Examples are: www.powerswitch.org.nz in New Zealand, www.powertochoose.com in Texas (USA), and www.energywatchuk.com in the UK.

(a) *Are non-price attributes of electricity services important determinants of supplier choice? If so, what values do residential consumers place on these attributes?*

(b) *What are the determinants of WTP for the attributes*

(c) *Do preferences for power bill savings differ across respondents? If so how do these preferences influence switching?*

(d) *Do attitudes towards switching play a systematic role in explaining preference heterogeneity?*

4.2 What's My Number campaign

New Zealand introduced retail competition in 1998 under the Electricity Industry Reform Act 1998. The main objective of the Act was "to increase consumer choice, encourage innovation, and ultimately result in lower prices than would otherwise be charged" (Electricity Authority, 2010, p. 3). However, in 2009, a ministerial review of the performance of the electricity market determined that: (1) the current levels of consumer switching were insufficient to curb non-competitive behaviour by retailers, and (2) the full benefits of retail competition had not yet been realised, particularly for domestic customers who continued to face rapidly increasing prices (Electricity Authority, 2010). It was observed that the majority of electricity customers exhibited a tendency to stay with their default retailers even when cheaper competitors were available. The review determined that consumers could be better off by as much as $150 million per annum, in total savings, if they switched to the cheapest available retailer (Electricity Authority, 2011a). The estimated welfare benefits from switching were considered large enough to justify the establishment of a public funded consumer switching fund (Electricity Authority, 2010). However, it should be noted that the welfare benefits estimate is based on the seemingly unrealistic assumption of price convergence.

The Electricity Authority spent $15 million (2011 to 2014) on the WMN campaign promoting consumer switching. Consumers were made aware of the ability to switch and the benefits (bill savings) from switching which averaged $150 per customer per year, and were encouraged to shop around for lower prices (Electricity Authority, 2011a, 2012b). An independent one-stop-shop website called "Powerswitch" was revamped to provide consumers easy access to a single central switching service (Electricity Authority, 2010). The benefits promoted under this campaign were based only on price differences between retailers. This ignored the value that consumers place on non-price attributes of electricity supply and any possible influence these may have on switching behaviour and supplier choice.

International studies show that factors such as lack of information, perceived information search costs, perceived low economic benefits from switching, attitudes, and loyalty to incumbent suppliers, among others, may prevent consumers from switching to the cheapest supplier (e.g., Gamble et al., 2007, 2009; Gärling et al., 2008; Giulietti et al., 2005; Rowlands et al., 2004). The WMN campaign and Powerswitch appear to have been targeted at addressing the first three issues.

A number of local studies and reviews were commissioned under the Switching Fund to provide the Electricity Authority and Ministry of Consumer Affairs with research that underpins the fund (see, Electricity Authority, 2010), and to conduct market research to assess the performance of the WMN campaign and Powerswitch website (see, Electricity Authority, 2011a, 2012a, 2012b, 2013b, 2013c). The studies suggest that since 2009, switching rates in NZ have increased from an annual rate of 10.5% in 2009 to 20.8% in 2013 (e.g., Electricity Authority, 2013c). New Zealand switching rates were the second highest in the world after Victoria, Australia, in 2011, and were the highest in 2012-2014 (VaasaETT, 2013). Authorities attribute this increase in switching to the WMN campaign and related regulation. Although the studies show an increase in switching activity compared to the pre-campaign period, they also show that a large number of consumers, more than 79%, did not switch in any particular year despite high average savings available in the market (see Table 4-1). Furthermore, the combined market share for the Big 5 has remained high at 95% and is similar to most jurisdictions in Europe (see, Defeuilley, 2009; Giulietti et al., 2010).

Table 4-1: Switching rates and benefits (2011-2013)[1]

	Year		
	2011	2012	2013
Average annual household savings	$165	$175	$155
Switching rate	20.7%	19.1%	20.8%
National savings if all customers switched to the cheapest retailer in their region	$280 million	$295 million	$267 million

[1] Source: Electricity Authority, (2013c)

4.3 Overview of the switching literature and the contribution of this chapter

The non-market valuation literature on consumer switching in retail electricity markets is relatively limited and has, for some time, been dominated by a few American and British studies conducted around the late 1990s (e.g., Cai et al., 1998; Goett, 1998; Goett et al., 2000; Revelt & Train, 2000). Switching rates observed in most countries seem to be lower than expected, and have not placed sufficient pressure on incumbent retailers to induce competitive behaviour (see, Brennan, 2007; Defeuilley, 2009; Electricity Authority, 2010). It is not surprising that interest in studying consumer switching in retail electricity markets is increasing as regulators seek a better insight into the determinants of switching. This chapter contributes to this small but growing body of literature by identifying and valuing non-price attributes of electricity services and identifying market segments with homogeneous preferences.

The focus of studies of consumer choice of electricity supplier varies depending on the main objective. In some studies the focus is on identifying important determinants of supplier choice or switching by valuing the attributes of electricity services (e.g., Abdullah & Mariel, 2010; Amador et al., 2013; Cai et al., 1998; Goett et al., 2000; Hensher et al., 2014; Kaenzig et al., 2013; Revelt & Train, 2000). Some studies focus on identifying the attitudes that motivate or prevent consumers from switching (Gamble et al., 2009). An increasing number have focused on barriers to switching (Electricity Authority, 2010, 2011a, 2012a, 2013b; Electricity Commission, 2008; Gamble et al., 2007; Gärling et al., 2008; Giulietti et al., 2005). Others focus on the determinants of WTP for the attributes of electricity services (Abdullah & Mariel, 2010; Amador et al., 2013). Whilst results from these studies show that attributes of electricity suppliers such as price, length of contract, reliability of supply, share of renewables, discounts, and type of supplier, among others, are important determinants of supplier choice, other factors such as attitudes, past experience, perceived barriers, and socio-demographic characteristics of consumers have also been found to play an important role in supplier choice or switching.

Different approaches have been adopted in previous studies estimating WTP for the attributes of electricity services. The studies also target different sets of attributes. For example, Amador et al. (2013) use a mixed logit panel model with error components to estimate Spanish households' WTP for supply reliability, share of renewables, availability of a complementary energy audit service, and supplier type. The study used a labelled experimental design (ED) in which the status quo alternative is labelled as 'current supplier' and the other two alternatives are labelled as 'supplier from the electricity sector' and 'supplier from another industry'. Estimates of the alternative specific constants for the non-status quo alternatives are used to measure the values of the respective supplier type. Kaenzig et al. (2013) use a hierarchical Bayes model to investigate German consumers' preferences for fuel mix, type of supplier, location of generation plant, green certification, cancellation period, and monthly power bill. In both studies consumers were found to be willing to pay significant amounts for the non-price attributes of electricity services.

In a US study, Goett et al. (2000) use a sample of small and medium businesses to investigate customer choice among retail electricity suppliers based on a set of 40 attributes of suppliers which were grouped into five clusters described as: pricing/discounts, value added services, green energy choices, customer services, and community services. An unlabelled experimental design with four alternatives was used to generate the choice tasks. This study was conducted prior to the introduction of competition in the retail market to provide insight on the attributes that would influence consumer switching and how the entry and behaviour of new entrants would affect the incumbent retailer's market share. Cai et al. (1998) use double bounded questions on price discounts on separate samples of residential and business customers in the USA to estimate the share of customers that would switch to a competitor under various discounts and service attributes such as renewable energy sources, reliability, energy conservation assistance and customer service.

New Zealand studies have mainly focused on tracking consumer switching activity and evaluating the effectiveness of the WMN campaign in promoting retail competition (e.g., Electricity Authority, 2011a, 2012a, 2012b, 2013b, 2013c). Although these studies identify the factors that influence switching, assess the importance of the attributes of electricity services using Likert-type rating scales, and identify consumer segments using cluster analysis, none of these studies attempt to estimate WTP for the attributes of electricity services. However, Daglish (2015) differs from these studies by applying the MNL model to analyze household switching decisions in a regional market dominated by a single gentailer. This study uses revealed preference data for the period 2007-2012 to measure the extent to which customers switched from incumbent supplier in response to the WMN campaign, and information about incumbent's directors' bonuses and a competitor's local ownership. Results from this study indicate the presence of strong status quo effects which work in favour of the incumbent. However, the WMN campaign was found to have been successful in reducing loyalty to incumbent, and publicity about local ownership by one of the competitors attracted significant switches. Although the study does not estimate WTP *per se*, estimates of what the author terms "discount equivalent," which are equivalent in magnitude to specific price differentials, are provided.

This chapter contributes to the literature on consumer switching in electricity retail markets and increases our understanding of consumer preferences for the attributes of electricity services. It differs from previous literature in this area in a number of ways. First, we extend the application of one of the advanced discrete choice models to consumer switching. Although the latent class (LC) model has been applied to analyse consumer preferences in a number of contexts, it has not been applied in the context of switching in retail electricity markets[14]. Second, we extend on previous studies by examining a different subset of attributes which include: call waiting time, length of fixed rate contract, discounts, loyalty rewards, local ownership of supplier and supplier type. Third, we target a different

[14] At the time of writing the author is not aware of any previous applications of the latent class model in the context of supplier choice.

consumer type from studies that targeted small to medium size firms (e.g., Goett et al., 2000; Kaenzig et al., 2013). Fourth, we estimate a model that explicitly accounts for differences in marginal utility of income for respondents who exhibit different sensitivities to the level of savings that would induce a switch. Fifth, this chapter also contributes to non-market valuation literature by providing the first WTP estimates for the attributes of electricity services in New Zealand.

4.4 Consumer switching in the retail electricity market in New Zealand

In this section we provide sample statistics on consumer switching and present results of the analysis of responses to attitudinal questions that provide insight into consumer switching behaviour in the retail electricity market in New Zealand. Unlike previous New Zealand studies commissioned by the Electricity Authority, in addition to general attitudinal questions we use constructs based on the theory of planned behaviour (TPB) to give the responses theoretical validity and increase accuracy in measuring consumers' attitude towards switching. A discussion of the theory of planned behaviour and the construction of the questions was presented in Chapter 2.

The dataset used in this chapter is derived from responses to an online survey which was conducted in 2014. Details of the survey were provided in Chapter 2. Sample statistics are provided in the next section, followed by analysis of responses to questions about switching activity, and attitudinal questions relating to switching behaviour including the TPB constructs.

4.4.1 Sample statistics

A summary of the sample statistics is presented in Table 4-2. In general the sample closely resembles the New Zealand population in terms of most variables. Females are slightly over-represented by 2%, whilst males are under represented by the same percentage. Quotas set in the survey for age groups allowed us to perfectly match the age distribution in the population.

Table 4-2: Summary statistics of SDCs and attitudinal covariates for sample and national populations

Characteristics		Sample[1]	National[2]
Gender (%)	Male	47	49
	Female	53	51
Ethnicity (%)	NZ European	77	70
	Maori	5	12
	Asian	9	10
	Other	9	7
Age Group (%)	18 – 24 yrs.	13	13
	25 – 34 yrs.	17	17
	35 – 44 yrs.	20	21
	45 – 54 yrs.	18	18
	55 + yrs.	32	31
Income Group (%)	0 - $15,000	13	34
	$15,001 - $30,000	20	24
	$30,001 - $40,000	10	14
	$40,001 - $50,000	13	9
	$50,001 - $70,000	15	10
	$70,001 - $$100,000	14	4
	$100,001 and above	5	4
	Not stated	11	1
Average annual personal income		$45,000	$37,500
Highest level of education (%)	High School and below	39.3	-
	Vocational/Trades	5.8	-
	Diploma or Certificate	24.6	-
	Bachelors	17.4	12.1
	Honours Degree/PG Certificate	7.6	2.7
	Masters or PhD	5.3	3.2
Property ownership (%)	Property owner	75	68.2
	Renter	25	31.8
Average household size		3.2	2.7
Households with children below the age of 18 years (%).		40.6	41.3
Average monthly power bill		$174	$190*

Retailer	Market share	
	Sample	Actual
Contact Energy and Empower	23	23
Genesis and Energy Online	30	27
Meridian Energy and Powershop	18	15
Mercury Energy, Bosco Connect, and Tiny Mighty Power**	14	20
TrustPower	9	11
Other (mainly Energy Direct, Just Energy, Nova Energy, King Country)	6	4

[1]Sample size = 224. [2]Data source: NZ Statistics – 2006 Census Data and NZ Income Survey June 2012 Quarter. *Source: MED Energy Data File 2012. **Mighty River Power retail brands

The average personal income of respondents ($45, 000) is higher than the national average of about $37, 500. The difference may be attributed to the exclusion of minimum wage earners in the 15 – 17 years age group in the sample average, which are included in the national average. Furthermore, a sizeable proportion

(11%) of respondents in the sample did not disclose their income compared to the general population (1%). Maori are under-represented by more than 50% whilst NZ-Europeans are slightly overrepresented. The sample average monthly electricity bill is lower than the national average. This is expected as the national average includes high winter bills whereas the sample average is based on respondents' most recent power bill for a summer month.

In addition to the above statistics we also collected information on respondents' current electricity retailers, which allows us to compare sample and actual market shares for the major retailers (see bottom part of Table 4-2). The sample and actual market shares for the major retailers are, in the main, similar except for Mighty River Power's retail brands, Mercury Energy, Bosco Connect, and Tiny Mighty Power, which are under-represented in the sample (14% vs. 20%). The sample statistics suggest that apart from being closely representative of the population, the sample is also closely representative of the market as all major retailers are reasonably represented.

4.4.2 Reasons for choosing current supplier

A summary of the reasons given for choosing the current supplier is presented in Table 4-3. The most popular reason given for choosing the current supplier is "offered a better package of price and service" (49%), followed by "well-known power company" (36%). About a quarter of respondents did not choose their current supplier as the power company was already supplying power to the premises when they moved in. This represents a group of consumers who appear not to care who their supplier is. Approaches by power companies (16%) seem to be more effective than advertising (9%) as a way of attracting customers.

Table 4-3: Reasons for choosing current supplier (N = 224)

What were your reasons for choosing this company? Please select <u>all</u> relevant reasons from the list below.	Number of responses	%
Offered a better package of price and service	110	49
Well-known power company	79	36
Power company was already supplying power to the premises	56	25
Approached by supplier	35	16
Recommended by friends or family	24	11
Responded to an advertisement or visited a price comparison website	21	9
Other (please specify)	20	9

Most respondents (at least 73%) are at least “somewhat satisfied” with their current supplier in terms of “general overall service” and “value for money” (see Figure 4-1). This may indicate an improvement in customer satisfaction from 67% and 51% for “general overall service” and “value for money” reported for 2012 by the Electricity Authority (2012a). The improvement in satisfaction with current supplier may be a result of dissatisfied customers switching to preferred suppliers and/or suppliers improving their offerings in the face of increasing competition. An alternative explanation could be the differences in sampling methods. About 26% of respondents are either neutral or dissatisfied with their current supplier in terms of the above criteria. This group of respondents is more likely to switch, and direct approaches by retailers offering better packages may induce switching. The majority of respondents (67%) have occupied in their current residence for at least three years which provides a large sample of respondents who would have switched supplier in the past two years for reasons other than “moving house.”

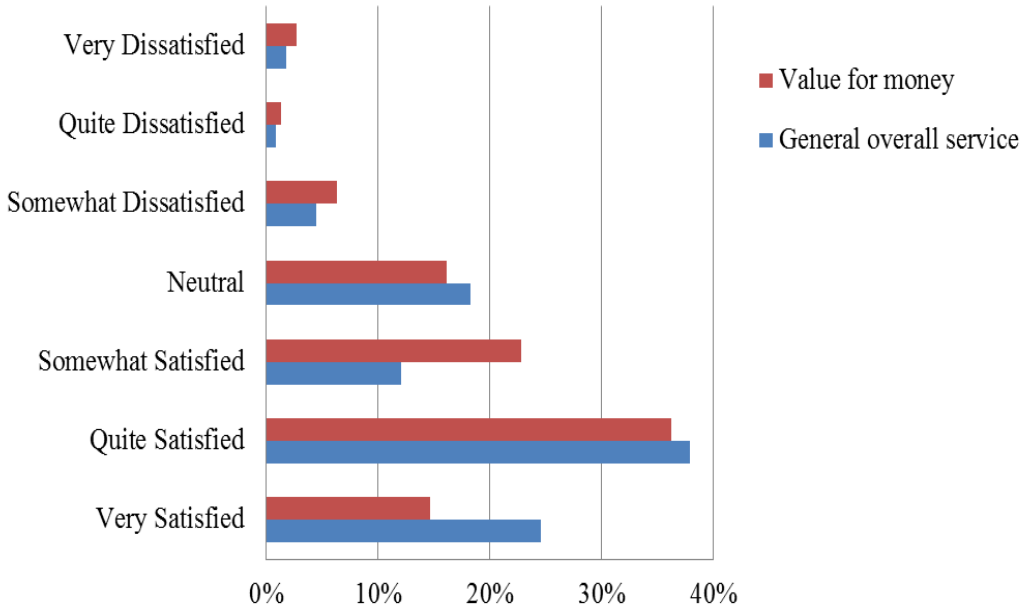


Figure 4-1: Distribution of ratings of satisfaction with current supplier

4.4.3 Switching activity

In the past two years, only 21% of respondents switched supplier. This is lower than the 30% reported in Electricity Authority (2013b). However, it should be noted that there is a one-year difference in the two studies and the switching rates may not be directly comparable. Of those who switched supplier, 75% switched once, 23% switched twice and only 2% switched three times. The proportion of respondents who switched supplier twice in the past two years is nearly double that reported for 2012 suggesting increased activity among switchers. Figure 4-2 presents a summary of the search activity of electricity consumers. About 44% of respondents are more or less passive participants as 22% have never looked for opportunities to switch and an equal proportion have only looked for opportunities to switch once every two years or more. This group represents respondents who are less likely to be influenced by any short term advertising campaigns which may, in part, help to explain the observed customer inertia. About 28% of respondents look for opportunities to switch once a year whilst 26% look for opportunities once every six months.

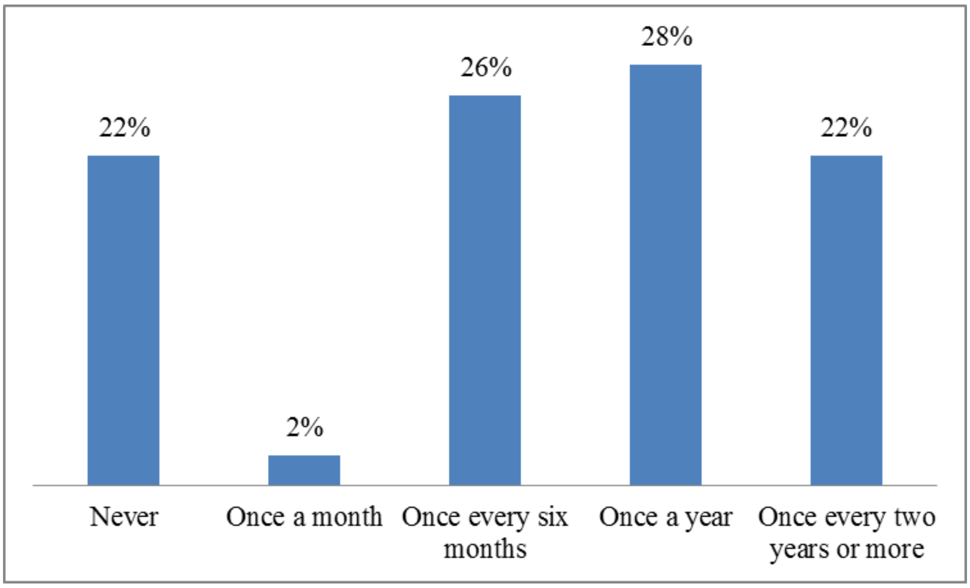


Figure 4-2: Search activity: (*Question: How often do you look for opportunities to switch supplier?*)

4.4.4 Reasons for switching supplier

Respondents were asked to rate the importance of a list of reasons often given for switching supplier. A 5-point Likert-type scale with points marked as “Not at all important’ (NAI) (1), “Not really important” (NRI) (2), “Somewhat important” (SI) (3),”Quite important” (QI) (4), and “Very important” (VI) (5) was used for the ratings. Response summaries are presented in Table 4-4. The distribution of responses is spread over all response categories showing that respondents have different views on these issues. The most important reason for switching supplier, rated by 96% of respondents as “somewhat important” to “very important”, is high power bills followed by discounts (93.8%) and poor customer services (90.7%). The least important reasons include bundled services and a combined gas and electricity account with the same supplier. These are rated as important by about 38% of respondents. The distribution of responses suggests that the most important information required for switching decisions is the price and whether a discount is offered. Financial incentives, which are currently used by some major retailers, are rated as less important than customer service. It is interesting to note that although some reasons are rated less important than others, none are rated as “not at all important” or “not really important” by 100% of respondents, which suggest that retailers can still attract some customers based on any of the reasons for switching. For example, a retailer offering a gas and electricity account may be attractive to 38% of the market and it might be worthwhile for such a retailer to promote itself as offering such a service.

Table 4-4: Distribution of ratings on the importance of reasons for switching retail supplier (N = 224)

Below is a list of reasons often given for switching electricity supplier. Please rate how important each reason would be for you if you were to consider switching supplier.

	NAI* (%)	NRI (%)	SI (%)	QI (%)	VI (%)	Mean Rating	Rank
High power bills	1.3	2.7	13.4	32.1	50.4	4.28	1
Prompt payment /on-line payment discounts offered by other suppliers	2.2	4.0	23.2	39.7	30.8	3.93	2
Poor customer service by incumbent	1.3	8.0	28.6	30.4	31.7	3.83	3
Financial incentives offered by other electricity suppliers	1.8	6.3	31.7	34.4	25.9	3.76	4
Fixed power rates offered by other electricity suppliers	4.5	16.1	44.6	25.9	8.9	3.19	5
Electricity supplier is 100% NZ-owned	12.5	20.1	31.3	24.6	11.6	3.03	6
Prefer to buy from a retailer producing electricity from sustainable sources	13.4	23.2	37.5	20.5	5.4	2.81	7
To have other services e.g. broadband services with the same electricity supplier	24.6	37.5	22.3	11.6	4.0	2.33	8
To have a gas and electricity account with the same company	41.5	21.0	14.3	16.5	6.7	2.26	9

*NAI, NRI, SI, QI, VI, are “not at all important”, “not really important”, “slightly important”, “quite important”, and “very important” respectively

4.4.5 Reasons for not switching supplier in the past 24 months

Respondents who did not switch supplier in the past two years, accounting for 79% of the sample, were asked to indicate if each reason for not switching listed in Table 4-5 was applicable to them or not. The results show that about 86% of this group of ‘non-switchers’ were “happy with service from current supplier” and 77% “did not trust there would be real gains from switching”. These appear to have been the main barriers to switching in the past two years. Furthermore, a sizeable proportion of respondents (64%) were happy with the price charged by their retailers and believed their retailers could match any deals offered by competitors. About 53% believe that switching is a hassle whilst 43% were too busy to shop around for better deals. Fixed term contracts prevented about 16% of respondents from switching.

These responses seem to suggest that non-switchers are in the main uncertain about the benefits of switching, that is, how long the benefits could last and if they would be better-off in the long run with the new retailer, and whether they would be able to switch if they are not happy with the new retailer. To promote future switching by this group of ‘non-switchers’ the Electricity Authority needs to convince these customers that they can get better services from competitors, that the benefits of switching to the cheapest available supplier are real, and that switching is no longer a hassle as a simpler and more efficient switching system has been set up.

Table 4-5: Reasons for not switching supplier in the past two years (N = 177)

Please indicate which of the following reasons for not switching in the past 24 months apply to you.	Applies	Does not apply
Happy with service from current retail supplier	86%	14%
Did not trust there would be real gains from switching	77%	23%
Happy with price of current supplier plus current supplier will match any deals	64%	36%
Switching seemed too much hassle	53%	47%
Too busy to investigate the best deals available	43%	57%
Was already locked into a contract	16%	84%

4.4.6 Consumer sensitivity to the level of savings (power bill savings)

Respondents were asked if they would have switched supplier in the past two years if they could have saved certain amounts per year on their power bills. All respondents were first presented with an annual power bill saving of $100 and asked if they would have switched supplier in the past two years if they would have achieved this level of savings. Those who said “No” were then presented with an amount of $200 and asked if they would have switched at this level of savings. For all “No” responses, the amount was increased to $300, then to $400 and those who still said “No” were asked to state the minimum amount at which they would have switched supplier. Responses are summarized in Table 4-6.

Table 4-6: Level of savings and stated switching rates

Question	Yes	No
Would you have switched supplier in the past 24 months if it could have saved you $100 per year on your power bill?	139 (62%)	85 (38%)
Now suppose you could have saved $200 per year, would you have switched supplier in the past 24 months?	45 (20%)	40 (18%)
How about a saving of $300 per year, would you have switched supplier in the past 24 months?	18 (8%)	22 (10%)
What about saving $400 per year, could this have been enough to make you switch supplier in the past 24 months? If not please state the minimum amount of savings per year that would have been enough to persuade you to switch	11 (5%)	11 (5%)
Respondents stating $500 as their minimum are recoded as “yes” to $500 and the rest as “no”	6 (3%)	5 (2%)

The results show that the majority of respondents (62%) would have switched supplier in the past two years if they had believed they could save $100 per year in power bills. This is nearly three times the switching rate for this sample and twice the national rate reported in Electricity Authority (2013b) where average savings were $150 per year. Of those who indicated that they would have switched at $100 only 31% had actually switched supplier in the past two years. These results indicate a difference between stated behaviour and actual behaviour. Disparities between hypothetical and real behaviour are well documented in previous literature investigating WTP in various contexts (e.g., Champ & Bishop, 2001; Champ et al., 1997). We do not believe that lack of awareness of the potential savings from switching is a significant factor in explaining the difference between stated and actual switching behaviour in our sample. Although we did not collect information on awareness of potential savings from switching during the past two years, it is reasonable to assume that most respondents were aware based on results from the Electricity Authority (2013b) which indicate that 82% of electricity consumers in New Zealand were aware of the WMN campaign used to promote awareness of the benefits of price comparison and switching.

Of those who switched supplier in the past two years, about 90% said "Yes" to savings of $100 per year and the remaining 10% said "Yes" to $200 which indicates that switchers are generally more sensitive to savings than non-switchers. The difference between stated and actual switching behaviour for the majority of respondents in our sub-sample may be explained in terms of the hypothetical nature of the survey questions, which may have induced "yea saying". Another factor could be that the majority (69%) of respondents in the sub-sample may not have believed that the average level of savings suggested in the WMN campaign was achievable as shown in the previous section (see Table 4-5). A logit regression of the "yes" response to the savings level of $100 indicates that respondents who have switched supplier before and those with at least a bachelor's degree are most likely to switch at this level of savings. This makes intuitive sense as switchers have the experience and respondents with higher educational qualifications may perceive the cost of switching to be low.

About 18% of respondents are not willing to switch supplier at savings below $300, and 2% would not switch supplier based on savings even at the level of $500. The results from this analysis suggest that the current level of average savings of $150 have a potential of achieving switching rates of at least 62% provided consumers are convinced that such savings will be achieved and that switching is easy. The implication of the latter for the Electricity Authority's future activities is that more effort should focus on convincing consumers that the benefits of switching are real if higher rates are to be achieved.

4.4.7 Attitudes towards switching

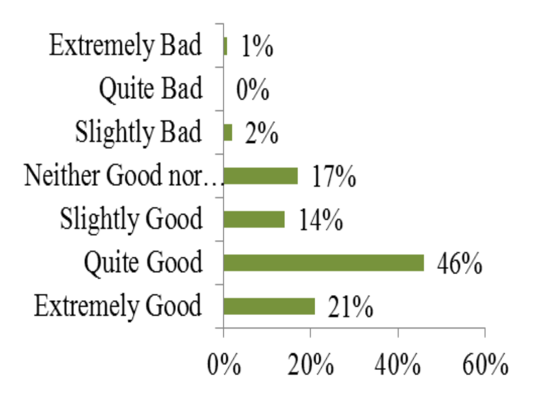
In this section we present the results of the analysis of responses to questions or statements measuring the theory of planned behaviour (TPB) constructs. The results from this analysis are used in model estimation in the next section to explore the influence of consumers' attitudes towards switching on supplier choice and valuation of the attributes of electricity services.

We use psychological constructs based on the TPB to measure attitudes towards switching electricity supplier. The TPB and its application in the context of consumer switching in the retail electricity market in New Zealand were discussed in section 2.4.2 of Chapter 2. To recap, the TPB postulates that an individual's intention to perform a behaviour [behavioural intention (BI)] is assumed to be a function of three independent determinants: the individual's positive or negative evaluation of performing the behaviour in question [attitude towards the behaviour (ATT)]; the individual's perception of the social pressure exerted on him/her to perform or not perform the behaviour in question [subjective norm (SN)]; and self-efficacy, or the perceived ease or difficulty of performing the behaviour [the degree of perceived behavioural control (PBC)]. In this context the behaviour is "switching supplier." Each construct is measured using two questions or statements, namely, ATT1 and ATT2, SN1 and SN2, PBC1 and PBC2, and BI1 and BI2 for ATT, SN, PBC, and BI, respectively.

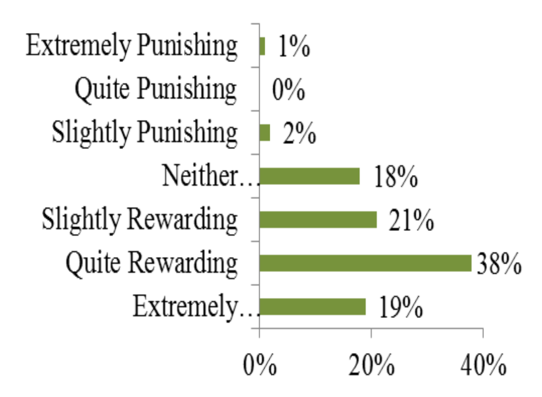
The distribution of responses to the statements measuring TBP constructs is presented in Figure 4-3 and Figure 4-4, and Table 4-7 presents the sample average scores for each construct. The results show that the majority of respondents (about 80%) have a positive attitude towards switching supplier, as indicated by selecting at least "slightly good or slightly rewarding" on the Likert scale. About 17% of respondents are neutral whilst 3% have a negative attitude towards switching. The bar charts for ATT1 and ATT2 show a definite negative skew. The average sample score for attitude towards switching (ATT) is approximately 2, which is equivalent to "quite good" on the Likert scale. These results suggest that the majority of New Zealanders have a positive attitude towards switching. Perhaps this is one of the reasons why New Zealand has the highest switching rates in the world.

The distribution of responses to the statements measuring subjective norm (SN) show that only 41% of respondents feel social pressure to switch supplier, 39% are neutral, and 20% do not feel any social pressure. The average sample score for SN is 0.33 (approximately zero), which is equivalent to the neutral point ("neither likely nor unlikely") on the Likert scale. This suggests that social norms may not play a significant role in influencing switching behaviour. About 62% of respondents believe that switching supplier is easy and that they can switch if they want to (PBC), 24% are neutral, and about 14% believe that switching is difficult and that their ability to switch is limited. The average sample score for PBC is 0.95 (approximately 1), which corresponds to "somewhat easy" or "somewhat agree" on the Likert scale indicating positive but low PBC.

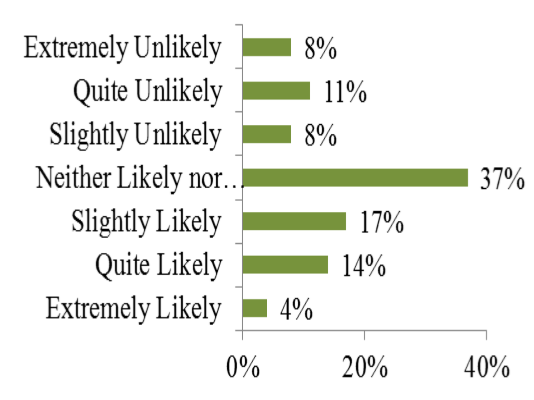
[ATT1] For me switching to a supplier offering a better package of price and services would be



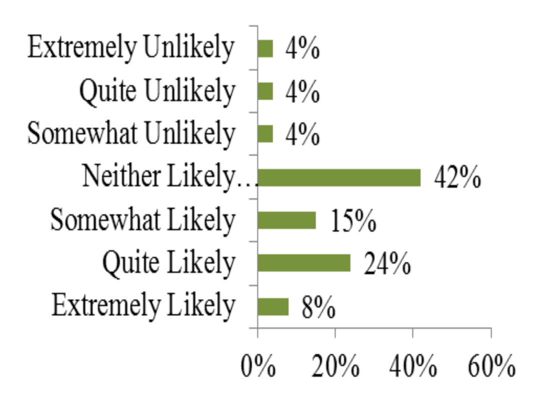
[ATT2] For me switching to a supplier offering a better package of price and services would be



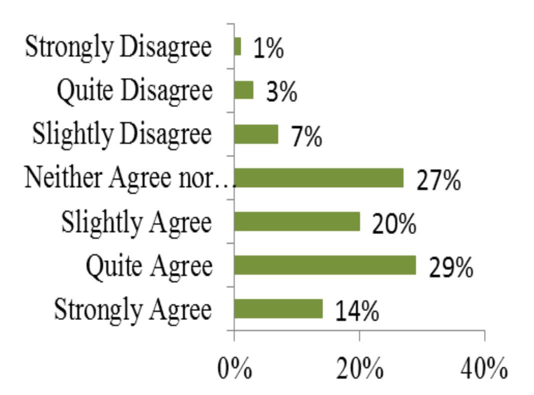
[SN1] How likely is it that most people who are important to you think that you should switch to a supplier offering a better package of price and services?



[SN2] How likely or unlikely is it that most people who are important to you would approve if you switch to a supplier offering a better package of price and services?



[PBC1] I believe that I can switch to a supplier offering a better package of price and services if I want



[PBC2] For me switching to a supplier offering a better package of price and services would be

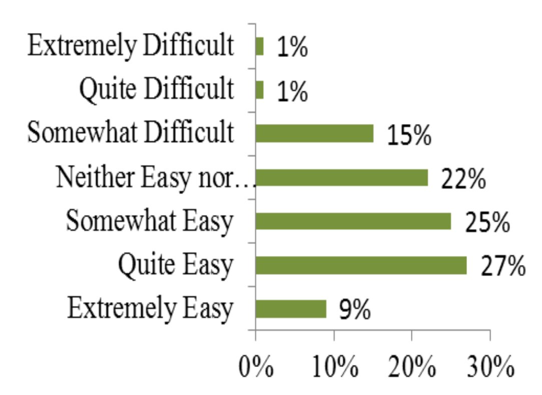


Figure 4-3: Distribution of responses to the TPB constructs

Note: "Neither Good nor ……". The missing word is "Bad." For the other midpoint response categories the missing words are the opposites.

Based on responses to the statements measuring behavioural intention (BI), only 38% of respondents expressed an intention to switch supplier in the next 12 months, 31% were neutral and 31% had no intention of switching. The average score for BI is -0.02 (approximately zero), which corresponds to the neutral point on the Likert scale. These results suggest that New Zealand may achieve even higher switching rates in future if authorities implement policies targeted at influencing neutral consumers and those who have no intention of switching supplier. The Electricity Authority is currently reviewing options for promoting retail competition by increasing consumers' propensity to compare and switch retailers (Retail Advisory Group, 2013, April 9), which may influence BI especially if 'stickier' consumer segments are targeted.

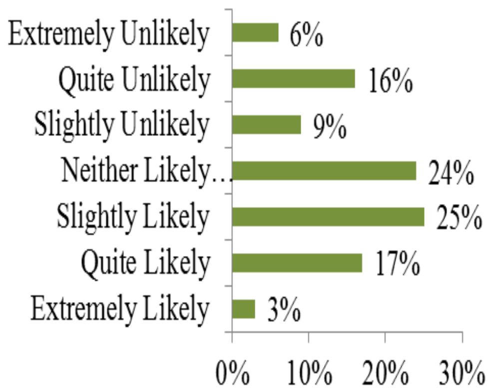
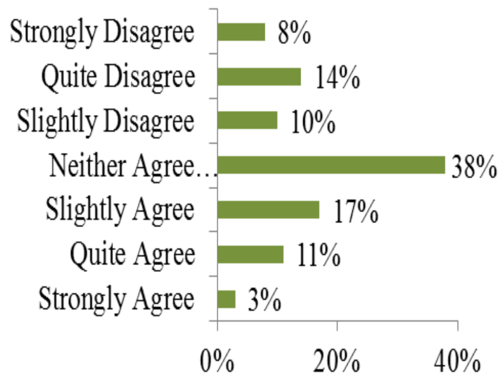
[BI1] How likely or unlikely is it that you will switch to a supplier offering a better package of price and services in the next 12 months?	**[BI2]** I intend to switch to a supplier offering a better package of price and services in the next 12 months.
	

Figure 4-4: Distribution of responses for behavioural intentions (BI)

Note: Neither Likely …., and Neither Agree ….: missing words are "nor Unlikely, and nor Disagree"

Table 4-7: Average scores for the TPB constructs (N = 224)

TPB construct	Sample average score
Attitude towards switching supplier (ATT): ATT = (ATT1 + ATT2)/2	1.57
Social norm (SN): SN = (SN1 + SN2)/2	0.33
Perceived behavioural control (PBC): PBC = (PBC1 + PBC2)/2	0.95
Behavioural intention (BI): BI = (BI1 + BI2)/2	-0.02

To assess whether each pair of statements measuring each TPB construct could be combined into a single index, a correlation analysis is carried out on each pair of statements measuring the same construct. Table 4-8 presents a summary of the results. The pairs of scores measuring ATT, SN, PBC, and BI have correlations ranging from 0.428 for the PBC items to 0.738 for the ATT statements and are all significant at the 5% level. The results suggest that each pair of items could be combined into a single index for each construct as presented before in Table 4-7.

Table 4-8: Correlation matrix (Pearson (n)) for the TPB constructs (N = 224)

Variables	ATT1	ATT2	SN1	SN2	PBC1	PBC2	BI1	BI2
ATT1	1	**0.738**	0.292	0.399	0.400	0.345	0.386	0.489
ATT2	**0.738**	1	0.338	0.422	0.355	0.321	0.283	0.418
SN1	0.292	0.338	1	**0.533**	0.189	0.155	0.346	0.489
SN2	0.399	0.422	**0.533**	1	0.220	0.213	0.258	0.390
PBC1	0.400	0.355	0.189	0.220	1	**0.428**	0.311	0.387
PBC2	0.345	0.321	0.155	0.213	**0.428**	1	0.236	0.262
BI1	0.386	0.283	0.346	0.258	0.311	0.236	1	**0.718**
BI2	0.489	0.418	0.498	0.390	0.387	0.262	**0.718**	1

Since the TPB assumes that behavioural intention (BI) is a function of attitude (ATT), social norms (SN), and perceived behavioural control (PBC), we test this assumption using correlation analysis, linear regression, and factor analysis. The correlations of ATT, SN, and PBC with BI are all significant at the 5% level and are 0.455, 0.460, and 0.382, respectively. Factor analysis of the mean scores measuring ATT, SN, and PBC shows that all three measures load heaviest on the first unrotated factor, which appears to represent BI as postulated in the TPB. This suggests that BI may be used in model estimation instead of the individual items. Linear regression results of BI on ATT, SN, and PBC are presented in Table 4-9. The coefficients of the constructs have the expected signs and are statistically significant at the 0.01 level. The results indicate that ATT, SN, and PBC are significant determinants of BI as postulated in the theory of planned behaviour. However, we note that the value of 0.32 for the model R^2 is rather low for predictive purposes i.e., the explanatory variables are rather poor predictors of the dependent variable.

Table 4-9: Linear regression results for BI on ATT, SN, and PBC (N = 224)

	Coeff.	S.E	| t |	p-value	95% CI	
					Lower	Upper
Intercept	-0.8449	0.1451	5.82	.0000	-1.1308	-0.5589
Attitude (ATT)	0.3056	0.0892	3.42	.0007	0.1298	0.4814
Social norm (SN)	0.3342	0.0676	4.94	.0000	0.2009	0.4674
Perceived behavioural control (PBC)	0.2498	0.0789	3.16	.0018	0.0941	0.4055
R^2 = 0.3212	Adj.R^2 = 0.3119					

4.5 Preferences and WTP for the attributes of electricity services

In this section we apply the MNL, LC, and RPL-EC models to the choice data set to provide answers to questions addressed in this chapter. The models are described in detail in Chapter 2. The main objectives of estimating the supplier switching models are to: (1) determine whether non-price attributes play a significant role in switching; (2) explore the influence of consumers' responsiveness or sensitivity to levels of power bill savings on switching; (3) estimate WTP for the non-price attributes and identify the determinants; and (4) explore the systematic role of attitudes in explaining preference heterogeneity.

As discussed earlier in this chapter, the Electricity Authority's programme for promoting switching provided a central switching system to reduce search costs and quicken the switching process. It also provided a regulatory environment allowing free switching. The benefits of switching promoted under the programme were based on price differences in each region. Although more consumers switched supplier than ever before as a result of the programme, the majority of consumers, at least 79%, did not switch and significant price differences still exist. The lack of recognition of the role of non-price attributes on supplier choice has resulted in scant attention to consumer preferences for these attributes, with an associated paucity of evidence of their influence on switching or supplier choice. Estimating the above models may provide valuable insights into consumers' preferences for power bill savings and non-price attributes.

In the sections that follow we provide a description of the variables used in the models, and regression results.

4.5.1 Description of variables

In this section we provide an example of a stated choice scenario (see Figure 4-5) used to elicit choice responses that we analyze in this and following chapters. This is followed by a discussion on how new variables and interaction terms used in the models have been created.

In the scenarios that follow please only consider the information provided in deciding whether to switch supplier or not. Assume that any information not provided is the same for the three suppliers. Which supplier would you prefer?

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	15 minutes	15 minutes	0 minutes
Fixed rate guarantee	0 months	36 months	0 months
Prompt payment discount	10%	0%	20%
Loyalty rewards	No	No	Yes
Electricity supplied from RENEWABLE sources	50%	100%	75%
NZ ownership	100%	100%	50%
Supplier type	Well-known electricity company	New electricity company	Well-known non-electricity company
Average monthly electricity bill	$250 ($225 after discount)	$250	$200 ($160 after discount)
Which supplier would you prefer?	○	○	○

Figure 4-5: Stated choice scenario and example of a choice task.

One of the main objectives in this chapter is to estimate consumer preferences for power bill savings. In section 4.4.6 we presented evidence suggesting that the minimum level of power bill savings that would induce switching varies across consumers. Therefore, assuming a single parameter for power bill savings, which implies homogeneous preferences, would be counterintuitive. Furthermore, evidence from literature on consumer switching in retail electricity markets indicates the presence of two market segments – switchers and non-switchers at prevailing savings levels (e.g., Defeuilley, 2009). In the case of New Zealand, about 30% of retail customers switched supplier over a period of two years when average annual savings from switching to the cheapest available retailer were estimated at $150 (Electricity Authority, 2013c). The Electricity Authority (2012b, p. 38) identifies "five clusters each with its own distinct attitudes, traits, demographic profile, media preferences and propensity to switch". Three of these clusters, accounting for 65% of respondents, were identified as being less likely to switch supplier. About 77% of respondents in our sample expressed uncertainty about achieving meaningful benefits from switching whilst 53% indicated that switching is a hassle, implying a higher perceived cost of switching.

The weight of evidence presented above seems to point to significant differences in preferences among consumers and provides strong support for the approach we adopt. We create four indicator variables, $Switch_1$, $Switch_2$, $Switch_3$ and $Switch_4$ for the respective minimum level of savings of $100, $200, $300, and $400+ required to induce a switch as presented before in Table 4-6. A variable referred to as *Savings* is created as the difference between the net power bills (after discount) of "Your Current Supplier" (status quo [SQ]) alternative and the other alternatives. The level of *Savings* for the SQ alternative is zero since this is the reference point. The SQ represents the traditional or incumbent supplier and the non-status quo (non-SQ) alternatives represent new suppliers or new market entrants or other traditional competitors. In the choice tasks, the selection of a non-SQ alternative represents a switch from the incumbent to an entrant or other traditional competitor.

The indicator variables described above are interacted with the *Savings* variable to create four interaction terms referred to as $Switch_1\_Savings$, $Switch_2\_Savings$, $Switch_3\_Savings$, and $Switch_4\_Savings$, respectively. This effectively splits the sample into four groups of customers, each characterized by the level of power bill savings at which they would switch supplier and allows for the estimation of different coefficients for *Savings* for each group. The proportion of respondents in each group is indicated under the "Yes" column in Table 4-6. The variables used in model estimation are described in Table 4-10. Note that discount is not included in the variables used in model estimation as it is accounted for in the savings variable[15]. This is consistent with the current practice in New Zealand where the estimation of power bill savings takes into account the various

[15] Preliminary estimation produced insignificant parameter estimates for the discount variable indicating that its effect was fully captured in the savings variable.

discounts offered by retailers. Furthermore the literature suggests that the aggregation of common-metric variables is one of the information processing strategies that individuals in real or choice experiments may adopt in making choices as a form of cognitive rationalization (Hensher & Greene, 2010).

Table 4-10: Variable description

Variable	Description
Time	Continuous variable measuring the average time for telephone calls to be answered by a customer service representative (0, 5,10, and 15 minutes)
Fixed	Continuous variable indicating the period over which prices are guaranteed (0, 12, 24, and 36 months)
Rewards	Dummy variable indicating that a supplier offers loyalty rewards (1, 0)
Renewables	Continuous variable measuring the proportion of electricity generated from renewable sources (25%, 50%, 75%, and 100%)
Ownership	Continuous variable measuring local ownership of supplier (25%, 50%, 75%, and 100%)
New electricity company	Dummy variable (1 if supplier is a new electricity company, 0 otherwise
New non-electricity company	Dummy variable (1 if supplier is a new non-electricity company, 0 otherwise
Well-known electricity supplier	Dummy variable (1 if supplier is a well-known electricity company, 0 otherwise
Well-known non-electricity company	Dummy variable (1 if supplier is a well-known electricity company, 0 otherwise)
Savings	Continuous variable measuring implied savings from switching from current supplier to a competitor
$Switch_1$_Savings	Interaction term between Savings and $Switch_1$
$Switch_2$_Savings	Interaction term between Savings and $Switch_2$
$Switch_3$_Savings	Interaction term between Savings and $Switch_3$
$Switch_4$_Savings	Interaction term between Savings and $Switch_4$
Behavioural intention	This variable is the average score for BI as defined in Table 4-8

4.5.2 Utility function

The systematic effect of consumer sensitivity to the level of savings on switching behaviour is captured by employing an indirect utility specification similar to that suggested by Morey, Sharma, and Karlstrom (2003), which uses a piecewise linear formulation for the bill savings parameter. In this formulation, the utility of savings is assumed to be a step function of bill savings. This approach allows us to explore differences in preferences for consumers with different bill savings sensitivities instead of estimating a single parameter for the savings variable, which would imply homogeneous preferences among customers. Nonlinear effects of continuous variables such as income have been studied in the past and the evidence suggests that incorporating such effects in random utility maximization (RUM) models improves model fit and provides estimates of marginal utility of income (MUI) that are more intuitive than assuming constant MUI (see, Goett et al., 2000; Herriges & Kling, 1999; Layton & Lee, 2006).

The indirect utility function of alternative *i* is specified in equation (4-1).

$$U_{in} = \begin{cases} \alpha_1 Switch_1\_Savings_{in} + \boldsymbol{\beta}'\mathbf{x}_{in} + \varepsilon_{in} & if\ Switch_1 = 1;\ \forall\ Switch_d = 0 \\ \alpha_2 Switch_2\_Savings_{in} + \boldsymbol{\beta}'\mathbf{x}_{in} + \varepsilon_{in} & if\ Switch_2 = 1;\ \forall\ Switch_d = 0 \\ \alpha_3 Switch_3\_Savings_{in} + \boldsymbol{\beta}'\mathbf{x}_{in} + \varepsilon_{in} & if\ Switch_3 = 1;\ \forall\ Switch_d = 0 \\ \alpha_4 Switch_4\_Savings_{in} + \boldsymbol{\beta}'\mathbf{x}_{in} + \varepsilon_{in} & if\ Switch_4 = 1;\ \forall\ Switch_d = 0 \end{cases} \tag{4-1}$$

where $\alpha_1, \ldots, \alpha_4$ are the marginal utilities of savings for respondents who would switch supplier at \$100, \$200, \$300 and \$400+ levels of savings, respectively, **x** is a K×1 vector of non-price attributes including $x = 1$ for the alternative specific constant for the status quo alternative, $\boldsymbol{\beta}'$ is a 1×K row vector of associated population parameters to be estimated, ε_{in} is a random term that is i.i.d. extreme value Type 1 distributed as described in Chapter 2, and d = 1, 2, 3, 4.

4.5.3 Hypotheses

The following hypotheses are tested.

- Hypothesis 1 (*H1*): Non-price attributes are important determinants of switching. This hypothesis relates to question 1(a) on whether or not non-price attributes of electricity services are important determinants of supplier choice. We test the null hypothesis that all β's (betas) are equal to zero; that is, non-price attributes are not important determinants of switching, against the alternative that at least one beta is not equal to zero.

- Hypothesis 2 (*H2*): Respondents' SDCs determine WTP for the attributes of electricity services. This hypothesis relates to research question 1(b) on the determinants of WTP for the attributes. The null hypothesis is that SDCs of respondents do not explain observed heterogeneity of preferences for the non-price attributes of electricity services.
- Hypothesis 3 (*H3*): Respondents with different bill savings thresholds for switching have different preferences for power bill savings. This relates to research question 1(c), which deals with preferences for power bill savings. Specifically, we test whether respondents with lower savings thresholds have higher taste intensities for power bill savings than those with higher thresholds, that is, $\alpha_1 > \alpha_2 > \alpha_3 > \alpha_4$. The utility function specified in equation (4-1) allows for the estimation of these parameters. NLOGIT command for the Wald test of linear restriction is used to test for equality of the alphas from the MNL model, and the LRT, AIC and BIC are used to compare the restricted and unrestricted models.
- Hypothesis 4 (*H4*): The TPB constructs play a systematic role in explaining preference heterogeneity. This hypothesis relates to question 1(d). The null hypothesis tested is that none of the TPB constructs (ATT, SN, PBC, and BI) play a systematic role in explaining preference heterogeneity, i.e., all the parameters are equal to zero.

4.6 Models

We apply five specifications of logit models, M1, M2, M3, M4, and M5 to a supplier choice dataset with 2,688 choice observations of 224 respondents to provide formal answers to the research questions stated at the beginning of this chapter. M1 and M2 are the standard MNL models that we use as base models for comparison purposes. In model M1 we assume that preferences for power bill savings are homogeneous across respondents, this implies $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4$, hence a single parameter α is specified for the bill savings variable. M2 is specified to reflect the hypothesis of heterogeneous preferences across savings thresholds (*H3*) as presented in the utility function in equation (4-1). M3 is a latent class model in which the class membership sub-model is the basic Heckman and Singer (1984) model, which assumes that all parameters are the same across classes except for the class-specific constants. M4 extends on M3 by using psychological constructs based on the TPB to sharpen class membership. Both M3 and M4 choice models are based on the utility function specified in equation (4-1) and are used to test hypothesis 4 (*H4)*. Model M5 is a random parameter logit with error components and is estimated to provide additional support and evidence of preference heterogeneity for the attributes of electricity services. All the parameters are specified as generic except for the alternative specific constant for the status quo. Since the non-SQ alternatives are unlabelled, they share the same constant which is normalized to zero for identification purposes. A panel specification is used in all the models to take into account the correlation among choices by the same respondent. Preliminary estimation showed that accounting for the panel nature of the choice dataset improves model fit.

The MNL models M1 and M2 impose the restrictive IIA assumption and homogeneity of preferences for non-price attributes across respondents as discussed in Chapter 2. To relax the assumption of homogeneity of preferences, the LC and RPL-EC models are estimated. The LC models (M3 and M4) allow for the identification of latent classes in which preferences are homogeneous within but heterogeneous across classes. The assumption of the LC models is that preferences in the sampled population can be characterized with a discrete distribution (Boxall & Adamowicz, 2002; Greene & Hensher, 2003). As such, the LC model provides additional insights into consumer preferences in terms of the number and respective sizes of market segments with distinct preferences. On the other hand, the panel RPL-EC model (M5) accounts for individual heterogeneity and allows for more flexible substitution patterns induced by correlations in the error terms of non-status quo alternatives (Scarpa et al., 2005).

4.7 Results

In this section we present and discuss the results from the models illustrated in the previous section. We relate the findings to the specific research questions and hypotheses. All the models presented in this section are estimated using NLOGIT 5 software.

4.7.1 Regression results

All the models are estimated with data coded for attribute non-attendance (AN-A) in order to account for ignored attributes as recommended in the literature (Hensher et al., 2005b; Hensher et al., 2012; Scarpa, Gilbride, et al., 2009). A detailed discussion of AN-A and the different approaches to accounting for it is provided in Chapter 5. The estimation of the MNL models is straightforward once the utility functions are specified. However, the estimation of the RPL-EC and LC models may be a lengthy process. For example, for the RPL-EC model, Hensher et al. (2005a) suggest that the researcher should investigate different distributional assumptions for each attribute, especially where the sign is important[16]. On the other hand, the challenge in estimating LC models is in identifying the optimum number of latent segments supported by the choice dataset.

Selection of the number of latent classes

The number of classes retained in a latent class model "is exogenously defined and outside the space of estimable parameters" (Scarpa & Thiene, 2005, p. 434). To determine the number of classes retained in the latent class models we follow standard practice and use information criteria (IC), and other factors such as the pattern of significant parameters and relative signs, ease of interpreting the results, parsimony and the need to avoid over-fitting the model.

The *pros* and *cons* of using each IC in determining the number of classes or segment retention was discussed in section 2.2.4 of Chapter 2. Table 4-11 and Figure 4-5 present the information criteria used in segment retention for the preferred model. The information criteria indicate the presence of three or four classes with clearly distinct preferences for the attributes of electricity services. The CAIC and BIC indicate that only three classes may be retained whilst HQC, AIC, crAIC and CAIC3 indicate four classes. However, when the number of classes is increased from 5 to 6, HQC, AIC, crAIC, and CAIC3 improve slightly but the number of insignificant parameters increases and all parameters in the last class are statistically insignificant. The model with three classes is selected based on CAIC and BIC, which have been found to have a tendency of lower over-fitting rate (Andrews & Currim, 2003a), and the need for parsimony.

[16] We discuss this issue further in Chapter 6

Table 4-11: Criteria used to determine the number of classes for model M4

Number of classes	Number of Parameters	*lnL*	AIC	crAIC	AIC3	CAIC	BIC	HQC
1	13	-2075	4176.1	4176.2	4189.1	4265.8	4252.8	4203.8
2	28	-1816	3688.9	3689.5	3716.9	3882.0	3854.0	3748.6
3	43	-1681	3448.1	3449.5	3491.1	**3744.6**	**3701.6**	3539.8
4	58	-1636	**3387.8**	**3390.4**	**3445.8**	3787.8	3729.8	**3511.5**
5	73	-1622	3390.4	3394.5	3463.4	3893.9	3820.9	3546.1
6	88	-1591	3357.2	3363.2	3445.2	3964.1	3876.1	3544.9

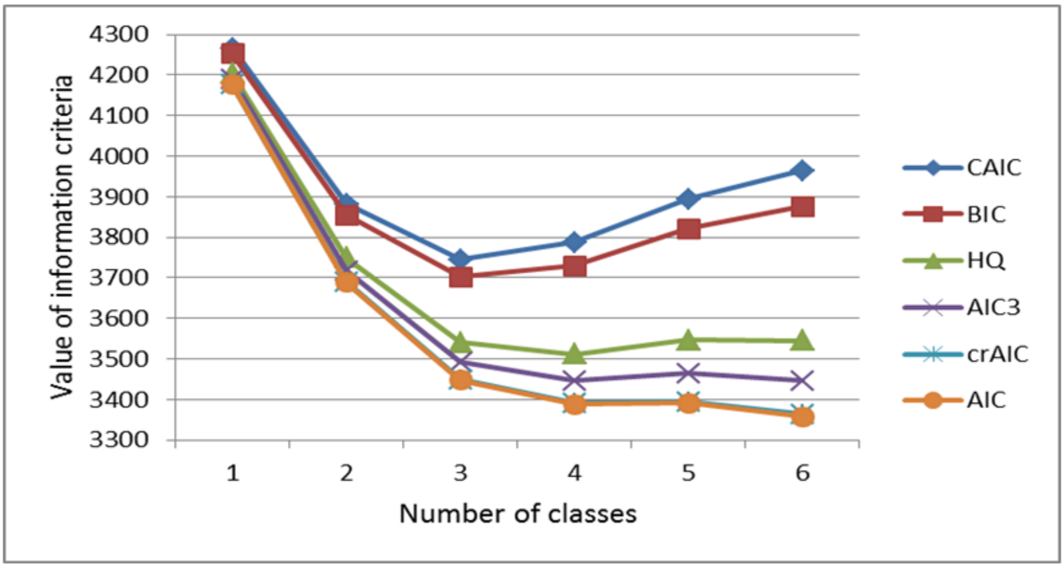


Figure 4-6: Information criteria and segment retention for M4

Comparison of models

We estimated a number of LC models in which the TPB constructs, ATT, SN, PCB, and BI are used in the class membership sub-model to predict class membership. Only model M4 results are reported as it is preferred over the competing models using ATT, SN, and PBC to sharpen class membership based on better model fit. Furthermore, a comparison of M4 with another competing LC model with a single coefficient for the bill savings variable indicates that M4 performs better based on the LRT ($\chi^2_{(9\ \text{d.f.})} = 35.14 > \chi^2_{(9,\ \alpha\ =\ 0.05)} = 16.92$). This supports our hypothesis of different parameter estimates for respondents with different savings thresholds for switching. We provide further discussion of this issue later as it relates to research question 1(c).

The least performing model is M1 whilst M4 is the best. In terms of AIC, BIC, pseudo- R^2 and the likelihood ratio test ($\chi^2_{(3\ d.f.)} = 123.82 > \chi^2_{(3,\ \alpha = 0.05)} = 7.81$), the MNL model (M1) with a single coefficient for the savings variable performs worse than M2, which provides support for the utility specification presented in equation (4-1). The null hypothesis (*H3*) of a single coefficient for the savings variable is rejected based on the Wald test of linear restrictions with $\chi^2 = 123.62$ and p-value = .0001. However, the parameter estimates of the non-price attributes are all significant at the 0.05 level and of similar magnitude in both M1 and M2. However, a direct comparison of betas across the models is inappropriate due to confounding with the Gumbel error scale.

The three models fit the data well with pseudo-R^2 values ranging from 0.294 for the MNL model M2 to 0.431 for the LC model M4. Hensher et al. (2005a, p. 338) suggest that "a pseudo-R^2 of 0.3 represents a decent model fit for a discrete choice model". All the models presented here meet this criterion. Model M4 performs better than M2 and M3 in terms of LL, AIC, pseudo-R^2, and the likelihood ratio test ($\chi^2_{(30\ d.f.)} = 788$ and $\chi^2_{(2\ d.f.)} = 10.30$ against M2 and M3 respectively), but performs marginally worse than M3 based on BIC. The difference of 0.002 in normalized BIC (BIC/N) between M3 and M4 is very small, hence overall M4 is preferred. The overall goodness-of-fit for both latent class models M3 and M4 is significantly better (-1681.05 and -1686.19 respectively) than the RPL-EC model M5 (-1848.69). Furthermore, the LC model allows for the identification of market segments, which is not possible with the other models.

The assumption of IIA in M2 is rejected based on Hausman and McFadden's (1984) test for IIA ($\chi^2_{(13\ d.f.)} = 38.49$, Pr(C>c) = .00024). This supports the estimation of more advanced models such as M3, M4, and M5, which allow for flexible correlation structures for the stochastic component of utility thereby allowing for heterogeneous preferences. Despite the rejection of the IIA assumption we still retain model M2 as our base model for comparison purposes as recommended by Hensher et al. (2005a).

Summary and discussion of regression results

A summary of the regression results for models M2, M3, and M4 is presented in Table 4-12 while those for M1 and M5 are reported in Appendix 4.

Table 4-12: MNL and LC model regression results (t values are in parentheses) (N= 224)

	MNL (M2)	LC Model (M3)			LC Model (M4)		
		Class			*Class*		
		1	2	3	1	2	3
ASC_SQ	0.608[c]	0.832[c]	0.088	2.854[c]	1.053[c]	0.102	2.549[c]
	(7.97)	(2.58)	(0.77)	(6.36)	(2.60)	(0.90)	6.68)
Time	-0.041[c]	-0.090[c]	-0.027[c]	-0.074[b]	-0.096[c]	-0.029[c]	-0.033
	(-5.50)	(-2.83)	(-2.89)	(-2.06)	(-2.80)	(-2.96)	(-1.12)
Fixed	0.005[b]	0.023[b]	0.007[b]	-0.023[a]	0.021[b]	0.009[c]	-0.028[b]
	(2.46)	(2.41)	(2.20)	(-1.91)	(2.11)	(2.97)	(-2.25)
Rewards	0.409[c]	0.142	0.491[c]	0.881[b]	0.035	0.479[c]	1.076[c]
	(5.67)	(0.59)	(4.53)	(2.42)	(0.15)	(4.51)	(2.85)
Renewables	0.009[c]	0.006	0.013[c]	0.016[c]	0.004	0.013[c]	0.013[b]
	(7.29)	(1.45)	(7.81)	(2.58)	(0.95)	(7.84)	(2.19)
Ownership	0.009[c]	0.020[c]	0.012[c]	0.033[c]	0.019[c]	0.012[c]	0.025[c]
	(6.96)	(4.36)	(6.35)	(3.83)	(4.01)	(6.46)	(3.31)
New electricity company	-0.364[c]	-0.317	-0.221	-1.158[b]	-0.483	-0.172	-0.641[a]
	(-3.77)	(-0.94)	(-1.60)	(-2.32)	(-1.29)	(-1.24)	(-1.67)
New non-electricity company	-0.667[c]	-0.052	-0.745[c]	-2.397[c]	-0.135	-0.663[c]	-1.538[b]
	(-5.35)	(-0.13)	(-4.34)	(-2.94)	(-0.33)	(-3.85)	(-2.49)
Well-known non-electricity company	-0.386[c]	0.250	-0.336[b]	-1.080[b]	0.154	-0.271[a]	-0.573
	(-3.32)	(0.48)	(-2.18)	(-2.01)	(0.26)	(-1.74)	(-1.16)
$Switch_1$_Savings [α_1]	0.033[c]	0.097[c]	0.024[c]	0.025[c]	0.101[c]	0.024[c]	0.021[c]
	(30.02)	(9.37)	(13.91)	(4.01)	(8.69)	(14.23)	(3.60)
$Switch_2$_Savings [α_2]	0.025[c]	0.083[c]	0.016[c]	0.038[c]	0.084[c]	0.013[c]	0.045[c]
	(16.86)	(7.15)	(7.76)	(5.43)	(6.78)	(5.95)	(7.53)
$Switch_3$_Savings [α_3]	0.019[c]	0.057[c]	0.009[b]	0.028[c]	0.072[c]	0.013[c]	0.022[c]
	(9.10)	(5.43)	(2.17)	(3.13)	(3.91)	(3.54)	(2.73)
$Switch_4$_Savings [α_4]	0.013[c]	0.052[c]	0.011[c]	0.004	0.054[c]	0.012[c]	0.001
	(7.18)	(6.11)	(3.00)	(0.52)	(5.31)	(3.09)	(0.14)
Class probability model							
Constant					1.240[c]	1.339[c]	0.0
					(4.71)	(5.04)	(Fixed)
Behavioural Intention (BI)					0.372[b]	0.569[c]	0.0
					(2.06)	(3.05)	(Fixed)
Class Probability		0.416	0.459	0.125	0.405	0.456	0.139
K	13		41			43	
LL	-2075.05		-1686.19			-1681.04	
AIC	4176.1		3454.4			3448.1	
BIC	4252.8		3696.1			3701.6	
McFadden Pseudo-R^2	0.294		0.429			0.431	

[c], [b], [a] Significant at .01, .05, and .1 level, respectively

All parameters are significant at the 0.05 level in M1, M2, and M5. In the LC models M3 and M4, the parameters of all the experimentally designed attributes are significant in at least one of the latent classes. Furthermore, all significant parameters have the expected signs. This provides a general affirmative answer to the first part of question 1(a) [*Are non-price attributes of electricity services important determinants of supplier choice?*] and provides empirical support for hypothesis 1 (*H1*) that non-price attributes are important determinants of switching. Even for the worst-performing model M1, the hypothesis that the starting values (zeros) are not significantly different from the maximum likelihood estimates (MLEs) is rejected based on the Lagrange multiplier statistic of 1752.76.

The results from M1, M2, and M5, show how each attribute contributes to explaining the variation in choices observed within the sampled population. Since all the parameters are significant, we can conclude that all non-price attributes included in the models are significant determinants of switching. Relating the specific results of the LC models M3 and M4 to the research questions and hypotheses requires further discussion since the models identify groups with different preference structures. For example, each group has its own set of utility functions which differ from other groups in terms of the values and/or signs of parameter estimates and the variables that enter the utility functions; that is, choices are determined by different sets of variables with their corresponding group-specific parameters. We provide an interpretation of the parameter estimates and a detailed discussion of the results of the LC models below.

As discussed in chapter 2, the parameter estimates for the switching models are interpreted as taste intensities or average marginal effects on the non-stochastic or deterministic component of indirect utility. The parameters of the non-stochastic component of the indirect utility function, which is specified as linear in parameters, are also the parameters of the nonlinear logit probabilities of alternatives. As such, the parameter estimates have no straightforward behavioural interpretation beyond the signs, which indicate whether a variable of interest has a positive or negative influence on choice probabilities (Hensher et al., 2005a). The order or size of parameter estimates also matter, but only for dummy variables.

For the best model (M4) the taste intensities for savings decrease as sensitivity to savings falls except in class 3, where α_2, the coefficient of $Switch_2$_Savings, is larger than that of $Switch_1$_Savings (α_1), and α_4 is highly insignificant. An $\alpha_2 > \alpha_1$ (and 95% confidence intervals don't overlap) is counter-intuitive as it implies that respondents with a higher savings threshold ($200) for switching are more sensitive to power bill savings than respondents with lower savings thresholds ($100). This result may be an indication that responses of respondents in class 3 who answered "yes" to switching at $100 may have been influenced by "yea saying". However, their choices over the choice tasks indicate lower sensitivity to savings as evidenced by a lower value estimate of α_1. As discussed earlier, one of the appeals of LC models is their ability to identify groups with similar response patterns. Recall that 62% of respondents indicated that they would have switched supplier in the past two years if they could have achieved savings of $100, yet only 31% actually switched supplier at average savings of $150. This suggests the presence of "yea saying" or hypothetical bias.

An insignificant α_4 for respondents who would not switch supplier for power bill savings is consistent with expectation. However, α_4 also captures the preferences of respondents who would only switch at $400 and above. This indicates that, on average, respondents in this group have a marginal utility of savings which is not significantly different from zero, and are likely to have ignored savings in their switching decisions in most or all choice scenarios. It should be noted that class 3 represents only 14% of the market, and it is also possible that this class includes some respondents who made choices that are inconsistent with their indicated savings threshold given the unexpected $\alpha_1 < \alpha_2$ for this class. For classes 1 and 2, accounting for at least 86% of the market, the relative magnitudes of the four bill savings coefficients suggest that respondents' choices are consistent with their responses to the question probing the level of savings at which they would switch supplier. So, in classes 1 and 2 we find evidence in support of the hypothesis that $\alpha_1 > \alpha_2 > \alpha_3 > \alpha_4$; that is, respondents with lower savings thresholds for switching have higher marginal utilities of power bill savings than those with higher savings thresholds (*H3*).

The MNL model results indicate that consumers have a negative preference for service attributes such as call waiting time; a negative preference for the three supplier types relative to the traditional supplier (well-known electricity company); and positive preferences for fixed rate contracts, loyalty rewards, renewables and local ownership of supplier. In model M4, class 1 represents about 40% of the market. Respondents in this class have positive preferences for the SQ (current supplier), local ownership of supplier, fixed rate and savings, and a negative preference for call waiting time. This group exhibits a strong preference for local ownership of supplier and loyalty to the incumbent retailer and would only likely switch to a competitor for substantially lower power bills with longer fixed term price guarantees. Respondents in this class are more likely to respond to campaigns like the WMN for higher savings and price guarantee but would require information on local ownership of supplier to make optimal switching decisions. Respondents in class 2, representing 46% of the market, exhibit no loyalty to their current supplier. They dislike longer call waiting time and non-traditional power companies, and have positive preferences for fixed rate contracts, loyalty rewards, renewables and local ownership of supplier.

Class 2 represents a more mobile market segment that may offer challenges to retailers wanting to retain or increase market shares as more factors influence switching behaviour. This class offers retailers an opportunity to compete in different ways based on marginal rates of substitution between attributes. For example, a supplier may price above competitors and still retain market share by offering commensurate increases (decreases) in non-price attributes for which respondents have a positive (negative) preference. In this class, all the design attributes influence switching which provides an answer to question 1(a).

On the other hand, class 3 represents the smallest market segment characterized by a large inertia or strong preference for the SQ. Unlike the other two classes, this class exhibits a negative preference for fixed rate contracts and doesn’t care about call waiting time. The large inertia exhibited by this group implies that only large changes in non-price attributes or unpleasant experience with the incumbent may induce switching. Recall that some respondents in this class will not switch supplier for any level of power bill savings, i.e. $\alpha_4 = 0$. This creates a challenge for regulators and an opportunity for retailers to behave non-competitively.

We observe significant SQ effects in M2 and M4 (classes 1 and 3) whereby respondents show a strong positive preference for the status quo. The observed preference for the SQ compared to the other alternatives in the choice set implies switching inertia and is consistent with reference-dependent utility theories (Kahneman, Knetsch, & Thaler, 1991; Kahneman & Tversky, 1979; Samuelson & Zeckhauser, 1988), or risk aversion. In the context of this study, the status quo (SQ) may have been preferred by some respondents for a number of reasons. One reason may be choice task complexity (see, Boxall, Adamowicz, & Moon, 2009) if some respondents found it hard to fully evaluate all alternatives in any given choice task and opted for the SQ as a coping strategy. Although less than 2% of respondents rated their understanding of the choice tasks below "fair", about 13% rated "How easy was it to make your choices in scenarios 1 to 12?" as either "difficult or somewhat difficult", but none rated it as "very difficult". A second reason may be protesting where respondents select the SQ throughout as a way of registering their protests. We did not collect information on protest responses but only 13 respondents (5.8%), for whatever reasons, selected the SQ throughout. Other reasons for the SQ effect often proffered in the literature include loss aversion (Kahneman & Tversky, 1979), regret avoidance (Samuelson & Zeckhauser, 1988), and loyalty to the incumbent (Gamble et al., 2009; Gärling et al., 2008).

Class membership sub-model and TPB constructs

Now focusing on the class membership sub-model in the previous table, we observe that all the parameter estimates are significant at the .05 level. For identification purposes, all parameters in class 3 are normalized to zero as this class is used as a reference point. The constants in classes 1 and 2 are positive indicating the average influence of unobserved effects on class membership relative to class 3. The coefficient for *BI* is positive in classes 1 and 2 indicating that respondents who intend to switch supplier (potential switchers) have a higher likelihood of belonging to these classes compared to class 3. This makes sense as class 3 is characterized by large inertia and less sensitivity to power bill savings. Furthermore, the coefficient for *BI* is largest in class 2 implying that potential switchers have the highest likelihood of belonging to this class, and we can compute marginal probabilities.

Recall that class 2 was identified as representing a mobile segment of the market. We find that the results of the class membership model are consistent with the results of the choice model. Apart from improving model fit, the inclusion of *BI* in the class membership model influences the relative sizes of the market segments. For example, class membership probabilities of classes 1 and 2 fall slightly by 2.64% and 0.65% respectively whilst that of class 3 increases by 11.2%. A conclusion that may be drawn from these findings is that the inclusion of *BI*, a psychological construct based on the TPB, improves the characterization of heterogeneity of preferences. This addresses research question 1(d) [*Do attitudes towards switching play a systematic role in explaining preference heterogeneity?*]. Based on the significant parameter estimates of BI we reject the null hypothesis that the TPB constructs do not help in explaining preference heterogeneity.

A summary of the latent preference classes

Before we move to the next section, which deals with WTP for the attributes of electricity services, we provide a summary of the three latent preference classes and the characteristics of respondents in each class. Table 4-13 presents a summary of the latent preference classes whilst Table 4-14 provides average characteristics of the respondents in each class. Identifying the SDCs and attitudes of respondents in each segment is important for policy targeting and marketing strategies for product differentiation.

Class 1 respondents may be described in general as “bargain hunters” since their main interest seems to be on securing better price deals, which implies information gathering, hence a strong dislike for call waiting time. We will show in the next section that although this group cares about local ownership, they have the weakest preference for this attribute compared to the other classes. The class consists of younger retail customers (44 years) with the highest average personal income ($48,200), highest switching rate (28%) and highest likelihood of having dependent children (48%). This class has the highest proportion of customers with at least a bachelor’s degree, and has the largest average household size, which may explain the observed high sensitivity to power bill savings and high switching rate. The group has the lowest environmental attitude score, which may explain why they don't care about renewables. It is interesting to note that class 1's average BI score of -0.08, which is basically zero and hence indicating neutrality, is consistent with a positive but relatively weaker preference for the status quo.

We describe class 2 respondents as "mobile and discerning" since they exhibit no loyalty to the incumbent, express a positive intention to switch supplier (BI = 0.3), and would choose a retailer based on the value of all attributes. This group is dominated by females, has lower average income ($43, 800) than class 1, and the highest average environmental attitude score (54.03) hence a liking for renewables. This is consistent with findings from previous studies that women tend to be more pro-environmental than men (e.g., Clark et al., 2003; Ek & Soderholm, 2008). Class 3 respondents may be described as "captive and loyal patriots" since they exhibit very strong preferences for the SQ, loyalty rewards, and local ownership of supplier. They have the highest average age, lowest income, smallest household size and are least sensitive to power bill savings.

Table 4-13: Summary of preference classes

Attributes	Class		
	1 (Bargain hunters)	2 (Mobile and discerning)	3 (Captive and loyal patriots)
Status quo	+	0	++
Time	- -	-	0
Fixed price guarantee	+	+	-
Loyalty rewards	0	+	++
Renewables	0	+	+
Local ownership	+	+	++
New electricity company	0	0	-
New non-electricity company	0	-	- -
Well-known non-electricity company	0	-	0
Power bill savings	strong	moderate	weak
Segment size	40.5%	45.6%	13.9%

Notes: +,-, 0, indicate positive, negative, and neutral preferences. Double signs = stronger preferences

Table 4-14: Summary of characteristics of respondents in each class

SDC and attitudinal characteristics of respondents in market segments			Class 1	Class 2	Class 3
Segment size			92 (41%)	101 (45%)	31 (14%)
Gender (proportion of males) %			50	46	42
Average age (years)			44	45	47
Average Income (NZ$)			48,200	43,800	39,100
Ethnicity	NZ-European (%)		74	78	84
	Maori (%)		2	6	6
	Other (%)		24	16	10
Child (% with at least one child)			48	38	29
Average Household size			3.4	3.2	2.9
At least Bachelors (%)			37	28	19
Switched supplier in the past 2 years (%)			28	17	13
Behavioural intentions (%)			-0.08	0.30	-0.89
Environment attitude score			50.18	54.03	51.94
Said “yes” to switching at savings of:		$100	68%	64%	32%
		$200	17%	20%	29%
		$300	7%	8%	13%
		$400 +	8%	8%	26%

In the next section we estimate WTP for non-price attributes of electricity services and discuss their implications for retail competition.

4.7.2 WTP estimates

We follow standard practice and calculate average marginal WTP for each non-price attribute (k) as the ratio of the marginal utility of the attribute to the marginal utility of power bill savings as indicated below:

$$WTP_k = \frac{\frac{d}{dx_k}\lambda\beta_k x_k}{\frac{d}{dx_S}\lambda\alpha_i S} = \frac{\beta_k}{\alpha_i}, \qquad i = 1, 2, 3, 4 \tag{4-2}$$

where S is the bill savings interaction term as defined previously and λ is a scale parameter. The marginal utilities of the attributes are the first partial derivatives of the utility function with respect to each attribute, which turn out to be the parameter estimates in Table 4-12 since the non-stochastic component of indirect utility is specified as a linear function. Note that WTP is scale free and can be compared across models and datasets.

Table 3-15 presents marginal willingness to pay (WTP) estimates for the MNL model and the latent class model (M4). The columns under each model and/or class heading labelled as $\alpha_{1,}$ α_2, α_3, and α_4 represent the four groups of respondents who would switch supplier at savings levels of \$100, \$200, \$300, and \$400+ (includes those who indicated they would not switch for any level of savings), respectively. Since there are four parameters for the savings variable, we estimate WTP for each attribute based on each parameter estimate. The standard errors for the WTP estimates are computed using the delta method. We first discuss WTP estimates based on the MNL model M2 before moving on to the LC model M4.

For the MNL model all WTP estimates are significant at the 0.05 level, indicating that irrespective of the level of sensitivity to savings level, respondents value all the attributes of electricity services. Preferences for the attributes of electricity services become stronger as sensitivity to bill savings falls, i.e. respondents who are only prepared to switch supplier when the savings level is at least \$400 and those who stated they would not switch based on any of the investigated level of savings value non-price attributes of electricity services the most, followed by those who would switch at \$300. The absolute values of WTP for all attributes increase as we move from α_1 to α_4. The results of the MNL model suggest that respondents who value the attributes of electricity services more are less likely to switch supplier on the basis of savings alone. This has important implications for policies designed to promote switching in the retail electricity market. For example, an effective strategy to encourage switching should include information on non-price attributes if consumers are to make decisions that maximize utility.

Marginal WTP estimates for fixed rate contract, loyalty rewards, renewables, and ownership are positive, implying that retailers offering higher levels of these attributes may attract customers compared to similar retailers offering lower levels of the attributes. All new entrants in the retail electricity market are perceived negatively by customers and have to charge between \$10.04 and \$52.05 less per month compared to incumbent retailers (well-known electricity companies) to attract customers, *ceteris paribus*. New non-electricity companies are the least preferred supplier type. These results offer one possible explanation why the rapid increase in the number of new retailers in recent years has not resulted in a significant decline in market shares for the traditional retailers and why some customers have not switched supplier when average savings have been as high as $150. For example, respondents (with $\alpha = \alpha_1$) who would normally switch supplier if savings are $100 would not switch to a "New non-electricity company" for savings of $100 per year because, other things being equal, this company should charge $20.26 less per month or $243.12 less per year compared to incumbent traditional suppliers. To attract this group of customers the new company must therefore charge $343.12 ($243.12 + $100) less per year compared to traditional suppliers. In this case, the negative preference for "New non-electricity company" relative to traditional retailers far outweighs the average savings of $150 currently available in the market and customers would not switch to this supplier type at current average savings. We discuss this issue further in the next section.

Table 4-15: WTP for the attributes of electricity services (NZ$$_{2014}$)[1]

	MNL (M2)				Latent Class Model (M4)										
					Class 1				Class 2				Class 3		
	α_1	α_2	α_3	α_4	α_1	α_2	α_3	α_4	α_1	α_2	α_3	α_4	α_1	α_2	α_3
Time	-1.24 (0.22)	-1.61 (0.31)	-2.16 (0.45)	-3.17 (0.72)	-0.95 (0.31)	-1.14 (0.43)	-1.34 (0.53)	-1.78 (0.72)	-1.20 (0.41)	-2.14 (0.81)	-2.29 (1.01)	-2.47 (1.14)	*NS*[2]	*NS*	*NS*
Fixed	0.16 (0.07)	0.21 (0.09)	0.28 (0.12)	0.42 (0.18)	0.21 (0.10)	0.25 (0.13)	0.30 (0.16)	0.39[a] (0.22)	0.39 (0.14)	0.70 (0.28)	0.75 (0.33)	0.81 (0.37)	-1.36 (0.67)	-0.64 (0.27)	-1.30[a] (0.70)
Rewards	12.42 (2.17)	16.22 (3.00)	21.73 (4.44)	31.91 (7.01)	*NS*	*NS*	*NS*	*NS*	19.87 (4.45)	35.61 10.01)	38.07 (14.06)	41.04 (16.80)	51.32 (22.84)	24.17 (9.35)	49.26 (24.59)
Renewables	0.28 (0.04)	0.36 (0.05)	0.48 (0.08)	0.71 (0.14)	*NS*	*NS*	*NS*	*NS*	0.53 (0.08)	0.96 (0.19)	1.02 (0.32)	1.10 (0.38)	0.60 (0.31)	0.28 (0.13)	*0.58*[a] *(0.32)*
Ownership	0.29 (0.04)	0.38 (0.06)	0.51 (0.09)	0.75 (0.14)	0.19 (0.04)	0.23 (0.05)	0.27 (0.09)	0.36 (0.09)	0.51 (0.08)	0.91 (0.19)	0.97 (0.30)	1.05 (0.37)	1.17 (0.37)	0.55 (0.15)	1.12 (0.43)
New electricity company	-11.04 (2.88)	-14.41 (3.81)	-19.30 (5.30)	-28.35 (8.23)	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*	-30.57[a] (18.59)	-14.40[a] (8.39)	-29.35[a] (18.00)
New non-electricity company.	-20.26 (3.84)	-26.46 (5.16)	-35.44 (7.57)	-52.05 (12.16)	*NS*	*NS*	*NS*	*NS*	-27.50 (7.27)	-49.28 (14.81)	-52.68 (20.17)	-56.78 (23.72)	-73.36 (33.73)	-34.54 (13.93)	-70.40 (35.13)
Well-known non-electricity company.	-11.74 (3.51)	-15.33 (4.65)	-20.53 (6.44)	-30.15 (9.95)	*NS*	*NS*	*NS*	*NS*	-11.24[a] (6.46)	-20.15[a] (11.99)	*NS*	*NS*	*NS*	*NS*	*NS*
Class Probability					40%				46%				14%		

[1]NZ$1 = US$0.8389. [2]*NS* indicates that WTP is not statistically different from zero based on the respective parameter estimates which are insignificant even at the 10% level. [a]Significant at .1 level. Note: figures in parentheses are the standard errors. The column for α_4 is omitted in class 3 as the coefficient of $Switch_1$_Savings is highly insignificant and WTP may not be estimated.

WTP estimates based on the latent class model provide insight into the preferences of consumers in three segments of the retail market and allow for possible product designs or offerings and policies targeted at specific market segments. For example, any supplier type offering low call waiting time, longer fixed rate contracts and higher local ownership may target the market segment represented by class 1. However, class 1 has the lowest WTP for the attributes of electricity services. Respondents in this class are willing to pay between $4.75 and $9.00 more per month to a retailer offering 25% more local ownership compared to between $12.75 and $26.25 for respondents in class 2, *ceteris paribus*[17]. It should be noted that the upper value for each range of WTP values for each class only applies to a small proportion of the market, which consists of customers who would only switch supplier at annual savings level of at least $400 and those who would not switch for any level of savings.

Respondents in class 2 are willing to pay on average between $19.87 and $41.04 more per month to a supplier offering loyalty rewards and between $5.30 and $11.00 to secure a 10% increase in renewables in their fuel mix. For an increase of 10% in local ownership these respondents are willing to pay on average between $5.10 and $10.05 more per month. A retailer offering a 24 months fixed rate contract may charge between $9.36 and $19.44 more per month compared to similar retailers offering no fixed rate contract without losing its customers to competitors. Informing consumers in class 2 that switching from this supplier to similar competitors would save them between $112.32 ($9.36 x 12) and $233.28 ($19.44 x 12) per year would not result in any switches if the competitors are not offering at least 24 months fixed rate contracts. To attract customers, non-electricity companies entering the retail market have to charge between $11.24 and $56.79 less per month compared to traditional electricity companies. A retailer able to reduce call waiting time by 5 minutes may charge between $6 and $12.35 more per month without losing its market share, other things being equal.

[17] The WTP amounts are obtained by multiplying the marginal WTP estimates presented in Table 4-15 with the respective changes in the level of the attributes. This is based on the assumption of constant marginal WTP which may be criticised as evidence of lack of scope sensitivity, an issue that is well documented in the literature. However, we use relatively small changes which are likely to be realistic and less likely to be seriously affected by lack of scope sensitivity if any.

The absolute values of marginal WTP estimates for respondents in class 3 tend to be higher than those of respondents in other classes except in the case of renewables in class 2. This is expected as class 2 has a higher average environmental attitude score than class 3 as shown previously in Table 4-14. The negative preference for fixed rate contract means that retailers offering 24-month fixed rate contracts have to charge between \$15.36 and \$32.64 less per month to retain customers in this market segment. A new non-electricity company has to charge between \$34.54 and \$73.36 less per month in order to attract customers in this class compared to traditional retailers.

The marginal WTP estimates for supplier type clearly indicate that incumbent traditional retailers enjoy large premiums in the market and this offers one possible explanation for the observed price dispersion in the retail electricity markets in New Zealand and why new entrants have difficulty making significant inroads in the retail market. We explore this issue further in the next section.

4.7.3 Supplier type and switching inertia

The results presented in the previous section suggest that the current practice of estimating the benefits from switching using exclusively power bill savings based on price differences may be inappropriate. Potentially it may under- or over-estimate the true benefits based on expected or perceived savings which take into account differences in the levels of non-price attributes of competing retailers. The significant WTP estimates presented in the previous section suggest that consumers would be more likely to switch supplier if the expected savings are positive, *ceteris paribus*. The difference between the two measures may in part explain the perceived ‘stickiness’ of customers. We show that based on a measure of benefits from switching, which takes into account the values of non-monetary attributes as well as price differences, the minimum amount of savings required to induce indifference (i.e., a 50-50 chance of success) between staying with an incumbent traditional retailer and switching to a competitor varies depending on the type of retailer, market segment, and stated savings threshold for switching. These amounts differ from the \$150 advertised during the WMN campaign.

We use the model parameters presented previously in Table 4-12 to simulate the likelihood of a switch when a typical customer of a traditional retailer is approached by a new entrant or other traditional competitor at various levels of power bill savings. For each supplier type we use the logit probability formula to estimate choice probabilities over a range of savings assuming that all other attribute levels are the same across retailers. We focus on supplier type and savings for two main reasons. First, a new market entrant and other traditional competitor trying to attract customers from an incumbent traditional retailer cannot change its “type”. However, it may be possible to offer other non-price attribute levels to match the incumbent. Second, the perceived customer ‘stickiness’ relates to lack of response to power bill savings, which have been used as the main instrument for promoting switching.

The plots for the predicted probabilities of switching for each level of sensitivity to power bill savings are shown in Figures (4-7) to (4-14). Table 4-16 provides a summary of the predicted minimum amounts of savings required to induce indifference between the incumbent and each supplier type. Figure 4-7 shows, based on the MNL estimates and the most savings-sensitive group ($\alpha = \alpha_1$), the probabilities of switching from an incumbent traditional retailer (well-known electricity company) to each new entrant type or other traditional competitor at various levels of savings. Recall that the MNL model failed the IIA test. The switching predictions based on subsets of the choice sets may not be reliable. We present the predicted probabilities for comparison purposes only.

Based on the MNL model, the minimum monthly (annual) power bill savings required to induce indifference between an incumbent traditional retailer (well-known electricity company) and a new entrant range from $24 ($288), for a traditional competitor, to $44 ($528), for a new non-electricity company. These savings are far above the average power bill savings available in the market, which may explain the current relatively low switching rates or observed ‘stickiness’[18]. When prices are equal across retailers the probability of switching to a new entrant ranges from 0.1915 for a new non-electricity company to, 0.2388 for a well-known non-electricity company, 0.2430 for a new electricity company, and 0.3159 for other traditional competitor. These probabilities are in line with the

[18] We refer to current rates as low relative to expectations based on the benchmark of price convergence or the law of one price.

21% switching rate observed for our sample and the 30% reported by the Electricity Authority (2013b)

Table 4-16: Minimum savings required to induce a 50-50 chance of switching (NZ$$_{(2014)}$)

		Well-known electricity company	New electricity company	Well-known non-electricity company	New non-electricity company
MNL		24.00 (288.00)*	34.50 (414.00)	36.00 (432.00)	44.00 (528.00)
Class 1	$Switch_1$	10.46 (125.52)	10.46 (125.52)	10.46 (125.52)	10.46 (125.52)
	$Switch_2$	12.50 (150.00)	12.50 (150.00)	12.50 (150.00)	12.50 (150.00)
	$Switch_3$	14.70 (176.40)	14.70 (176.40)	14.70 (176.40)	14.70 (176.40)
	$Switch_4$	19.50 (234.00)	19.50 (234.00)	19.50 (234.00)	19.50 (234.00)
Class 2	$Switch_1$	0.00	0.00	11.25 (135.00)	27.60 (331.20)
	$Switch_2$	0.00	0.00	20.25 (243.00)	49.30 (591.60)
	$Switch_3$	0.00	0.00	21.60 (259.20)	52.75 (633.00)
	$Switch_4$	0.00	0.00	23.50 (282.00)	56.75 (681.00)
Class 3	$Switch_1$	122.00 (1,464.00)	*WNS*	122.00 (1.464.00)	*WNS*

*Annual amounts are in parentheses, *WNS* denotes will not switch to this supplier type

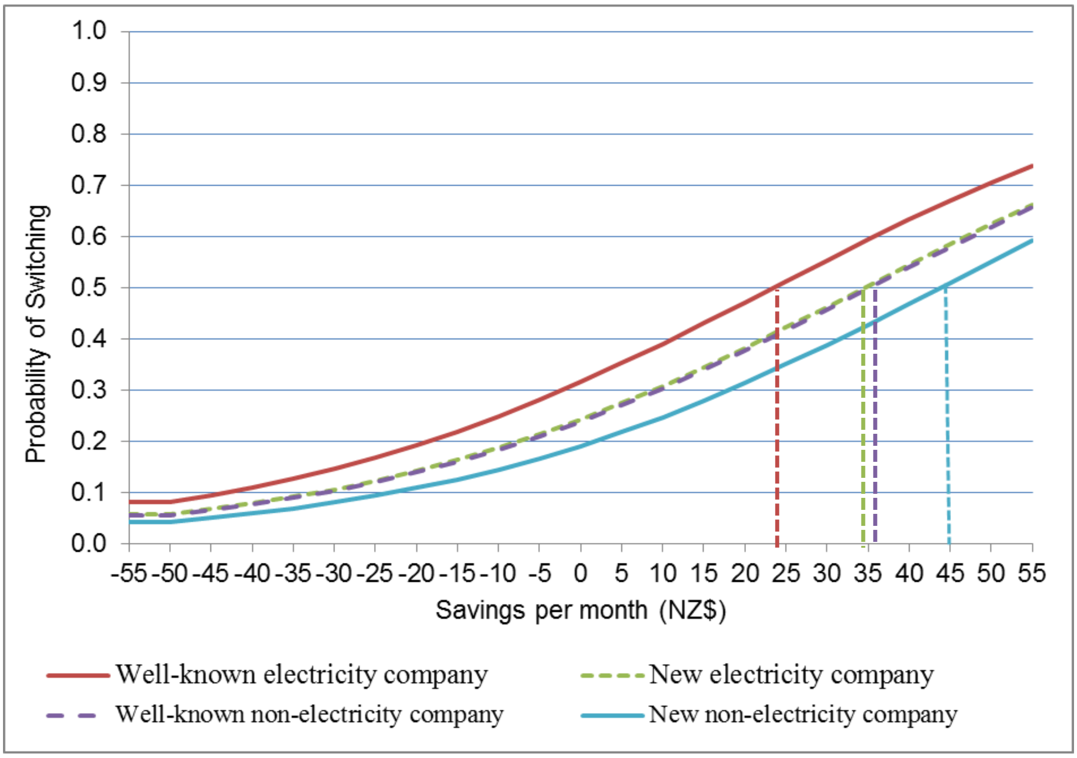


Figure 4-7: Predicted probability of switching [MNL model (switch$_1$, $\alpha = \alpha_1$)]

When the parameter estimates from the latent class model (M4) are used, we get a different picture for each market segment, reflecting a heterogeneity of preferences that is masked in the simpler MNL model. For class 1 respondents, representing 40% of the sample, the estimated minimum monthly (annual) savings required to induce indifference range from about \$10.46 (\$125.52) to about \$19.50 (\$234.00) depending on sensitivity to power bill savings. However, for each level of sensitivity to savings, the amount is the same across all supplier types and reflects inertia or SQ effects since respondents are indifferent over supplier types. Any supplier type approaching a typical customer of an incumbent traditional supplier with a matching price has a probability of success of 0.2587 (see Figure 4-8). This indicates that the incumbent has considerable market advantage over competitors even when all attribute levels, including the price, are the same across suppliers. The savings estimated for this market segment (class 1) are within the range of achievable savings in the market. Since the status quo effects appear to significantly constrain switching, it would be worthwhile to target future policies at reducing the status quo effects in this market segment, after further investigation of its determinants.

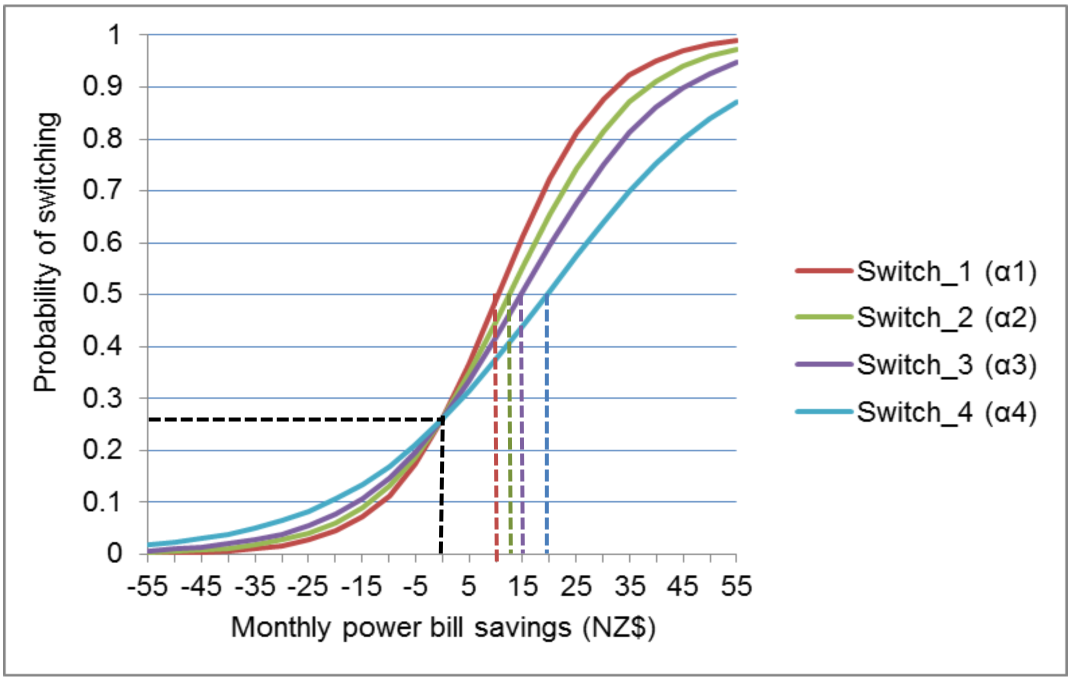


Figure 4-8: Probability of switching to any competitor for bargain hunters (class 1)

In class 2, where respondents have no loyalty to their incumbent but dislike non-electricity companies, the minimum monthly (annual) savings required to induce indifference ranges from about $11.25 ($135.00) to about $52.75 ($681) for non-electricity companies depending on sensitivity to savings, and is zero for electricity companies. These amounts reflect differences in preferences for supplier types. A new electricity company or other traditional supplier has a 50% chance of poaching a customer from a traditional incumbent if they match the price of the incumbent, *ceteris paribus.* However, a well-known non-electricity company has a 43% chance whilst a new non-electricity company has a 34% chance of poaching a customer from a traditional incumbent if they match the price. For new non-electricity companies, penetrating this market segment, which represents 46% of the market, would be extremely difficulty given that even the most savings-sensitive customers would require a minimum of $331.20 ($27.60x12) in annual savings to induce indifference.

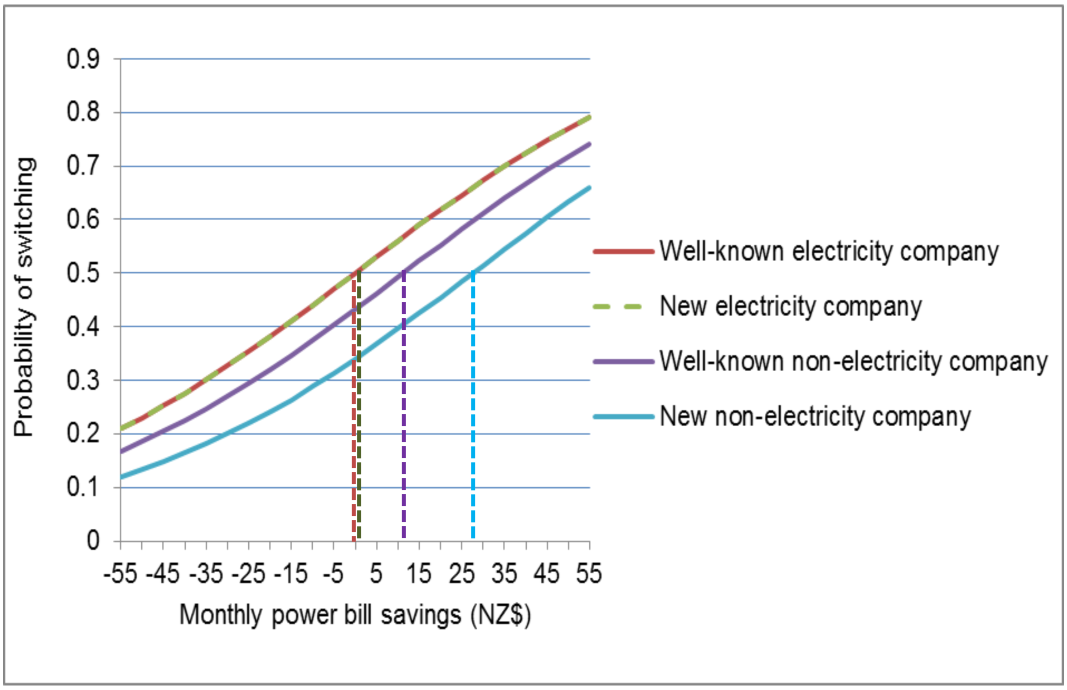


Figure 4-9: Probability of switching to different supplier types [class 2 (switch$_1$, $\alpha = \alpha_1$)]

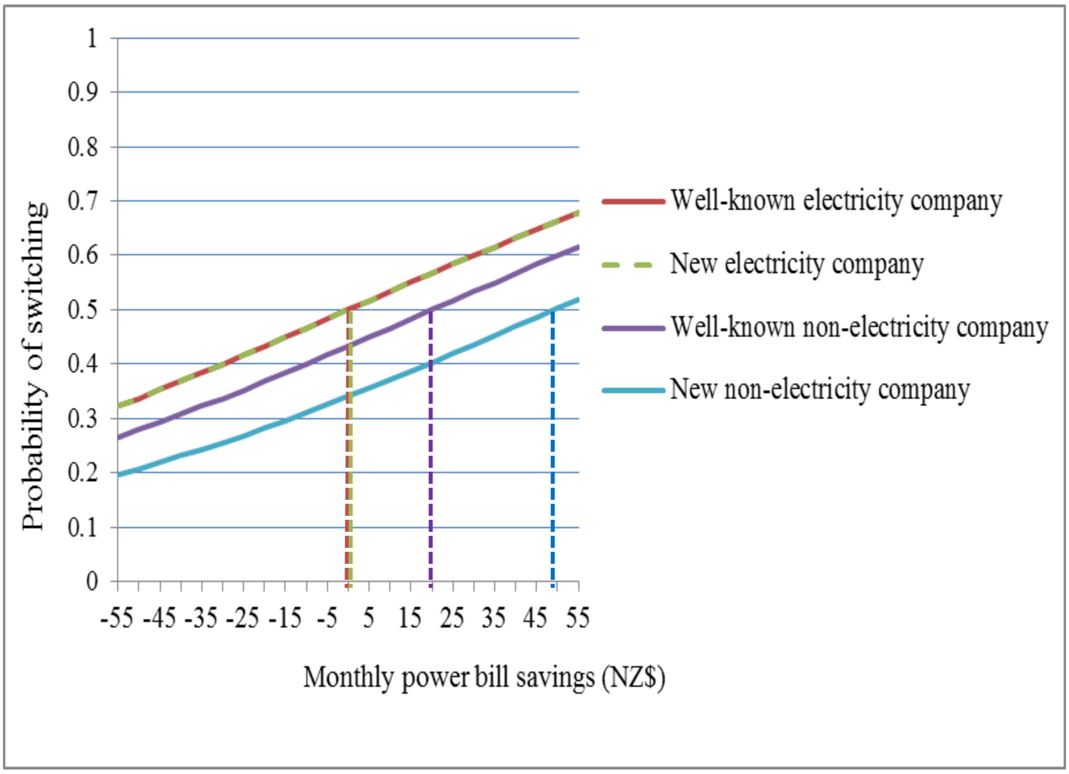


Figure 4-10: Probability of switching to different supplier types [class 2 (switch$_2$, $\alpha = \alpha_2$)]

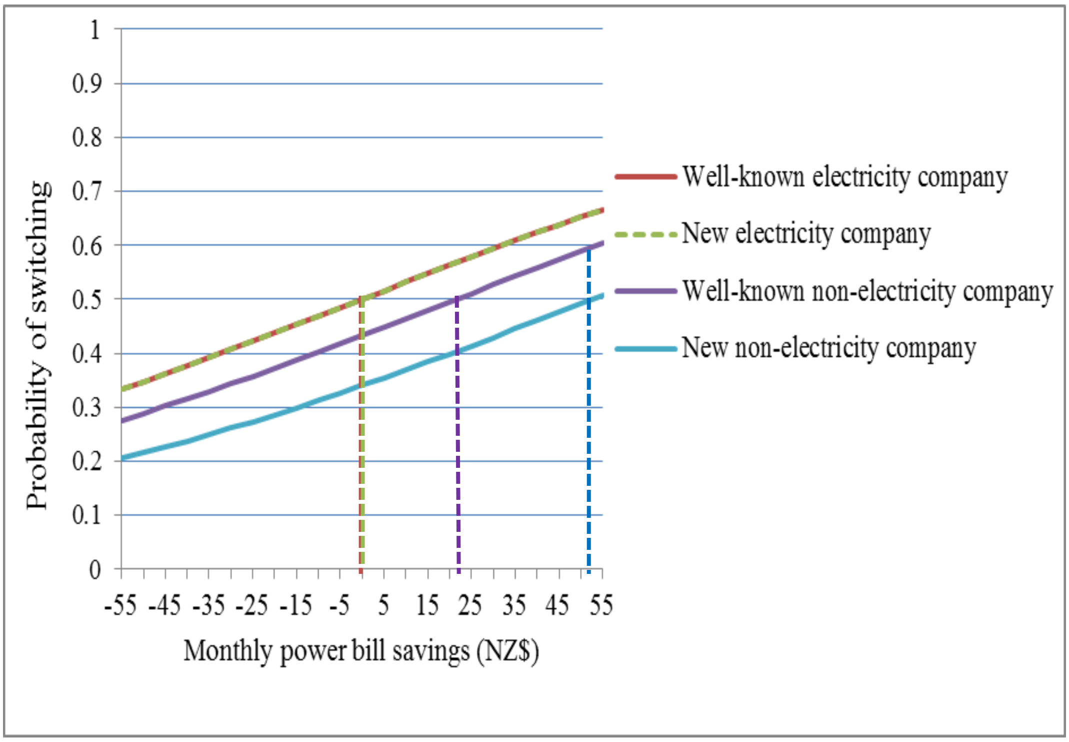


Figure 4-11: Probability of switching to different supplier types [class 2 (switch$_3$, $\alpha = \alpha_3$)]

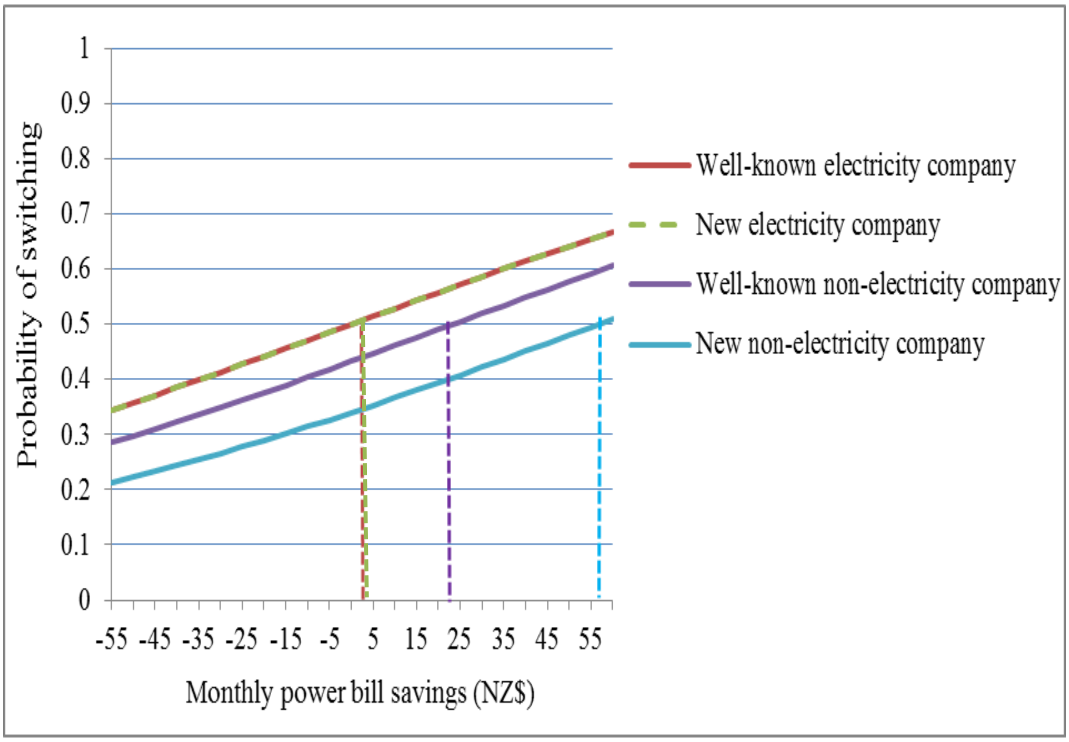


Figure 4-12: Probability of switching to different supplier types [class 2 (switch$_4$, $\alpha = \alpha_4$)]

The market segment represented by class 3 (captive and loyal patriots) accounting for about 14% of the sampled population is potentially a no-go area for all competitors as the minimum monthly (annual) savings required to induce indifference between staying with the incumbent and switching to a well-known competitor is $122.00 ($1,464.00). Respondents would not switch to an unfamiliar entrant at any reasonably achievable level of savings. When prices are equal the probability of poaching a customer from a traditional incumbent is 0.0724 for well-known competitors, 0.0395 for a new electricity company and 0.0165 for a new non-electricity company (see Figure 4-13).

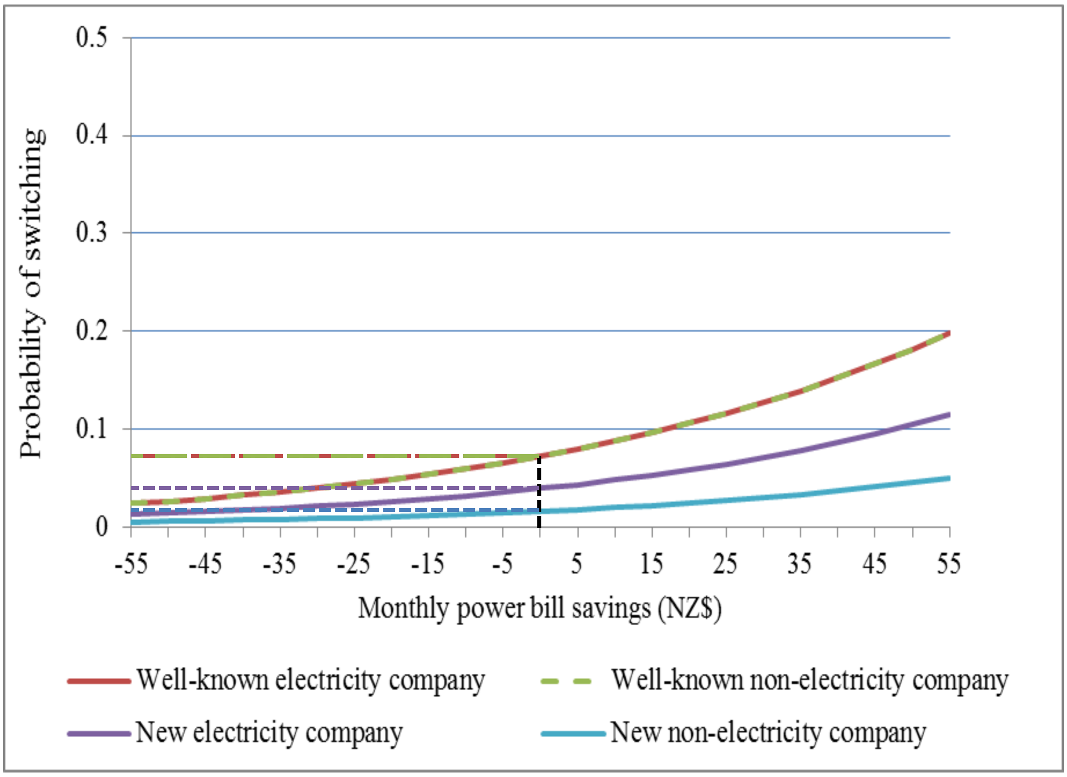


Figure 4-13: Probability of switching to different supplier types [class 3 (switch$_1$, $\alpha = \alpha_1$)]

Given the forgoing, the high proportion of non-switchers under the prevailing price differences between retailers in the New Zealand electricity retail markets is understandable. Furthermore, these results demonstrate that the structure of consumer preferences for supplier types combined with positive preferences for the SQ makes it very difficult for new entrants to make a significant impact in terms of market share captured. Traditional incumbent retailers can afford to ignore modest price discounts offered by new entrants without losing significant market share. The price differences currently prevailing in the market are in part driven by consumer preferences and may continue as an observed feature of the retail electricity markets as long as preferences do not change.

4.7.4 Determinants of WTP for the attributes of electricity services

To investigate the determinants of WTP for the attributes of electricity services, we first obtain individual-specific parameters based on the best switching model M4. Recall that M4 is a latent class model in which BI is used to sharpen class membership. In Chapter 2 the LC model was formally stated. Here, we briefly describe how the conditional individual-specific parameter estimates and the corresponding individual-specific WTP estimates are derived. The conditional individual-specific WTP estimates are then used as a dependent variable in an OLS regression on SDCs and other attitudinal variables.

As presented in Chapter 2, the conditional choice probability of alternative j by individual n in choice situation s is $P_{jns}|c$ and the class probability is π_{nc}.The conditional and unconditional probabilities of the observed sequence of choices by individual *n* are, respectively,

$$\mathrm{P_{jn}|c} = \prod_{\mathrm{s=1}}^{\mathrm{S}} \mathrm{P_{jns}\,|c}, \qquad \text{and}$$

$$P_{jn} = \sum_{c=1}^{C} \pi_{nc} \prod_{s=1}^{S} P_{jns}|c\,, \qquad \text{c = 1, 2, 3 and s = 1, 2, …, 12} \tag{4-3}$$

P_{jn} is the term that enters the log likelihood for the estimation of the latent class model. Since *'j'* indicates the choices that individual *n* actually made, Bayes' theorem can be applied to P_{jn} to obtain a conditional (posterior) estimate of the individual-specific class probabilities as (Greene, 2012),

$$Prob(class = c|choices, data) = \frac{\pi_{nc} \prod_{s=1}^{12} P_{ins}|c}{\sum_{c=1}^{3} \pi_{nc} \prod_{s=1}^{S} P_{ins}|c} \tag{4-4}$$

Equation (4-4) provides an individual-specific set of conditional estimates of the class probabilities ($\hat{\pi}_{nc}^{*}$) from which we can obtain individual-specific posterior parameters (Greene, 2012), by integrating out the class probabilities over class coefficients:

$$\hat{\beta}_n = \sum_{c=1}^{3} \hat{\pi}_{nc}^{*} \hat{\beta}_c \tag{4-5}$$

We used NLOGIT software to generate the parameter estimates in equation (4-5) and the corresponding WTP estimates used in the OLS regression. The regression results are presented in Table 4-17. For each attribute we ran a regression using SDCs hypothesised to influence WTP as independent variables. Each regression is represented by a single column in Table 4-18. In all the regressions the model R^2 is very low, indicating that most variables are poor predictors of WTP. However, low R^2 values in secondary regressions of this nature are not unusual given that most information about choices, which was used in the estimation of WTP, is not included in the regressions.

The only variables that are found to be significant determinants of WTP (at least at the 10% level) are age, income, environmental attitude and behavioural intention. All the variables are dummy-coded except BI. The age variable was dummy-coded to capture WTP for young and old respondents relative to the 30-59 years age group (middle aged). The results show that older respondents dislike all non-traditional suppliers and would require larger price reductions to switch to these supplier types compared to middle aged respondents. They also value fixed price guarantees less compared to middle aged respondents. The dummy variable indicating low income is significant for *Ownership* and ‘supplier types’, indicating that low income earners value local ownership and dislike non-traditional suppliers more than high income earners. As expected, the dummy variable indicating higher environmental attitude score is positive and significant at the .05 level for *Renewables*. This indicates that on average, respondents with high environmental attitude scores are willing to pay more to secure an increase in renewables in their fuel mix. For example, they would be willing to pay $6.30 more per month to secure a 10% increase in renewables compared to respondents with lower environmental scores. Behavioural intention (BI) influences WTP for all non-price attributes except local ownership of retailer. However, BI is only significant at the 10% level for supplier types.

Table 4-17: OLS regression results (t values are in parentheses)

	Time	Fixed	Rewards	Renewables	Ownership	New electricity company	New non-electricity company	Well-known non-electricity company
Constant	-0.46	0.22	0.46	-0.10	-0.09	1.02	2.92	1.43
	(-0.60)	(0.36)	(0.60)	(-0.25)	(-0.19)	(0.12)	(0.14)	(0.18)
Gender	-0.5	-	0.05	-0.07	-	-	-	-
	(-0.08)		(0.08)	(-0.26)				
Age18_29	-1.15	-0.94	1.15	0.48	0.79	-18.71	-47.63	-18.01
	(-1.48)	(-1.38)	(1.48)	(1.35)	(1.36)	(-1.25)	(-1.33)	(-1.35)
Age_60+	**-1.47**	**-1.47**	**1.47**	**1.06**	**1.26**	**-25.93**	**-63.79**	**-24.07**
	(-1.82)	**(-2.07)**	**(1.82)**	**(2.87)**	**(2.08)**	**(1.81)**	**(-1.86)**	**(-1.88)**
Low_Income	-0.53	-0.63	0.53	0.23	**0.96**	**-25.93**	**-62.63**	**-23.33**
	(-0.82)	(-1.11)	(0.82)	(0.80)	**(2.00)**	**(2.07)**	**(-2.08)**	**(-2.08)**
Child	-0.78	-0.57	0.78	0.14	0.46	-	-	-
	(-1.13)	(-0.93)	(1.13)	(0.46)	(0.92)			
Switched	-0.65	0.57	-0.65	-0.49	-0.56	-	-	-
	(0.88)	(0.88)	(-0.88)	(-1.45)	(-1.01)			
Power Bill	0.52	0.35	-0.52	0.08	-	-	-	-
	(0.82)	(0.63)	(-0.82)	(0.28)				
Environmental attitude	-	-	-	**0.63**	-	-	-	-
				(2.28)				
Bachelors+	-	-	-	0.03	0.06	-	-	-
				(0.09)	(0.13)			
BI	**0.65**	**0.42**	**-0.65**	**-0.22 -**	-0.23	**7.20**	**17.03**	**6.35**
	(2.95)	**(2.20)**	**(-2.95)**	**(2.14)**	(1.39)	**(-1.72)**	**(1.69)**	**(1.69)**
R^2	0.081	0.066	0.081	0.100	0.063	0.058	0.059	0.060

4.8 Chapter summary

The main objective of this chapter was to provide insight into residential consumer switching in the retail electricity markets in New Zealand. Customer switching plays an important role in the development of competitive retail electricity markets. The introduction of retail competition and the promotion of switching rely mainly on the belief that consumers are price sensitive and that only price matters. Consequently, switching in most jurisdictions, including New Zealand, has been promoted on the basis of welfare benefits in the form of power bill savings. However, results from previous studies on consumer switching in retail electricity markets show that a majority of consumers have not switched supplier even where significant power bill savings are achievable. Consumer inertia has continued even when consumers are provided information on prices and a simplified central system for switching is provided. This chapter provides a number of insights into consumer switching and shows that the belief that only the price matters may be misguided based on the results of econometric analysis applied on a choice data set generated using an online stated choice experiment.

The results presented in this chapter show that price is not the only important determinant of switching as all non-price attributes included in the LC model are at least significant in one of the preference classes. This indicates a potential for product differentiation as retail companies may compete by offering different service packages. Three latent classes with clearly distinct preferences for the attributes were identified. Class 1 represents a market segment consisting of about 40% of respondents who can be described as "bargain hunters" since they are mainly concerned about lowering their power bills. Since these respondents are indifferent to supplier type, they are more likely to switch to a competitor offering a lower price equivalent to at least $19.50 per month in power bill savings, *ceteris paribus*. This amount represents switching inertia for the least savings-sensitive respondents in this market segment (see Table 4-16). Class 2, representing about 46% of the market consists of respondents who may be described as "mobile and discerning". Respondents in this market segment exhibit no loyalty to the incumbent supplier. However, they have a dislike for non-electricity companies and this is worse still if the company is new. The least savings-sensitive consumers in this segment would only consider switching to a new non-electricity company when they can achieve at least $56.75 per month in power bill savings. Class 3 accounts for about 14% of the market and may be described as “captive and loyal customers.” They have a strong preference for the status quo, dislike unfamiliar new electricity companies, and are most unlikely to switch, with some consumers not willing to switch supplier on the basis of savings.

The results also suggest that when the value of non-monetary attributes of electricity services are taken into account, the current average level of savings may not be adequate to induce some respondents to switch from traditional suppliers to new entrants due to the relative negative preference for market entrants and preference for the status quo provider. These findings offer one possible explanation why, despite the increase in the number of new retailers, the five traditional retailers continue to dominate the retail market. The significance of the values of non-monetary attributes of electricity services may partly explain the perceived ‘stickiness’ or inertia in the electricity retail market where the price or the level of savings are assumed to be the only drivers for consumer switching.

The inclusion of behavioural intention in the class membership sub-model improved both the characterisation of market segments and model fit, highlighting the importance of including attitudes in models of consumer switching. However, SDCs were found to be poor predictors of WTP for the attributes of electricity services. Income, age, environmental attitude and behavioural intention were the only variables that were significant at least at the 10% level.

The main policy implication of the findings is that future campaigns targeted at promoting switching should also provide consumers with information on non-price attributes. From a competition policy perspective, price dispersion should be seen as a natural aspect of a market where consumers have a preference for the status quo (traditional supplier) and a dislike for new entrants, particularly non-traditional suppliers. Further research is required to find out why consumers prefer traditional suppliers and to dispel any perceptions about differences in reliability and security of supply. For retailers, the findings imply that they can differentiate their products and target specific market segments by offering packages designed to meet the specific tastes of customers in each segment.

Chapter 5. Attribute non-attendance and hypothetical bias in stated choice experiments for supplier choice

“The manner in which attributes describing alternatives in discrete choice modelling settings are processed in order to form an outcome choice is now recognised as a worthy area of research.” (Hensher et al., 2012, p. 236).

5.1 Introduction

In the previous chapter we estimated WTP for non-price attributes of electricity services using choice data that was coded for attribute non-attendance (AN-A). The effect of failing to account for AN-A in model estimation was not investigated. In this chapter we use discrete choice models based on the random utility maximization (RUM) framework to investigate the influence of AN-A and response uncertainty or hypothetical bias on model fit and WTP estimates in the context of supplier choice in New Zealand’s residential retail electricity markets. The main purpose of this chapter is to contribute to research that enhances the validity of WTP estimates obtained from stated preference (SP) methods.

Attribute non-attendance is an information processing strategy adopted by respondents in choice experiments (CEs), which involves ignoring one or more attributes of the alternatives presented in a series of choice tasks (Campbell et al., 2008; Hensher et al., 2005b; Scarpa, Gilbride, et al., 2009). On the other hand, hypothetical bias (HB) is the observed difference between people’s responses under hypothetical and real settings (Cummings & Taylor, 1999; List, 2001; Lusk, 2003; Norwood, Lusk, & Boyer, 2008; Ready et al., 2010). Possible information processing strategies or attribute processing rules which respondents in this CE may have used in choosing their preferred alternatives are explored, and their effects on WTP for the attributes of electricity services and predicted market shares are examined. Sensitivity of WTP estimates to different cut-off points on the Likert scales for certainty statements is investigated. The same dataset used in Chapter 4 is used in this chapter.

In the next section we provide a brief background and formally state the research questions addressed in this chapter. A detailed background was provided in Chapter 1. Section 5.3 presents a brief literature review on AN-A and hypothetical bias. Section 5.4 presents an analysis of self-reported AN-A responses and reports on the effect of inconsistences between reported non-attendance and the choices made on model fit and WTP estimates. Section 5.5 presents the results of inferred AN-A. Section 5.6 presents the results of the analysis of the effect of response uncertainty on WTP estimates. Section 5.7 provides the chapter summary and conclusions.

5.2 Brief background and research questions

In previous chapters we have described the role of the Electricity Authority as that of providing regulatory oversight of the electricity sector. We have also described how customer switching in New Zealand retail electricity markets has been promoted, highlighting the reliance of the "What's My Number" (WMN) campaign and associated programmes on the belief that consumers are price-sensitive, and that they will switch to the cheapest available supplier. At the time of our survey, the WMN campaign had been in operation for almost three years, during which New Zealand achieved the highest switching rates in the world. We argued that if consumers value non-price attributes, then providing information on price differences only may not be the optimal strategy where consumers are expected to maximise welfare from switching.

The experimental design (ED) used to generate choice sets for this CE recognizes the possible role of non-price attributes in supplier choice. The non-price attributes included in the ED were identified as important from focus groups, literature review and a pilot study. As opposed to switching promoted under the WMN campaign, respondents in the CE were asked to evaluate each supplier in a choice set in terms of all the attribute levels used to describe it. Given an environment where switching has been officially promoted on the basis of price comparisons only, how would consumers behave when additional information on important non-price attribute levels is also provided? Specifically, this motivates the following research question:

Question 2: Do respondents consider all the attributes of alternatives in making their choices? If not, how does this affect model fit and WTP estimates?

This question is broken down into five components as follows.

(a) *Are non-price attributes of electricity services ignored in choice experiments on switching or supplier choice? If so, which attributes are ignored?*

(b) *Are attributes ignored individually or in combinations?*

(c) *Are the choice responses of respondents who claim to have ignored the cost attribute consistent with their claim? If not, how does this affect model fit and WTP estimates?*

(d) *Do preferences of respondents who ignore an attribute differ from those who consider it?*

(e) *What are the effects of attribute non-attendance on WTP?*

A second question addressed in this chapter relates to the influence of respondents' uncertainty about their choices, which has been highlighted in the literature as a source of HB in welfare estimates obtained from SP data.

Question 3: What are the effects of response uncertainty on WTP estimates?

Answers to these questions have important implications for the Electricity Authority and electricity suppliers. For example, knowledge of which attributes are mostly ignored in the decision-making process of supplier choice provides insight into which variables to target for policy purposes. On the other hand, knowledge of attributes that are considered by customers in choosing their retailer provides opportunities for retailers to focus their advertising campaigns on the relevant attributes and to improve their offers. Identifying groups of respondents with similar attribute processing strategies may allow both policy makers and electricity retailers to target specific groups. Furthermore, the effect of ignoring an attribute or subset of attributes has important implications for researchers where the objective is the estimation of monetary values for the attributes. Accounting for respondents' choice uncertainty helps to reduce the gap between welfare estimates derived from revealed preference (RP) and SP methods. This increases the validity, and hence, the acceptability of estimates based on the state-of-the-art SP methods such as the CE developed for this thesis.

Different approaches to accounting for AN-A have been developed and applied in a number of valuation contexts (e.g., Carlsson et al., 2010; Hensher, 2004; Hensher et al., 2005b; Lockwood, 1999; Saelensminde, 2002; Scarpa, Gilbride, et al., 2009; Scarpa et al., 2010). Similarly, for HB, different approaches have been adopted in mitigating HB either *ex-ante* (e.g., Arrow et al., 1993; Cummings & Taylor, 1999) or *ex-post* (e.g., Blumenschein, Johannesson, Blomquist, Liljas, & O'Conor, 1998; Champ et al., 1997). However, in both cases, there is no general consensus on which approach is preferred. The differences in approaches are highlighted in the next section.

We use three approaches to investigate AN-A and its effect on WTP estimates. In the first approach we investigate the consistency of self-reported AN-A by examining whether the choices made by respondents who claimed to have ignored the cost attribute (monthly power bill) are consistent with their claims. Previous studies adopting a somewhat similar approach, but in different contexts, include Lockwood (1999) and Saelensminde (2002). We focus on the cost attribute in view of its importance in the estimation of WTP for non-price attributes. Ignoring the cost attribute implies a near zero or zero marginal utility of income for this group of respondents, which would result in implausibly high marginal WTP estimates for the attributes of electricity services. Furthermore, ignoring the cost attribute in the decision-making process does not mimic behaviour in real choice situations.

Following Hensher et al. (2005b) and Campbell et al. (2008), the second approach involves the estimation of the MNL, LC and RPL-EC models using data that has been coded to account for self-reported AN-A and comparing the results (i.e., model fit, significance and signs of parameter estimates including class probabilities, and WTP estimates) with those from the models estimated with the data assuming full attendance. Information on self-reported AN-A (also referred to as stated AN-A) was collected in the survey as part of the debriefing process at the end of the series of choice tasks. Each respondent was asked to indicate the attributes that they ignored when making their choices. Using self-reported AN-A in model estimation implies that the responses were made without error. Based on standard practice in previous studies, respondents who considered all attributes are identified as having continuous preferences, whilst those who based their decisions on a subset of attributes are identified as having discontinuous preferences with respect to these attributes (Campbell et al., 2008; Scarpa, Gilbride, et al., 2009). However, concerns have been raised on the reliability of responses to debriefing questions asking respondents to recall their attendance or non-attendance to attributes (Hensher, 2008; Hensher & Rose, 2009).

Previous studies have incorporated AN-A in model estimation by either assigning zero weights to ignored attributes (e.g., Campbell et al., 2008; Hensher et al., 2005b; Scarpa, Gilbride, et al., 2009), or assuming non-zero parameter estimates for ignored attributes (e.g., Carlsson et al., 2010). The former implies that preferences differ between respondents who consider an attribute and those who ignore it, whilst the latter allows the researcher to determine whether or not preferences differ between the two groups. An unresolved issue in the literature on stated AN-A is which of the two approaches is preferred. Therefore, we apply both approaches to the same dataset and explore whether preferences differ and whether or not it is reasonable to assign zero weights to ignored attributes in the context of supplier choice.

The third approach recognizes the limitation of using stated AN-A and avoids using self-reported AN-A in model estimation. This approach employs a latent class framework developed by Scarpa, Gilbride, et al. (2009), and recently extended by Hensher et al. (2012), to infer different patterns of AN-A. Instead of relying on stated AN-A, this approach utilizes the capabilities of the LC model to statistically infer the number of latent classes of AN-A that are supported by the data. AN-A characterized in this way is referred to as inferred AN-A. A number of recent studies identify the role of AN-A through model inference rather than relying on stated AN-A (e.g., Hensher & Greene, 2010; Hensher et al., 2012; Hess & Hensher, 2010; Hole, 2011; Scarpa et al., 2010).

To mitigate HB bias we use responses to certainty statements to identify respondents whose choice responses are likely to be the source of HB bias. Responses to certainty statements were collected as part of the debriefing process at the end of the choice tasks. We estimate a base model using choice responses from all respondents and compare it with models estimated using different cut-off points for certainty scores. In the original and subsequent applications of certainty statements, particularly in dichotomous choice contingent valuation settings, respondents who are less certain about their choices are either dropped from the sample or their “yes” responses are recoded as “no” or status quo/opt-out choices prior to model estimation (e.g., Champ et al., 1997; Ethier, Poe, Schulze, & Clark, 2000; Norwood, 2005). Either way, all information indicating the preferences of these respondents is completely lost. Furthermore, the treatment of certainty scores in this manner is open to criticism since the selection of the cut-off points is arbitrary and has no theoretical basis (Ready et al., 2010). Blumenschein, Blomquist, Johannesson, Horn, and Freeman (2008) point out that the issue of the cut-off level of certainty at which a hypothetical decision corresponds to a real decision has not been resolved.

We avoid the above criticism by including all responses in model estimation in a second round of estimation. Instead of selecting a cut-off point for certainty scores and omitting or recoding all responses below the cut-off point, we use indicator variables for each level of certainty. The indicator variables are interacted with the cost attribute in model estimation. Previous literature indicates that respondents who are less certain about their choices are the source of HB. This implies that, on average, these respondents select alternatives that are more expensive than what they would choose in real payment situations. Therefore, in our application of the certainty statements, it is hypothesized that respondents with lower certainty scores are less sensitive to the cost attribute compared to respondents who are more certain. Different parameter estimates for the power bill are estimated for each level of certainty, where a sufficient number of observations are available, relative to the neutral score of 5 and below. This approach provides estimates of sensitivity to the cost attribute for each level of certainty score above 5 relative to 5 and below (uncertain), which allows for the estimation of a measure of reduction in HB in the WTP estimates for each level of certainty. The author is not aware of this approach being applied elsewhere in non-market valuation literature.

5.3 A brief review of the literature on attribute non-attendance and hypothetical bias

In this section we provide an overview of the literature on AN-A and HB in a number of contexts. Literature on AN-A and/or HB in the context of consumer switching in retail electricity markets is not currently available and this study makes a first contribution in this area.

In consumer choice models, a simple theory of decision making is assumed. Consumers are hypothesized to approach choice situations with a predefined algebraic utility function which defines how the observed attribute levels of an alternative will be integrated to form an overall evaluation of desirability (Johnson & Meyer, 1984). Each alternative in a choice set is evaluated independently and the consumer chooses the alternative with the highest expected utility. This assumes that consumers have the capacity to process all the information about the attribute levels describing each alternative. However, literature suggests that consumers have bounded rationality due to limited capacity to process information among other constraints, and that choices are likely to be made using a variety of strategies which are contingent upon the characteristics of the choice alternatives. In the next two subsections, we provide definitions of AN-A and HB and review relevant literature.

5.3.1 Attribute non-attendance

Although AN-A has been investigated in stated CEs conducted in the fields of transportation, non-market valuation, marketing and health, it is still relatively unexplored in the literature that investigates consumer preferences for the attributes of electricity services in energy markets. Typically, respondents in CEs are asked to make a series of choices from a set of two or more alternatives described in terms of attribute levels. Respondents are assumed to consider all the information presented in each scenario in making their choice decisions. However, evidence from previous studies suggests that respondents in CEs may ignore a subset of attributes when evaluating the alternatives in choice tasks for a number of reasons which are explored later (e.g., Hensher et al., 2005b; Scarpa et al., 2010). Scarpa et al. (2010) describe two types of AN-A which they call “serial AN-A” and “choice task AN-A.” Serial AN-A is the information processing strategy in which a respondent systematically ignores the same attribute(s) across all choice tasks, whereas choice task AN-A refers to a strategy in which AN-A varies from choice task to choice task. In this chapter we focus on the former.

AN-A implies non-compensatory behaviour which violates the axiom of continuity or the assumption of unlimited substitutability between the attributes of alternatives in a choice set. As indicated earlier, respondents in CEs are assumed to evaluate all the attributes of alternatives and make trade-offs between all attributes within and between alternatives in a choice set, and select the most preferred alternative (Hensher et al., 2005b). When respondents adopt non-compensatory behaviour, it is not possible to compensate for a reduction in the level of one attribute by increasing the level of one or more attributes if they are included in the subset of ignored attributes; that is, there is no trade-off between ignored attributes and those that are attended to (Lockwood, 1996; Saelensminde, 2002; Spash, 2000).

Non-compensatory behaviour creates a challenge for researchers as this behaviour results in discontinuous preference orderings that cannot be represented by a conventional utility function (Lancsar & Louviere, 2006). However, where respondents ignore an attribute because they are genuinely not willing to pay anything for a change in the attribute levels, the choices made are still a reflection of the true underlying preferences and theoretically do not violate the axiom of continuity. Whether respondents ignore an attribute or subset of attributes as a coping strategy or because they have zero WTP for the attribute(s), marginal rates of substitution can still be derived from the estimated parameters at the sampled population level but are not computable at an individual level for these respondents (Carlsson et al., 2010).

There is accumulating empirical evidence that suggests the assumption of unlimited substitutability is often violated in CEs as respondents adopt non-compensatory decision-making strategies to reduce the cognitive burden associated with processing information embedded within attributes defining alternatives in choice sets (e.g., Campbell et al., 2011; Campbell et al., 2008; Carlsson, Kataria, & Lampi, 2009; Hensher, 2008; Hensher et al., 2005b; Lockwood, 1996; Scarpa, Gilbride, et al., 2009). Reasons advanced for AN-A in

CEs include: that it results from a coping strategy involving ignoring specific attributes in an attempt to reduce the perceived complexity of the task; the cost of evaluating an attribute is perceived to be higher than the benefit; and irrelevance of some attributes to the choices being made (Hensher et al., 2005b).

Results from studies investigating AN-A suggest that it is important to investigate its impact on welfare estimates (see, Campbell et al., 2011; Hensher, 2008; Hensher & Rose, 2009; Hensher et al., 2005b; Hensher et al., 2012; Hole, 2011; Johnson & Meyer, 1984; Scarpa, Gilbride, et al., 2009; Scarpa et al., 2010). For example, Campbell et al. (2011), Hensher and Greene (2010), and Hole (2011) find that WTP estimates based on the assumption of complete evaluation of attributes are statistically different from those based on incomplete evaluation of attributes. Given these findings, ignoring AN-A in model estimation where the objective is to quantify the welfare effects of a policy change may result in potentially wrong policy implications. However, Carlsson et al. (2010) warn against the direct comparison of WTP estimates from models with and without restriction of ignored attribute parameters to zero. They argue that this could be misleading since WTP is the average WTP for the whole sample where AN-A is not controlled for, while it is the average for the conditional sample of respondents who attended to the attribute where AN-A is controlled for.

Studies that use stated AN-A assume that respondents do not vary their information processing strategies between alternatives and across all choice tasks (e.g., Campbell et al., 2008; Carlsson et al., 2009; Gracia, Barreiro-Hurle, & Perez y Perez, 2012; Hensher et al., 2005b). The implicit assumption in these studies is that respondents provide accurate responses about their information processing strategies. Since stated AN-A is based on recall, some respondents may find it hard to provide accurate responses. For example, Hess and Hensher (2010) find inconsistencies between stated AN-A and inferred AN-A. On the other hand, Campbell (2007), Carlsson et al. (2010), and Gracia et al. (2012) find evidence that not all respondents who claim to have ignored an attribute did so and argue that such respondents seem to have put less weight on the attributes they claim to have ignored, rather than completely ignoring them. Another approach of identifying AN-A involves inspecting the pattern of choices to find out if a respondent consistently chose the alternatives that were best with respect to a particular attribute (e.g., Lockwood, 1999; Saelensminde, 2002). Studies that use inferred AN-A analyze the observed choice response pattern using a statistical model with degenerate distributions of taste intensities at zero (Campbell et al., 2011; Hensher et al., 2012; Scarpa, Gilbride, et al., 2009). These models employ a latent class framework in which the utility function of an alternative takes into account the possibility, up to a probability, of an attribute being ignored (Scarpa, Gilbride, et al., 2009). Each latent class represents a specific attribute processing strategy that may have been adopted by respondents (Campbell et al., 2011). These attribute non-attendance classes are represented by specific restrictions imposes on the utility functions reflecting the hypothesized processing strategy for each class. The number of classes is based on the number of hypothesized attribute processing strategies, which is different from the normal use of latent class models that allows the number of classes to vary.

5.3.2 Hypothetical bias in stated choice experiments

Hypothetical bias is an important issue that researchers need to address when conducting CEs. Although a number of stated preference studies find significant differences between hypothetical and real WTP values in various contexts (e.g., Brownstone & Small, 2005; Champ & Bishop, 2001; Champ et al., 1997; Hensher, 2010; Isacsson, 2007; Ladenburg, Dahlgaard, & Bonnichsen, 2010; List et al., 2006), some find no significant differences (e.g., Carlsson & Martinsson, 2001; Carson et al., 1996; Lusk & Schroeder, 2004). A meta-analysis of HB by List and Gallet (2001), using values from 29 SP studies, finds that on average respondents in hypothetical experiments overstate their preferences by a factor of about 3. Little and Berrens (2004) expand on the previous study by including more studies and find similar results. In another meta-analysis of HB, Murphy, Allen, Stevens, and Weatherhead (2005) use data from 28 SP valuation studies and find calibration factors ranging from 0.6 to 10 but also find that choice-based elicitation mechanisms reduce HB. Hensher et al. (2005a) argue that since WTP is calculated as a ratio between two parameters, it is sensitive to the attribute-level ranges used in the estimation of both parameters and the differences in WTP from SP and RP data may be accounted for in part, if not entirely, by differences in attribute-level ranges used in both data sets.

There is no theory of HB; hence there is no agreed calibration method. However, the general consensus in the literature is that HB stems from the hypothetical nature of the choice questions, and a lack of salient economic commitment in some survey responses, which may be mitigated by careful design and implementation of SP surveys (Norwood et al., 2008). Although CEs are incentive compatible, some previous studies find that HB can exist in CEs surveys (e.g., List et al., 2006; Lusk & Schroeder, 2004). Empirical evidence suggests that respondents who are unsure whether they would pay a specified amount to secure an increase in the provision of a public good tend to say “yes” to a DC contingent valuation question (Ready et al., 2010). Therefore, respondents who are uncertain about their responses are identified as the source of HB.

Ex-ante and *ex-post* approaches have been adopted in previous SP studies to mitigate HB. *Ex-ante* mitigation is achieved through the careful design and implementation of the surveys, use of referendum format for the CVM, and reminding respondents of the budgetary constraints and the availability of substitutes before posing the valuation question (Arrow et al., 1993). Another approach uses “cheap talk” (CT) scripts which make respondents aware of the problem of HB before they are presented with the valuation question (Cummings & Taylor, 1999). Studies investigating the effectiveness of CT scripts have produced mixed results (Blumenschein et al., 2008).

Ex-post mitigation has been achieved through a debriefing approach developed by Champ et al. (1997) that uses certainty statements where respondents are asked to rate how certain they are of their choices on a 10-point Likert-type scale. Respondents who indicate low levels of certainty, usually below 7, are identified as the source of HB, and are either dropped from the sample used to estimate the model, or their “yes” responses are recoded as “no” responses (Champ & Bishop, 2001; Champ et al., 1997). However, there is no consensus on the cut-off point at which hypothetical decisions would correspond to real decisions. To overcome this problem, a variant of this approach uses only two categories of certainty and asks respondents to indicate whether they are “probably sure” or “definitely sure” about their choices (Blumenschein et al., 2008; Blumenschein et al., 1998).

5.4 Stated attribute non-attendance

In this section we address the first three parts of *Questions 2*:

(a) *Are non-price attributes of electricity services ignored in choice experiments on switching or supplier choice? If so, which attributes are ignored?*

(b) *Are attributes ignored individually or in combinations?*

(c) *Are the choice responses of respondents who claim to have ignored the cost attribute consistent with their claim? If not, how does this affect model fit and WTP estimates?*

We analyze responses to survey questions and provide a summary of self-reported AN-A, explore the effect of inconsistent stated non-attendance to the cost attribute (monthly power bill), and the effect of AN-A on model fit, class probabilities, and WTP estimates. Information on stated AN-A was elicited as part of the debriefing after the completion of the choice tasks. Respondents were asked to indicate, by ticking the appropriate boxes, which attributes, if any, they ignored in making their choices. An option for "None", indicating full attendance, was also provided to ensure that all respondents provided a response to the question. This is the information that we use in this section.

5.4.1 Analysis of stated attribute non-attendance responses

The distribution of stated AN-A to the attributes of electricity services is presented in Table 5-1. Of the 224 respondents who completed the choice tasks, only 26 (12%) reported having attended to all attributes. This means that only 12% of the respondents provided choice responses that satisfy the axiom of continuity which is assumed to hold when models are estimated from choice data without taking into account AN-A. The choices made by these respondents reflect full compensatory behaviour, i.e. complete trade-offs between the attributes of the alternatives and these respondents are therefore identified as having continuous preferences for the attributes of electricity services. The low level of full attendance (12%) achieved in this CE suggest that assuming full attendance in model estimation would be unreasonable. Although none of the respondents ignored all attributes and therefore made random choices, 88% (198) of the respondents ignored at least one attribute in making their choices, and are identified as having various degrees of discontinuous preferences.

Table 5-1: Share of respondents who ignored a specific attribute

Attribute ignored	Responses	%	Rank
Call waiting time (*Time*)	134	60%	1
Supplier type (*Supplier type*)	106	47%	2
Loyalty rewards (*Rewards*)	98	44%	3
100% New Zealand owned (*Ownership*)	92	41%	4
Electricity supplied from renewable sources (*Renewables*)	77	34%	5
Fixed rate guarantee (*Fixed*)	74	33%	6
Prompt payment discount (*Discount*)	27	12%	7
Monthly power bill (*Bill*)	15	7%	8
NONE	26	12%	
All	0	0%	
At least one attribute	198	88%	

The attribute least attended to is *Time,* which was ignored by 60% of the respondents followed by *Supplier type* and *Rewards* which were ignored by 47% and 44% of the respondents respectively. However these attributes were not mainly ignored individually but in combination with other attributes since only about 20% of the respondents ignored only one attribute (see Table 5-2). The attributes most attended to are *Bill*, *Discount,* and *Fixed,* which were ignored by only 7%, 12%, and 33% of the respondents respectively. It is interesting to note that these three attributes are the main attributes commonly used to describe standard electricity plans offered by electricity suppliers. Hence, it is not surprising that they are the most attended to as respondents are more likely to be familiar with making trade-offs between them.

Highest attendance to the *Bill* followed by *Discount* is consistent with an environment where respondents have been conditioned to switching supplier on the basis of savings which are calculated based on price and discount. Furthermore, attendance to the *Bill* is expected to be high since power bills constitute a significant proportion of personal incomes in New Zealand. For example the monthly power bill range of $150 to $350 used in the CE would be 32-61% of gross weekly income for respondents on the minimum wage ($14.25 per hour) and 14-32% of gross weekly income for respondents earning average income (27.55 per hour). It would therefore be unrealistic for respondents to ignore the monthly power bill in choosing their preferred supplier given that power bills are a long term commitment. The financial commitments implied in the choices made in the context of supplier choice are of a more indefinite nature compared to financial commitments in contexts where the payment is for a fixed period (typically 5-10 years for environmental conservation programmes).

Renewables was ignored by 34% of the respondents indicating that the majority of respondents (66%) considered the environment when switching or choosing their preferred supplier. This is lower than non-attendance rates ranging from 84% to 96% for renewable energy sources (wind, solar and biomass) reported in Gracia et al. (2012). At least 60% of the respondents considered both *Renewables* and the *Bill* in making their choices. This is in line with the findings of a study conducted by the Electricity Commission (2008) in which at least 50% of the respondents stated that they would consider the environment in choosing a retail electricity supplier and 17% stated they would ‘very seriously’ consider switching to a retailer which promotes itself as using renewable energy. *Ownership* is also a relatively important attribute as 59% of the respondents considered it in making their choices. This is consistent with TV3 polls which showed that 62% of New Zealanders were opposed to the sale of state-owned assets, which included energy companies (Garner, 2012).

Table 5-2 provides additional information on the proportions of respondents who ignored specific numbers of attributes. About 20% of the respondents ignored only one attribute whilst about 15%, 22% and 13% ignored 2, 3, and 4 attributes respectively. However, smaller proportions of respondents (less than 9% in each case), ignored 5, 6, or 7 attributes. Few respondents (6.7%) based their choices on a single attribute, i.e. ignored seven out of eight attributes. Respondents who based their choices on the levels of a single attribute have lexicographic preferences for the respective attributes or had difficulties evaluating multiple attributes and therefore adopted an extreme simplifying strategy of evaluating alternatives in terms of a single attribute. Only one respondent expressed lexicographic preferences for *Renewables* whilst 14 (6.3%) expressed lexicographic preferences for *Bill*. Lexicographic preferences for the cost attribute are not surprising given that power bills constitute a significant proportion of personal income in New Zealand. Responses from such respondents do not provide any information on trade-offs between the attributes describing the alternatives, hence the implicit marginal WTP estimates for non-price attributes cannot be calculated for these individuals. Although only a small share of respondents attended to all the attributes, most respondents (93%) attended to the cost attribute, which is important in the estimation of marginal WTP.

Table 5-2: Share of respondents who ignored a specific number of attributes.

Number of attributes ignored	Number of respondents	Percentage
0 (full attendance)	26	11.61
1	44	19.64
2	34	15.18
3	49	21.88
4	29	12.95
5	19	8.48
6	8	3.57
7	15	6.70
8 (all: random choices)	0	0.00

Table 5-3 provides a summary of shares of respondents who jointly considered each attribute with the cost attribute (*Bill*), and therefore provided responses that include trade-offs between each attribute and *Bill*. The least trade-offs were between *Time* and *Bill* (35.71%) followed by *Supplier Type* and *Bill* (47.32%). Higher trade-offs were made between *Discount* and *Bill* (83.04%), *Fixed* and *Bill* (63.84%), and *Renewables* and *Bill* (60.27%). This suggests that it would be possible to estimate WTP for each attribute. However, the high level of stated AN-A highlights the importance of investigating and accounting for AN-A in CEs rather than assuming full attendance.

We provide additional information on respondents who attended to specific combinations of attributes in Table 5-4. It shows that a fairly wide spread of attribute processing rules were used by respondents in making their choices. The results also indicate that where more attributes were attended to, *Bill* was unlikely to be ignored. Further analysis of AN-A rules is provided in section 5.5.

Table 5-3: Proportion of respondents attending to each attribute and jointly with *Bill*

Attribute	Attendance to attribute		Joint attendance to attribute and *Bill*	
	Number of respondents	%	Number of respondents	%
Time	90	40.18	80	35.71
Fixed	150	66.96	143	63.84
Discount	197	87.95	186	83.04
Rewards	126	56.25	116	51.79
Renewables	147	65.63	135	60.27
Ownership	132	58.93	121	54.02
Supplier Type	118	52.68	106	47.32

Table 5-4: Proportion of respondents attending to combinations of attributes

Attributes and combinations of attributes attended to	Number	%
Time, Fixed, Discount, Rewards, Renewables, Ownership, Supplier Type, Bill	26	11.61
Time, Fixed, Discount, Rewards, Renewables, Ownership, Supplier Type	4	1.79
Time, Fixed, Discount, Rewards, Renewables, Ownership, Bill	10	4.46
Time, Fixed, Discount, Rewards, Renewables, Ownership	0	0.00
Time, Fixed, Discount, Rewards, Renewables, Supplier Type	0	0.00
Time, Fixed, Discount, Rewards, Supplier Type, Bill	3	1.34
Time, Fixed, Discount, Bill	4	1.79
Fixed, Discount, Rewards, Renewables, Ownership, Supplier Type, Bill	17	7.59
Fixed, Discount, Renewables, Ownership, Bill	9	4.02
Fixed, Discount, Renewables, Bill	4	1.79
Discount, Renewables, Ownership, Bill	3	1.34
Fixed, Discount, Bill	5	2.23
Discount, Bill	4	1.79
Time, Fixed, Rewards, Renewables, Ownership, Supplier Type, Bill	0	0.00

5.4.2 How AN-A in this study compares with AN-A in other study contexts

A summary of AN-A across a number of studies estimating WTP in different contexts is presented in Table 5-5 to provide a contrast with the levels of non-attendance reported for this study. Although the share of respondents attending to all attributes is low in this study, it is within the range of other studies. However, the proportion of respondents ignoring the cost attribute is relatively small in this study. For example, in some studies the cost attribute is ignored by a relatively large proportion of respondents - as high as 60% in Campbell et al. (2011) - whilst attendance to all attributes may be as low as 1% as reported by Scarpa, Gilbride, et al. (2009). One possible explanation could be that the good in this study is closer to a private good while those of other studies are public goods.

A higher incidence of non-attendance to the cost attribute in studies dealing with environmental conservation or where rare species are involved may be explained in terms of respondents' protest against making trade-offs between money and environmental protection or respondents expressing their belief that the environment should be protected irrespective of cost (e.g., Lockwood, 1999). It should be noted that some of the AN-A rates presented in Table 5-5 are based on inferred AN-A and caution should be exercised when making comparisons between studies.

Possible reasons for the recorded rates of non-attendance for various attributes reported by respondents in this study may include: (1) unfamiliarity with making trade-offs between the attributes since only 21% of respondents have switched supplier before, and these may have switched on the basis of power bill savings as promoted by the WMN campaign; (2) some attributes may have been irrelevant or less important to some respondents, e.g., respondents who have never called their supplier may have found *Time* to be less important or irrelevant, hence the high incidence of non-attendance; and (3) choice task complexity, where some respondents might have found it difficult to process all the information in the decision-making process.

Table 5-5: Comparison of AN-A reported in previous studies.

Study	Country	Valuation Context (and model)	Ignored Cost	Attended to ALL	Most ignored attribute		Effect of accounting for AN-A on WTP
					Attribute	Share	
Carlsson et al. (2010)	Sweden	Environmental quality objectives (RPL)	24%	19%	Cost	24%	No difference
Campbell et al. (2008)	Ireland	Rural landscape improvements	31%	64%	Cost	31%	lower
Campbell et al. (2011)	Ireland	Rural landscape improvements* (LCM)	60%	3.3%	Cost	60%	lower
DeShazo and Fermo (2004)	Costa Rica	On-site services at a national park (MNL)	-	-	-	-	higher
Scarpa et al. (2009)	Ireland	Landscape* (LCM)	7%	1%	Farm tidiness	56%	Lower
Hensher and Rose (2009)	Australia	Choice of car routes (MNL)	-	-	-	-	higher
Hensher and Greene (2010)	Australia	Car travel** (LCM)	16&28%	54%	Running cost	28%	higher
Hensher et al. (2005b)	Australia	Travel time (RPL-EC)	-	-	Uncertainty of time	37%	lower
Hensher et al. (2012)	Australia	Car travel* (LCM)	27%	20%	Cost	27%	higher
Gracia et al. (2012)	Spain	WTP for renewable energy (RPL-EC)	18%	4%	Biomass	96%	higher
This study – Ndebele (2015)	New Zealand	Choice of retail electricity supplier	7%	12%	Time	60%	higher (lower for Discount and Fixed)

*Estimates are based on inferred attribute non-attendance, **Study includes common-metric attribute processing strategies, - Not provided

The next two sections specifically address research *Question 2(c): Are the choice responses of respondents who claim to have ignored the cost attribute consistent with their claim? If not, how does this affect model fit and WTP estimates?*

5.4.3 Consistency of stated non-attendance with observed choices

We consider whether respondents who state non-attendance to an attribute make choices that are consistent with their claim. Stated AN-A may be subject to reporting error and we explore possible errors or inconsistent responses by analysing the choices of respondents who claimed to have ignored the cost attribute to see if their choices are consistent with their claims. Responses of all respondents who claimed to have ignored the monthly power bill (*Bill*) are analysed and the frequency of selecting the cheapest alternative is recorded for each respondent. The results of this analysis are presented in Table 5-6.

Table 5-6: Characteristics of respondents who ignored the cost attribute

ID	Gender	Age	Income ($000)	Ethnicity	Education	Most recent power Bill	Occasions cheapest alternative selected
17	male	32	$22.5	Asian	Masters	200	91%
32	male	65+	-	Asian	Masters	100	91%
48	female	62	22.5	NZ Euro	High School	300	27%
58	male	65+	$22.5	NZ Euro	High School	300	82%
60	female	32	$45.0	NZ Euro	Diploma	60	18%
79	female	57	<$15.0	Other	High School	200	82%
80	male	32	$45.0	NZ Euro	Bachelors	200	55%
88	male	47	$45.0	NZ Euro	Diploma	200	64%
89	male	57	$60.0	NZ euro	High School	300	64%
95	male	47	$22.5	Other	Bachelors	100	82%
109	male	65+	$45.0	Maori	Trades	200	64%
153	female	27	$22.5	NZ Euro	High School	200	91%
169	male	42	$35.0	Other	Bachelors	200	82%
206	male	22	$60.0	NZ Euro	High School	200	82%
210	male	22	<$15k	Asian	High School	200	55%

Respondents stating that they ignored *Bill* are predominantly male (73%), and all ethnic groups are represented although Maori is the least represented (7%). Of the

15 respondents who indicated non-attendance to *Bill*, 13 (87%) are in the low income bracket and it is unrealistic to expect these respondents to ignore the cost of electricity in their choice of electricity supplier. One of the low income respondents, a male aged 65+ with a high school level of education (ID58) selected the status quo alternative throughout, which incidentally offers a lower level for power bill ($250) than his most recent power bill ($300) but does not offer the lowest level for *Bill* in all cases. Given this respondent's age and low level of education, and that none of the alternatives presented in the choice tasks had a power bill level higher than his most recent power bill, the selection of the status quo alternative is consistent with satisficing behaviour in which the information processing strategy is to select the first alternative that reaches a certain minimum threshold and therefore avoid a complete trade-off which violates the strict assumption of utility maximisation. An alternative explanation might be that he did not take the survey seriously since the level of the power bill was lower than his most recent power bill 75% of the time as our ED had attribute level balance.

A female respondent aged 32 years (ID60) with an annual income of $45,000 selected the alternative offering the lowest price 18% of the time. Her most recent power bill is $60 which is only 40% of the lowest attribute level for monthly power bill of $150 used in the experimental design. Since all the levels offered for the power bill in all alternatives and choice situations are above the respondent's monthly power bill, the cost element may have been viewed as unrealistic and thus ignored in choice selection. Another female respondent aged 62 (ID48) with an annual income of about $22,500 and only high school education selected the status quo eight times out of twelve. As in the case of respondent (ID58), the status quo power bill of $250 was lower than her most recent power of $300. She only selected the alternative with the lowest cost only 27% of the time, which incidentally represents the four occasions when she did not select the status quo. When other respondents' choices are analysed, no compelling evidence is found to suggest that they ignored the cost attribute; in fact the evidence suggests that the cost element may not have been ignored all the time as the least expensive alternative was selected on average 72% of the time. On the whole, the evidence seems to suggest that, in the main, the majority of respondents reporting non-attendance to the monthly power bill may have actually considered the attribute in making their choices. This suggests possible reporting errors by some respondents.

We compare the characteristics of respondents who ignored the cost attribute to those who considered it; the average statistics are presented in Table 5-7. It is interesting to note that compared to respondents who attended to the cost attribute, the group who ignored it has a larger proportion of men, lower average age and income, and higher reported most recent power bills. Respondents who ignored the cost attribute are less likely to have switched electricity supplier in the past two years compared to those who attended to it. The lower likelihood of switching may be explained by this group's indifference to the cost, which has been used as a major tool in promoting switching. The group also consists of a large proportion of 'Other' ethnic group and a lower proportion of NZ-Europeans. However an ANOVA test for differences in the means of the two groups shows that the only significant differences at the 0.05 level are gender and ethnicity.

Table 5-7: Characteristics of respondents who ignored or considered the cost attribute

Characteristics		Ignored power Bill (n = 15)	Attended to power Bill (n = 209)	Test for differences between groups (p-values)
Gender (male)		73%	45%	0.0336
Average Age (years)		44	45	0.8523
Average Income (ZN$$_{000}$)		38	45	0.3045
Education (post high school)		60%	61%	0.9535
	NZ-European	47%	79%	0.0033
Ethnicity	Maori	7%	4%	0.6706
	Other	47%	16%	0.0031
Switched supplier in the past 2 years		7%	22%	0.1601
Most recent power bill (NZ$)		183	173	0.6249

5.4.4 The effect of inconsistent stated attribute non-attendance on model estimation

To investigate the possible effects of inconsistent stated AN-A to the cost attribute, we estimate three LC models and compare the pattern of significant parameters, model fit, and class membership probabilities across the models. For the first model (M0) we use the original data and ignore all stated non-attendance; that is, we assume full compensatory behaviour or unlimited substitutability between the attributes. In the second model (M1) we use data that is coded to account for stated AN-A for all attributes, and in the third model (M2) we ignore all stated AN-A to the cost attribute whilst preserving stated AN-A for the other attributes.

For each model we progressively increase the number of classes, noting the pattern and signs of significant parameters, and model fit until the model fails to converge at least once. M1 and M2 failed to converge when the number of classes was set at six or seven and we terminated the search. M0 converges beyond five classes but we terminate the search as the number of insignificant parameters including class probabilities increased. Based on all the information criteria, M0 performs best followed by M2 for the estimated models with up to five classes. However, two classes (1 and 5) in M0 have insignificant parameters including class probabilities; hence M2 is the best model in terms of identifying segments with distinct preferences. This suggests that correcting for inconsistent stated AN-A improves model fit since M2 performs better than M1 throughout.

Determination of the number of latent classes

To determine the number of classes to retain in our final models we use the information criteria discussed in Chapter 2. The use of the likelihood ratio test (LRT) statistic to determine the number of classes is problematic because it does not allow the number of latent classes to be separated as its distribution is unknown and may not follow a χ^2 (McLachlan & Peel, 2000; Yang & Yang, 2007). The disadvantage of using information criteria is that they do not produce a number that quantifies the confidence in the results, such as a p-value.

Table 5-8 presents the criteria used to determine the number of classes. The bolded values indicate the minimum normalised information criteria for each model. All information criteria are normalised by dividing the values for each by the number of observations (2688). For all the models, the LL, AIC and crAIC indicate the presence of up to five latent preference classes. However, M0 has two classes in which all parameters including class probabilities are insignificant, suggesting overfitting (see Table 5-9). Although the class probabilities for M1 and M2 are all significant at the 0.05 level, the models appear to be over-parameterized. For example, very large standard errors are observed in some classes and the parameter for *Bill* is insignificant in one of the classes in both models. Retaining four classes is also problematic since class 3 probability is insignificant at the 0.05 level in M2 and two classes (3 and 4) have insignificant parameter estimates for the design attributes. In the latter case, no discernible differences in preferences between the two classes exist.

The AIC3, CAIC, BIC and HQC indicate the presence of up to three classes across the three models. In this case LL, AIC and crAIC clearly exhibit the tendency to over-fit or over-parameterize the models as suggested in the literature. We observed that as more than three classes are estimated for each model, the number of insignificant parameters increases. Where a latent class model has two or more classes with no significant parameters, it is not clear how preferences differ across these classes and WTP estimates may not be estimated. Thus, based on AIC3, CAIC, BIC and HQC, we retain only three classes for the three models.

The performance of the AIC3, CAIC, BIC and HQC in this study is consistent with findings from simulation studies investigating the performance of these criteria (e.g., Andrews & Currim, 2003a; Lin & Dayton, 1997; Yang & Yang, 2007).

Table 5-8: Information criteria used to determine the number of classes

Classes (pars)[1]	*lnL(LL)*			AIC			crAIC			AIC3			CAIC			BIC			HQC		
	M0	*M1*	*M2*	*M0*	*M1*	*M2*	*M0*	*M1*	*M2*	*M0*	*M1*	*M2*	*M0*	*M1*	*M2*	*M0*	*M1*	*M2*	*M0*	*M1*	*M2*
1 (11)	-2157	-2190	-2166	1.61	1.64	1.62	1.61	1.64	1.62	1.62	1.64	1.62	1.64	1.67	1.65	1.64	1.67	1.64	1.62	1.65	1.63
2 (23)	-1873	-1928	-1902	1.41	1.45	1.43	1.41	1.45	1.43	1.41	1.46	1.44	1.43	1.51	1.49	1.46	1.50	1.48	1.43	1.47	1.45
3 (35)	-1701	-1798	-1765	1.29	1.36	1.34	1.29	1.36	**1.34**	**1.30**	1.38	**1.35**	**1.38**	**1.45**	**1.43**	**1.37**	**1.44**	**1.42**	**1.32**	1.39	**1.37**
4 (47)	-1678	-1756	-1746	**1.28**	1.34	1.33	**1.28**	1.34	1.34	1.30	1.36	1.35	1.40	1.46	1.45	1.38	1.45	1.44	1.32	**1.38**	1.37
5 (59)	-1663	-1731	-1709	1.28	**1.33**	**1.32**	1.28	**1.33**	132	1.30	**1.35**	134	1.43	1.48	147	1.41	1.46	1.45	1.33	1.38	1.36
6 (71)	M1 & M2 failed to converge, M0 converged but 4 classes have insignificant parameters - search terminated																				
7 (83)	M1 and M2 failed to converge																				

[1]Denotes the number of parameters in the model

Table 5-9: Class probabilities

Classes		class 1	2	3	4	5	Comments
2	M0	0.60^{c}	0.40^{c}				
	M1	0.65^{c}	0.35^{c}				
	M2	0.62^{c}	0.38^{c}				
3	M0	0.48^{c}	0.41^{c}	0.11^{c}			
	M1	0.56^{c}	0.36^{c}	0.08^{c}			
	M2	0.53^{c}	0.36^{c}	0.11^{c}			
4	M0	0.48^{c}	0.41^{c}	0.02^{b}	0.09^{c}		class 3: all β's = 0, class 4: only ASC & *Bill* are significant
	M1	0.51^{c}	0.08^{c}	0.17^{c}	0.24^{c}		class 2: large standard errors for some parameters
	M2	0.53^{c}	0.32^{c}	0.04^{a}	0.11^{c}		class 3: all β's = 0; class 4: β's = 0 except ASC at 10%
5	M0	0.21	0.30^{c}	0.13^{c}	0.28^{c}	0.08	class 1: all β's = 0, class 5: all β's = 0
	M1	0.48^{c}	0.27^{c}	0.10^{c}	0.07^{c}	0.08^{c}	class 4: $\beta_{\_Bill}$ is insignificant; large s.e's in class 5
	M2	0.38^{c}	0.03^{c}	0.14^{b}	0.34^{c}	0.11^{c}	class 2: $\beta_{\_Bill}$ is insignificant
6 & 7	M1 & M2 failed to converge; M0 converged but 4 out of 6 classes have insignificant parameters						

^{c}, ^{b}, ^{a} Significant at .01, .05, and .1 level, respectively

Regression results

Results for the three models M0, M1 and M2 are presented in Table 5-10. The models are all statistically significant based on the Chi-square, and fit the data very well with pseudo-R^2 values ranging from 0.3913 for M1 to 0.4239 for M0. Hensher et al. (2005a, p. 338) argue that "a pseudo-R^2 value of 0.3 represents a decent model fit for a discrete choice model. …… In fact pseudo-R^2 values between the range of 0.3 and 0.4 can be translated as an R^2 of between 0.6 and 0.8 for the linear model equivalent." All significant parameters have the expected signs except the parameter for *Well-known non-electricity company,* which is positive for classes 1 and 3 in M0 and M1 respectively. A positive parameter for this variable implies that respondents in these classes prefer a well-known non-electricity company to a traditional electricity supplier – a possible and not worrisome outcome given the small class size in M1 and the fact that the parameter is only significant at the 10% level in the respective class in M0. This group represents consumers who are likely to consider buying electricity from one of their well-known companies; perhaps those currently providing good services in areas such as telecom, insurance, and fuel etc., and would provide bundled services if they entered the retail electricity market.

As indicated earlier, M0 performs best in terms of all IC and pseudo-R^2. Although all three models identify three latent classes with clearly distinct preferences, for some attributes, preferences differ between the same classes across the three models. For example, class 1 differs across the models in terms of SQ effects and preferences for *Renewables* and *Well-known electricity company*, and class 2 differs in terms of SQ effects and preferences for fixed term price guarantee, while class 3 differs in terms of preferences for *Discount* and *Well-known non-electricity company*. In all three cases each parameter is insignificant in one or two models. It should be noted that this comparison is only in terms of significant versus insignificant parameter estimates as absolute values across the models are not directly comparable. WTP estimates, which are directly comparable across classes and models, will be used in the next section to test for differences across the models.

The fact that M0, an unrestricted model, performs better than the other two models with restricted parameters for ignored attributes may not be surprising given the data requirements for estimating large numbers of parameters in latent class models and the relatively small sample size used in this analysis. However, M2 produces significant parameter estimates that are consistent with *a priori* expectations and is the preferred model.

Class probabilities differ across the models. When AN-A is accounted for in model estimation, we observe a redistribution of probability mass from classes 2 and 3 to class 1. Comparing M1 and M2, the net effect of correcting for inconsistent stated AN-A to the power bill in model estimation is a redistribution of the probability mass (about 6%) away from class 1. As a result, classes 2 and 3 are larger in M2 than in M1 by about 2% and 41%, respectively, whilst class 1 is smaller by about 6%. In the next section we provide a test for differences in class probabilities across the models.

Table 5-10: Latent class model results (z-values are in parentheses)

Variables	M0 (original data)			M1 (data coded for AN-A)			M2 (Corrected inconsistent AN-A)		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
ASC_{SQ}	1.4315	0.0834	2.8755	0.0276	0.2792	6.758	0.4295	0.0858	3.1274
	(2.56)	(0.56)	(5.22)	(0.18)	(2.31)	(4.14)	(2.26)	(0.69)	(6.13)
Time (minutes)	-0.0350	-0.0253	-0.0142	-0.0507	-0.0369	-0.0595	-0.0433	-0.0401	-0.0501
	(-1.53)	(-3.62)	(-0.51)	(-3.39)	(-3.39)	(-0.72)	(-2.33)	(-3.37)	(-1.24)
Fixed Term (months)	0.0092	0.0054	-0.0228	0.0086	0.0027	-0.0388	-0.0032	0.0111	-0.0073
	(0.89)	(1.72)	(-1.67)	(1.58)	(0.69)	(-1.14)	(-0.50)	(2.65)	(-0.53)
Discount	-0.0421	0.0122	0.0621	0.0017	0.0211	0.0081	-0.0034	0.0159	0.0539
	(-1.49)	(3.08)	(3.04)	(0.34)	(4.58)	(0.18)	(-0.54)	(3.60)	(2.77)
Loyalty Rewards	0.9639	0.1709	0.3693	0.2680	0.4729	1.8706	0.3344	0.3740	0.4587
	(1.96)	(2.11)	(1.07)	(2.07)	(3.81)	(1.87)	(2.13)	(3.13)	(1.15)
Renewables	-0.0249	0.0129	0.0068	0.0129	0.0120	-0.0049	0.0051	0.0141	0.0031
	(-1.57)	(8.86)	(1.10)	(4.11)	(5.80)	(-0.33)	(1.24)	(7.54)	(0.46)
NZ Ownership	0.0214	0.0124	0.0017	0.0068	0.0098	0.0479	0.0093	0.0107	0.0060
	(3.11)	(6.61)	(0.17)	(2.67)	(4.31)	(1.86)	(3.16)	(4.97)	(0.59)
New Electricity Company	-0.5268	-0.2267	-0.5133	0.3436	-0.1265	1.6420	0.0052	-0.1110	-0.4803
	(-1.29)	(-1.84)	(-1.02)	(1.74)	(-0.79)	(1.25)	(0.03)	(-0.70)	(-0.83)
New Non-Electricity Company	0.9089	-0.5556	-1.0093	-0.4228	-0.7645	1.4508	-0.4168	-0.7633	-1.3865
	(1.08)	(-3.71)	(-1.49)	(-1.77)	(-3.94)	(0.94)	(-1.43)	(-3.98)	(-1.65)
Well-Known Non-Electric Company	2.0949	-0.2356	-0.6637	-0.2686	-0.3610	2.8896	-0.0192	-0.4095	-0.3784
	(1.71)	(-1.59)	(-1.18)	(-1.13)	(-2.06)	(1.99)	(-0.62)	(-2.35)	(-0.73)
Monthly Power Bill	-0.1024	-0.0182	-0.0143	-0.0546	-0.0145	-0.0339	-0.0581	-0.0139	-0.0126
	(-5.36)	(-11.00)	(-2.04)	(-16.44)	(-8.48)	(-2.07)	(-12.71)	(-8.20)	(-2.00)
Probability of Class	0.4769	0.4089	0.1141	0.5575	0.3581	0.0844	0.5244	0.3637	0.1119
	(11.87)	(10.24)	(5.27)	(13.24)	(8.68)	(4.53)	(11.83)	(8.14)	(5.03)
AIC		3472.5			3665.2			3600.1	
BIC		3678.9			3871.6			3806.5	
McFadden Pseudo-R^2		0.4239			0.3913			0.4023	
Chi-square (35 d.f.)	2503.67 (p-value = .00001)			2310.89 (p-value = .00001)			2376.04 (p-value = .00001)		

Willingness to pay

Our main interest is how correcting for inconsistent stated AN-A to the power bill attribute influences WTP estimates and class probabilities or market segmentation. We compare WTP estimates and class probabilities between the models (e.g., M1 versus M2) to determine the effect of correcting for inconsistent stated AN-A, and M0 versus M2 to determine the influence of accounting for AN-A in model estimation. The average marginal WTP estimates and the asymptotically normal test statistic (ANTS) results are presented in Table 5-11.

Respondents in class 1 in M1 and M2 have a negative preference for call waiting time (*Time*) while those in M0 are indifferent. Recall that *Time* was the most ignored attribute, with 60% of respondents ignoring it. It would appear that accounting for non-attendance allows for greater precision in estimating the parameter and hence WTP for this attribute. Where WTP for an attribute is significant in class 1 across all the models (e.g., *Rewards* and *Ownership*), estimates obtained from M0 are higher compared to the other models. The opposite is true for class 2 in the case of *Time, Discount, Rewards, Renewables* and *New Non-Electricity Company*. However, WTP estimates are generally higher in M2 compared to M1 and M0, particularly for class 2. For example, class 2 WTP estimates for all attributes except *Discount* and *Rewards* are between 1.04 and 1.22 times higher in M2 compared to M1, and between 1.13 and 2.86 times higher in M2 compared to M0, except *Fixed* and *New Electricity Company*.

Tests for differences in the estimated marginal WTP estimates reveal significant differences in some estimates across the three models. The last four columns in Table 5-11 report the results (absolute values) of the ANTS. The bolded values indicate significant differences at the 95% confidence level (values greater than 1.96 indicate significant differences). A conclusion that may be drawn from these results is that correcting for inconsistent self-reported AN-A to the cost attribute in model estimation has a significant effect on WTP estimates, class probabilities, significance and signs of parameters for some attributes in this study. The implication for researchers is that it may be worthwhile investigating inconsistences in self-reported AN-A, particularly for the cost attribute as its coefficient is key in estimating marginal WTP for non-price attributes.

Table 5-11: Estimates of WTP for the attributes of electricity services (NZ$$_{(2014)}$)

	M0 (original data)			M1 (data coded for AN-A)			M2 (Corrected inconsistent AN-A)			| ANTS | M1 vs M2		| ANTS | M0 vs M2	
Attribute	Class1	Class2	Class3	Class1	Class2	Class3	Class1	Class2	Class3	Class1	Class2	Class1	Class2
Time	NS	-1.39^{c} (0.38)	NS	-0.93^{c} (0.27)	-2.55^{c} (0.81)	NS	-0.74^{b} (0.32)	-2.88^{c} (0.93)	NS	1.08	0.73	**2.31**	1.76
Fixed	NS	NS	NS	NS	NS	NS	NS	0.80^{b} (0.34)	NS	0	**3.03**	0	**2.33**
Discount	NS	0.67^{c} (0.24)	NS	NS	1.45^{c} (0.40)	NS	NS	1.15^{c} (0.38)	NS	0	**2.41**	0	1.61
Rewards	9.41^{b} (4.50)	9.38^{b} (4.36)	NS	4.91^{b} (2.39)	32.61^{c} (8.86)	NS	5.75^{b} (2.69)	26.88^{c} (8.86)	NS	0.67	**36.24**	1.01	**2.27**
Renewables	NS	0.71^{c} (0.10)	NS	0.24^{c} (0.06)	0.83^{c} (0.17)	NS	NS	1.01^{c} (0.18)	NS	**3.41**	**2.98**	0	**1.99**
Ownership	0.21^{c} (0.05)	0.68^{c} (0.09)	NS	0.12^{c} (0.05)	0.68^{c} (0.15)	1.41^{c} (0.63)	0.16^{c} (0.05)	0.77^{c} (0.15)	NS	**2.60**	**2.33**	**6.25**	0.69
New electricity company	NS	-12.93^{a} (6.48)	NS	6.30^{a} (3.57)	NS	NS	NS	NS	NS	**22.34**	0	0	1.92
New non-electricity company	NS	-30.48^{c} (8.12)	NS	-7.75^{a} (4.41)	-52.72^{c} (14.40)	NS	NS	-54.88^{c} (14.68)	NS	0.23	0.76	0	**2.00**
Well-known non-electricity company	20.45^{b} (8.85)	NS	NS	NS	-24.90^{b} (12.06)	NS	NS	-29.44^{b} (12.76)	NS	0	1.09	**2.31**	**2.31**
Segment size	47.7%	40.9%	11.4%	55.8%	35.8%	8.4%	52.4%	36.4%	11.2%	**2.40**	0.32	**6.39**	**4.95**

Values in parentheses are the standard errors. ANTS for class 3 probabilities are 2.27 and 2.70 for M1 vs. M2 and M0 vs. M2 respectively

5.4.5 Alternative approaches for accounting for stated AN-A in model estimation

In this section we use the MNL and RPL-EC models to analyze the data and extend the analysis carried out in the previous section by applying different approaches to accounting for stated AN-A in model estimation. The main objective is to examine and contrast the effect of adopting the alternative approaches on model fit and WTP. This addresses research *Question 2(d, e) [(d) Do preferences of respondents who ignore an attribute differ from those who consider it? (e) What are the effects of attribute non-attendance on WTP?]*, and contributes to the debate on the unresolved methodological issue of how the parameters of ignored attributes should be treated in model estimation.

For each model, three specifications for the utility functions of alternatives in a choice set are used. The first specification ignores all stated AN-A and the utility functions of the alternatives assume full attendance to the attributes (full compensatory behaviour). This specification implies that all the attributes used to describe the alternatives are relevant to all respondents. The specification for the utility of an alternative for the MNL and RPL-EC models is the same as specified in Chapter 2, except that the subscript *s* indicating choice task is omitted as we assume that the attribute processing rule is the same in all choice tasks. For models MNL1 and RPL1, the respective utility specifications for alternative *i* and for respondent *n* are:

$$U_{in} = \sum_k \beta_k X_{ikn} + \varepsilon_{in} \qquad (5\text{-}1)$$

$$U_{in} = \sum_k \beta_{nk} X_{ikn} + \alpha_{sq} + \mu_n' z_{in} + \varepsilon_{in}\,, \; i = SQ, Supplier\ A, Supplier\ B$$

where α_{sq} equals zero for non-status quo alternatives and $\mu_n' z_{in}$ is zero for the status quo (SQ) alternative (Brownstone & Train, 1999).

Following Hensher et al. (2005b) and Scarpa, Gilbride, et al. (2009), the second specification explicitly accounts for stated AN-A in the utility functions of the alternatives by restricting the parameters of ignored attributes to zero. The reason for assigning a zero weight for the taste intensities of attributes that are ignored by respondents is that the levels of these attributes did not influence the choices made. Although assigning zero weights to the parameters of ignored attributes is equivalent to assigning zero levels for these attributes, it does not necessarily imply zero marginal WTP for these attributes. Respondents may have ignored these attributes because the benefit of full evaluation of the specific attributes is perceived to be less than the cost of evaluation (Carlsson et al., 2010; Hensher et al., 2005b). For models MNL2 and RPL2, the respective utility functions may be expressed as:

$$U_{in} = \sum_k (\delta_k \beta_k) X_{ikn} + \varepsilon_{in}$$
$$U_{in} = \sum_k (\delta_k \beta_{nk}) X_{ikn} + \alpha_{sq} + \mu_n' z_{in} + \varepsilon_{in}\,, \qquad (5\text{-}2)$$

where δ_k is a dummy indicating attribute-processing rule and takes a value of 1 if attribute *k* is attended to and zero if it is ignored.

The third specification allows for the testing of differences in preferences between respondents who attended to specific attributes and those who ignored them. This addresses research *Question 2(d)*. We did not apply this specification to the latent class model estimated in the previous section because the model captures heterogeneity of preferences and any differences in preferences between respondents who attend to an attribute and those who do not are already captured in the latent classes. Following Carlsson et al. (2010) and Gracia et al. (2012), we create a dummy variable for each attribute indicating whether or not an attribute was ignored and include it in the utility function as an interaction with the levels of the respective attribute. We specify the utility function of an alternative for MNL3 and RPL3 models respectively as:

$$U_{in} = \sum_k \beta_k X_{ikn} + \sum_k \gamma_k d_k X_{ikn} + \varepsilon_{in}$$
$$U_{in} = \sum_k \beta_{nk} X_{ikn} + \sum_k \gamma_{nk} d_k X_{ikn} + \alpha_{sq} + \mu_n' z_{in} + \varepsilon_{in}\,, \qquad (5\text{-}3)$$

where, d_k is a dummy variable which takes a value of 1 if an attribute is not attended to and zero otherwise, and γ_{nk} is respondent *n*'s taste intensity for the ignored k^{th} attribute.

A significant parameter estimate of the interaction term indicates significant differences in preferences between those who attended to the attribute and those who ignored it. On the other hand, an insignificant parameter estimate suggests that respondents who ignored an attribute and those who attended to it have similar preferences for the attribute (Carlsson et al., 2010; Gracia et al., 2012). This provides a test for the hypothesis that preferences for specific attributes differ between respondents who ignored the attributes and those who considered them. Alternatively it provides a test for whether or not the taste intensities or parameter estimates of ignored attributes are equal to zero.

An alternative to the above approach, in the case of the RPL-EC model, is to establish whether attendance or non-attendance is systematically linked to heterogeneity across respondents by specifying the mean and standard deviations of each random parameter as functions of a dummy variable indicating non-attendance (Campbell et al., 2008; Hensher et al., 2005b).

Regression results

The models estimated here correspond to the respective indirect utility specifications in equations (5-1) to (5-3). All RPL-EC models are estimated with simulated maximum likelihood using 300 Halton draws, which display better equi-dispersion properties than random draws (Hensher et al., 2005a; Train, 2009). Train (2009) provides a detailed discussion of simulated maximum likelihood and Halton draws. To determine which parameters are specified as random, a series of preliminary estimations were conducted. Only parameters with significant standard deviations were specified as random with normal distribution assumed in the final model. We follow a common practice in similar studies and specify the parameter for the cost attribute (monthly power bill) as fixed to avoid the complications associated with estimating WTP as a ratio of two distributions (e.g., Goett, 1998; Revelt & Train, 2000).

A summary of the results for the MNL and RPL-EC models is presented in Table 5-12. The estimated models fit the data well with pseudo-R^2 values ranging from 0.263 to 0.382 for MNL2 and RPL3 respectively. All three specifications of the RPL-EC model outperform the MNL models based on the likelihood ratio test (LRT), LL, AIC, BIC and pseudo-R^2. For example, the worst-performing RPL-EC model (RPL2) performs better than the best-performing MNL (MNL3) based on an LRT statistic of 379.6 which is greater than the critical $\chi^2_{(5,\ 0.05)}$ value of 11.07.

Table 5-12: Regression results for the MNL and RPL-EC models of supplier choice

Attribute	MNL1	MNL2	MNL3	RPL1	RPL2	RPL3
ASCALT1	0.7221[c]	0.5152[c]	0.7627[c]	0.3315[a]	0.6690[c]	0.5250[c]
Time	-0.0236[c]	-0.0484[c]	-0.0399[c]	-0.0348[c]	-0.0541[c]	-0.0486[c]
Fixed	0.0063[c]	0.0030	0.0049[b]	0.0050[a]	0.0057	0.0041
Discount	0.0110[c]	0.0083[c]	0.0117[c]	0.0150[c]	0.0105[c]	0.0162[c]
Rewards	0.1226[b]	0.4175[c]	0.3618[c]	0.1399[b]	0.3628[c]	0.2814[c]
Renewables	0.0085[c]	0.0091[c]	0.0103[c]	0.0133[c]	0.0130[c]	0.0160[c]
Ownership	0.0036[c]	0.0068[c]	0.0077[c]	0.0087[c]	0.0090[c]	0.0166[c]
New electricity company	-0.0942	-0.2758[c]	-0.2816[c]	-0.4157[c]	-0.1879	-0.5355[c]
New non-electricity company	-0.3516[c]	-0.7243[c]	-0.5868[c]	-0.9448[c]	-0.8737[c]	-1.1056[c]
Well-known non-electricity company	-0.1911[a]	-0.4981[c]	-0.3647[c]	-0.7366[c]	-0.5803[c]	-0.8576[c]
Monthly power Bill	-0.0252[c]	-0.0252[c]	-0.0264[c]	-0.0370[c]	-0.0333[c]	-0.0383[c]
ERC				0.0 (Fixed Parameter)		
Ignored attributes						
Time			0.0271[c]			0.0244[b]
Fixed			0.0051			0.0013
Discount			-0.0058			-0.0151
Rewards			-0.5388[c]			-0.2862[b]
Renewables			-0.0046[b]			-0.0082[c]
Ownership			-0.0108[c]			-0.0164[c]
New electricity company			0.4292[c]			0.2393
New non-electricity company			0.4974[c]			0.3116
Well-known non-electricity company			0.4163[c]			0.2204
Monthly power Bill			0.0078[c]			0.0125[c]
Standard deviations of random parameters						
Fixed				0.0166[c]	0.0275[c]	0.0159[c]
Discount				0.0215[c]	0.0191[c]	0.0146[b]
Renewable				0.0105[c]	0.0149[c]	0.0087[c]
Ownership				0.0178[c]	0.0169[c]	0.0140[c]
Ignored_Discount						0.0227[a]
Ignored_Renewable						0.0087[c]
Ignored_Ownership						0.0141[c]
ERC (σ)				1.8714[c]	1.7707[c]	2.0712[c]
Model fit						
K (number of parameters)	11	11	21	16	16	28
LL	-2156.7	-2165.6	-2103.6	-1849.4	-1913.8	-1826.0
AIC	4335.3	4353.1	4249.1	3730.9	3859.6	3708.1
BIC	4400.2	4418.0	4373.0	3825.2	3954.0	3873.2
Psuedo-R^2	0.266	0.263	0.284	0.3737	0.352	0.382

[c], [b], [a] Significant at the .01, .05, and .1 level, respectively.

All the estimated parameters have the expected signs confirming our prior beliefs about the marginal effects of the respective attributes on choice probabilities. Furthermore, the signs of all parameters are consistent across all models. Another noticeable consistency across the models is the positive and significant constant for the SQ which reveals significant preference for the SQ in the sampled population. The SQ represents a traditional incumbent retailer which is used as a base for supplier type. The negative coefficients of the other three supplier types imply that on average, customers prefer the traditional supplier to other types, which is consistent with the findings of Goett et al. (2000). Although the parameter for *Fixed* is insignificant at the .05 level across the three RPL-EC models, its standard deviation is highly significant, indicating heterogeneity of preferences for this attribute. The estimated standard deviation (σ) of the error component (ERC) is significant at the .01 level in all the RPL models which lends support to the indirect utility specifications with an error component for the mixed logit model in equations (5-1) to (5-3). The estimated total unobserved component of utility associated with the experimentally designed alternatives gives a total variance ($\sigma^2+\pi^2/6$) which ranges from 3.66 to 4.81 for RPL2 and RPL3 respectively.

The significance of the parameters indicates that on average all the attributes used in the experimental design were relevant to the choices made. The parameter estimate for the cost attribute (monthly power bill or *Bill*) is important given the objective of estimating and comparing WTP for the attributes of electricity services. This parameter is significant at the .01 level and has the expected negative sign, which allows for the estimation of meaningful WTP estimates. Recall that we assumed a fixed parameter for the cost attribute. We acknowledge that assuming a fixed parameter for this attribute could result in biased estimates where there is significant heterogeneity of tastes for the attribute.

Restricting parameter estimates for the attributes that respondents claimed to have ignored to zero reduces model fit in both MNL2 and RPL2 compared to the respective unrestricted models estimated with original data. This suggests that assuming zero parameters for all ignored attributes may not be appropriate in this study context. We also note that the parameter estimate for *Fixed* becomes insignificant in both models, whilst the parameter for *New electricity company* becomes significant in MNL2 but the opposite holds in the case of RPL2. With the exception of *Discount*, *Fixed*, and *Bill*, all the parameter estimates are relatively larger and have higher t-scores in MNL2 than in MNL1, indicating that based on the MNL model, restricting the parameter estimates of ignored attributes increases the magnitude and precision of estimates of taste intensities for the other attributes. *Discoun*t and *Fixed* differ from the other non-price attributes in that they are normally included with the price in most electricity plans currently on offer and respondents are most likely to be familiar with making trade-offs among them. Restricting the parameter estimates for these two attributes to zero for respondents who report having ignored them reduces the precision in estimating their parameters in both MNL2 and RPL2.

The models specified with non-zero parameters for the ignored attributes, MNL3 and RPL3, perform better than the respective base models MNL1 and RPL1 based on all information criteria. This indicates that the utility specifications used in MNL3 and RPL3 are better than those specified in equations (5-1) and (5-2). All significant coefficients of the interactions of the dummy variables indicating non-attendance to specific attributes with the respective attribute levels have the opposite signs to those of the respective attributes. As discussed earlier, all significant interaction terms indicate significant differences in preferences between respondents who ignored an attribute and those who attended to it. *Fixed* and *Discount* have insignificant coefficients for the interactions in both models, suggesting that the preferences of respondents who reported non-attendance to these attributes are not significantly different from those who attended to the attributes. Whilst this indicates that restricting the parameters for these two attributes to zero based on stated non-attendance is inappropriate in this case, it also provides, with respect to these two attributes, a “NO” answer to research *Question 2(d)* [*Do preferences of respondents who ignore an attribute differ from those who consider it?*]. This offers a possible explanation of why MNL2 and RPL2 perform worse than MNL1 and RPL1, respectively, since MNL2 and RPL2 turn out to be mis-specified by assuming zero values for the parameters of ignored attributes. Additionally, all interaction terms for the three supplier types are insignificant in RPL3, indicating no significant differences in preferences for respondents stating non-attendance and those reporting full attendance. What can be inferred from these results is that stated non-attendance to these attributes is inconsistent with the respective respondents' observed pattern of choice responses. A possible explanation is that some respondents may have made errors by checking the wrong boxes or had problems recalling which attributes they actually ignored.

For the attributes with significant interaction terms, the taste intensities for respondents who ignored the attributes are obtained by adding the estimated parameter for the attribute to that of the respective interaction term. For example, based on MNL3, respondents who reported non-attendance to *Time* have a lower negative taste intensity (-0.03982+0.02702 = -0.0128) for this attribute compared to respondents who attended to it (-0.03982). Those who reported non-attendance to the power bill have a lower marginal disutility of income (-0.02636+0.00776 = -0.0186) compared to -0.02636 for those who attended to it. Since the coefficients of the interaction terms have opposite signs to those of the respective attributes, the taste intensities for respondents who ignored the attributes are lower than those who did not. This is consistent with suggestions that respondents who state non-attendance to specific attributes may have instead placed lower weights on the attributes rather than completely ignoring them (Carlsson et al., 2010; Gracia et al., 2012). This provides a "YES" answer to research *Question 2(d)* for these attributes.

These results suggest that, other than for *Fixed* and *Discount*, an assumption of different preferences between respondents who ignored an attribute and those who attended to it is justified, but the assumption of zero taste intensities for respondents who ignored an attribute may not be justified in all cases as none of the taste intensities for respondents who ignored an attribute is zero. These findings suggest that the attributes may have not been ignored because their value is zero but were ignored purely as a coping strategy, or that they were not completely ignored but less weight was placed on them.

Estimates of WTP under different assumptions about the parameters of ignored attributes

Willingness to pay for a specific attribute is estimated as a ratio of the partial derivative of the utility function with respect to the attribute to the negative of the partial derivative of the utility function with respect to the cost attribute. For

MNL1, MNL2, RPL1 and RPL2, the point estimates of WTP are simply the ratio of the coefficient of a non-price attribute *(β_k)* to the negative of the coefficient of the cost attribute *($-\beta_c$)* since the models do not involve interaction terms. For MNL3 and RPL3 the partial derivatives contain additional coefficients multiplied by the dummy variable indicating non-attendance. The formulae for WTP estimates for the k[th] attribute are shown in equations (5-4) and (5-5).

$$WTP_k = \frac{\beta_k}{-\beta_c} \tag{5-4}$$

$$WTP_k = \frac{(\beta_k+\gamma_k d_k)}{-(\beta_c+\gamma_c d_c)} \tag{5-5}$$

Equation (5-5) estimates WTP for four possible groups of respondents depending on the attribute processing rule adopted. (1) Full attendance: $WTP_k = \frac{\beta_k}{-\beta_c}$, where respondents attended to both attributes and d_k and d_c are equal to zero. (2) Ignored attribute: $WTP_k = \frac{(\beta_k+\gamma_k d_k)}{-\beta_c}$, where only attribute k is ignored but the cost is not. (3) Ignored cost: $WTP_k = \frac{\beta_k}{-(\beta_c+\gamma_c d_c)}$, where attribute k is attended to but cost is ignored. (4) Ignored both: $WTP_k = \frac{(\beta_k+\gamma_k d_k)}{-(\beta_c+\gamma_c d_c)}$, where both attribute and cost are ignored.

WTP estimates from the models estimated above are presented in Table 5-13. Based on MNL2 and RPL2, accounting for AN-A results in different WTP estimates. Accounting for stated AN-A in MNL2 and RPL2 produces generally higher values for most attributes, with the notable exception of *Discount* and *Fixed* whose values decline, becoming insignificant even at the 90% level of confidence in both models. On the other hand MNL3 and RPL3 provide WTP estimates corresponding to different attribute processing rules. With the exception of *Discount* and *Fixed* in both MNL3 and RPL3, and supplier type in RPL3, respondents who ignore a non-price attribute are found to have a lower WTP for the ignored attribute compared to those who considered it. In most cases, WTP for ignored attributes is significantly different from zero, with exceptions where joint non-attendance to an attribute and cost produces mixed results.

Table 5-13: Estimates of average marginal WTP for the attributes of electricity services based on MNL and RPL-EC models (NZ$$_{(2014)}$)

Attribute	MNL1	MNL2	MNL3				RPL1	RPL2	RPL3			
	Assuming full attendance	AN-A coded data	Attended both	Ignored attribute	Ignored power bill	Ignored both	Assuming full attendance	AN-A coded data	Attended both	Ignored attribute	Ignored power bill	Ignored both
Time	-0.94[c] (0.20)	-1.92[c] (0.29)	-1.51[c] (0.29)	-0.49[b] (0.24)	-2.15[c] (0.47)	-0.69[b] (0.35)	-0.94[c] (0.16)	-1.62[c] (0.26)	-1.27[c] (0.23)	-0.63[c] (0.19)	-1.88[c] (0.39)	-0.94[c] (0.30)
Fixed	0.25[c] (0.08)	NS	0.18[b] (0.09)	0.18[b] (0.09)	0.26[b] (0.13)	0.26[b] (0.13)	0.14[a] (0.07)	*NS*	*NS*	*NS*	*NS*	*NS*
Discount	0.44[c] (0.11)	0.33[c] (0.11)	0.44[c] (0.11)	0.44[c] (0.11)	0.63[c] (0.18)	0.63[c] (0.18)	0.41[c] (0.10)	0.32[c] (0.11)	0.42[c] (0.09)	0.42[c] (0.09)	0.63[c] (0.15)	*NS*
Rewards	4.86[b] (2.25)	16.60[c] (2.74)	13.73[c] (2.76)	-6.72[c] (3.04)	19.45[c] (4.46)	-9.52[b] (4.44)	3.78[b] (1.75)	10.90[c] (2.50)	7.35[c] (2.23)	*NS*	10.89[c] (3.52)	*NS*
Renewables	0.34[c] (0.04)	0.36[c] (0.05)	0.39[c] (0.05)	0.22[c] (0.07)	0.55[c] (0.09)	0.31[c] (0.11)	0.36[c] (0.04)	0.39[c] (0.06)	0.42[c] (0.04)	0.20[c] (0.06)	0.62[c] (0.09)	0.30[c] (0.10)
Ownership	0.14[c] (0.05)	0.27[c] (0.05)	0.29[c] (0.05)	-0.12[a] (0.07)	0.41[c] (0.09)	*NS*	0.23[c] (0.06)	0.27[c] (0.07)	0.43[c] (0.06)	*NS*	0.64[c] (0.11)	*NS*
New electricity company	*NS*	-10.97[c] (3.71)	-10.69[c] (4.04)	*NS*	-15.14[c] (5.84)	*NS*	-11.23[c] (2.87)	*NS*	-13.98[c] (3.39)	-13.98[c] (3.39)	-20.72[c] (5.30)	-20.72[c] (5.30)
New Non-electricity company	-13.94[c] (4.33)	-28.80[c] (4.86)	-22.27[c] (5.07)	*Ns*	-31.55[c] (7.91)	*NS*	-25.53[c] (3.63)	-26.24[c] (4.92)	-28.86[c] (4.42)	-28.86[c] (4.42)	-42.78[c] (7.79)	-42.78[c] (7.79)
Well-known non-electricity company	-7.58[a] (4.26)	-19.81[c] (4.53)	-13.84[c] (4.92)	*NS*	-19.61[c] (7.21)	*NS*	-19.90[c] (3.78)	-17.43[c] (4.70)	-22.39[c] (4.45)	-22.39[c] (4.45)	-33.19[c] (7.25)	-33.19[c] (7.25)

[c], [b], [a] Significant at the .01, .05, .1 level, respectively. Note: Standard errors are in parentheses; NS denotes not statistically significant at the .1 level

Analysis of responses from the CE indicates that electricity consumers in New Zealand are willing to pay on average \$3.15 to \$9.40 per month to avoid an increase of 5 minutes in call waiting time. A supplier offering a 12-month fixed rate contract may charge up to \$3.12 more per month compared to similar suppliers offering no fixed rate contracts without losing its customers to competitors. Offering a discount of 10% may allow a supplier to charge up to \$6.30 per month above the monthly power bills charged by similar suppliers, others things being equal. Offering loyalty rewards may allow a supplier to charge up to \$19.45 more per month, for respondents who are less sensitive to the price, compared to similar suppliers who do not offer loyalty rewards. Consumers have positive preferences for both local ownership of supplier and electricity generated from renewable energy sources and would be willing to pay on average up to \$6.40 more per month to a supplier that has a 10% higher local ownership structure, and between \$2.00 and \$6.20 more to secure a 10% increase in electricity generated from renewable energy sources. Traditional electricity suppliers are preferred to any new entrants, including well-known companies diversifying into retail electricity. Entrants into the retail electricity market have to charge up to \$42.78 less per month to attract respondents who are less sensitive to the cost depending on the type of entrant, *ceteris paribus*.

To establish the effect of AN-A and the adoption of the alternative approaches for controlling for AN-A, the marginal WTP estimates are compared across the models. As indicated earlier, we observe a general upwards shift in WTP estimates when AN-A is accounted for in model estimation. To confirm this observation and also assess the statistical significance of the differences in WTP values we use the ANTS suggested by Campbell et al. (2008) to test for equality of the estimates. The test results and the ratios of WTP estimates are presented in Table 5-14. The results indicate, with the exception of *Renewables*, significant differences between WTP estimates obtained under MNL1 and MNL2. With the exception of *Discount* and *Fixed*, on average, MNL2 produces estimates that are 1.07 to 2.94 times larger than MNL1. In the main, similar results are observed for RPL1 and RPL2. These results imply that estimating a model without accounting for AN-A results in significant bias in WTP estimates. In this study, where significant differences in WTP estimates are observed, the bias is downwards for all attributes except for *Fixed* and *Discount*, which have an upwards bias.

Table 5-14: Tests of equality of WTP estimates based on the MNL and RPL-EC models

	MNL2 vs MNL1		MNL3* vs MNL1		MNL3* vs MNL2		RPL2 vs RPL1		RPL3* vs RPL1		RPL3* vs RPL2	
Variables	| ANTS |	WTP ratio	| ANTS |	WTP ratio	| ANTS |	WTP ratio	| ANTS |	WTP ratio	| ANTS |	WTP ratio	| ANTS |	WTP ratio
Time	**4.57**	2.05	**2.74**	1.62	**9.07**	0.79	**3.22**	1.73	**2.04**	1.35	**2.56**	0.78
Fixed	**4.93**	0.48	1.89	0.73	**2.77**	1.54	1.91	-	1.91	0.78	-	-
Discount	**3.99**	0.75	0.34	1.02	**3.30**	1.35	**2.36**	0.78	0.74	1.04	**2.42**	1.33
Rewards	**7.48**	3.42	**5.51**	2.83	**8.14**	0.83	**3.99**	2.88	**2.58**	1.94	**3.15**	0.67
Renewables	1.02	1.07	**2.39**	1.16	**11.82**	1.09	0.73	1.09	**2.97**	1.16	0.74	1.07
Ownership	**6.83**	1.92	**6.31**	2.07	1.44	1.08	1.08	1.15	**15.91**	1.84	**4.76**	1.61
New electricity company	**6.31**	2.94	**3.54**	2.86	0.17	0.97	**2.33**	-	1.52	1.24	**5.26**	**2.48**
New Non-electricity company	**6.79**	2.07	**3.17**	1.60	**4.50**	0.77	0.22	1.03	1.33	1.13	1.21	1.10
Well-known Non-electricity company	**7.86**	2.61	**2.54**	1.82	**3.11**	0.70	0.89	0.88	1.05	1.12	**3.31**	1.28

*WTP estimates are for respondents who attended to both attribute and power bill. NTS values of 1.96 and above indicate significant differences at the .05 level, and have been highlighted in bold. Missing values indicate that the ratio cannot be estimated where one of the WTP values is not significantly different from zero.

Apart from *Discount* and *Fixed*, these results are consistent with previous studies in various contexts that find a downward bias in marginal WTP values when AN-A is not controlled for (e.g., Campbell, 2007; Hensher & Greene, 2010). However, some studies find an upwards bias in WTP values as in the case of *Fixed* and *Discount* in this study (e.g., Campbell et al., 2008; Hensher, 2004; Hensher et al., 2005b). Recall that based on model MNL3 and RPL3, there are no significant differences in preferences between respondents who ignored *Fixed* and *Discount* and those who considered these attributes. Our results suggest that accounting for AN-A by imposing zero values on the parameters of ignored attributes, where preferences are not significantly different between those who ignore an attribute and those who consider it, results in lower WTP estimates, whilst the converse is true where preferences differ. The direction of the bias seems to depend on the differences in preferences of respondents who ignore an attribute and those who do not.

The downward bias in WTP values obtained from MNL1 and RPL1 may be explained in terms of less weight being assigned to ignored non-price attributes and also the fact that the power bill (cost) was the least-ignored attribute. Studies that find an upward bias in WTP values report higher non-attendance to the cost attribute which results in a smaller parameter estimate for the cost variable, hence higher WTP, given that WTP is estimated as a ratio of parameters where the parameter for the cost variable is the denominator.

5.5 Inferred attribute non-attendance

In this section we explore possible attribute processing rules using statistical models rather than relying on stated AN-A. Reliance on self-reported non-attendance has been criticized in previous studies because of reporting errors. This analysis provides additional answers to research *Question 2(d)* on whether or not attributes are ignored individually or in combinations.

5.5.1 A probabilistic decision process model for inferred AN-A

An alternative approach to the use of stated AN-A in model estimation employs probabilistic decision process models for AN-A (e.g., Hensher, 2008; Hensher & Rose, 2009; Hensher et al., 2012; Scarpa et al., 2010). In these models, inferred AN-A is modelled using a latent class framework to probabilistically capture decision processes or attribute processing rules that respondents may have used to evaluate the alternatives presented in the choice tasks. Each latent class represents a group of respondents who adopted the same attribute processing rule and the number of latent classes depends on the number of hypothesized or pre-defined attribute processing rules and the number of attributes used to describe the alternatives. Specific restrictions are imposed on the utility expressions for each class, where the coefficients of ignored attributes are constrained to zero and the coefficients of attributes attended to are assumed to be the same across classes (Hensher et al., 2012; Scarpa, Gilbride, et al., 2009). Hence each class is not defined by the attribute taking a value of zero within the class but by the corresponding coefficient taking the value of zero.

A distinguishing feature between the latent class formulation used to infer AN-A and the standard latent class formulation is that, in the former the non-zero coefficients are the same across the classes and the classes have specific behavioural meaning in terms of attribute processing rules. The maximum number of all possible attribute processing rules, which includes all possible combinations of non-attendance to the attributes, depends on the number of attributes and, is equal to 2^k, where k is the number of attributes (Hensher et al., 2012). In this study we have eight attributes, which gives a total number of possible attribute processing rules of 2^8 or 256. This approach may be criticized for ignoring heterogeneity of preferences for the attributes that are attended to by imposing equality of taste intensities for each attribute across classes. Alternative approaches that allow for heterogeneity of preferences as well as AN-A specify distributions for taste intensities (e.g., Hess & Hensher, 2010; Scarpa, Gilbride, et al., 2009).

5.5.2 Model specification

We use the probabilistic decision process model described by Hensher et al. (2012) to investigate attribute non-attendance in our sample of respondents. The model accommodates attribute non-attendance by assuming that individuals are sorted into Q (q = 1, 2, 3, ….., Q) classes that are distinguished by what attributes were ignored or considered in their choice process. The probability that an individual n chooses alternative i conditional on class membership of class q which ignores a certain attribute or subset of attributes is a multinomial logit;

$$Prob(n,i|q) = \frac{\exp(\boldsymbol{\beta}'_q \boldsymbol{x}_{in})}{\sum_{j-1}^{J} exp(\boldsymbol{\beta}'_q \boldsymbol{x}_{jn})} \qquad (5-6)$$

where βq is one of 2k possible vectors β in which m of the elements are zero and *K-m* are nonzero (Hensher et al., 2012). "Specifically, q can be thought of as a masking vector of the form (δ1, δ2, δ3, δ4, …), where each δ takes the possible values 0,1. βq is then the ''element for element product'' of this masking vector, with the standard coefficient vector β, indicating that the masking vector interacts with the coefficient vector" (Hensher et al., 2012, p. 238). The unconditional probability of individual *n* choosing alternative *i* is obtained by averaging over classes as follows (Hensher et al., 2012);

$$Prob(n,i) = \sum_{q=1}^{2^k} \pi_q \frac{exp(\boldsymbol{\beta}'_q \boldsymbol{x}_{in})}{\sum_{j=1}^{J} exp(\boldsymbol{\beta}'_q \boldsymbol{x}_{jn})} \qquad (5-7)$$

where $\sum_{q=1}^{2^k} \pi_q = 1$ and π_q is the prior class probability.

A baseline MNL model estimated in section 5.4.4 assuming full attendance is used to provide a contrast for the hypothesized attribute processing strategies operationalized by imposing parameter restriction for ignored attributes. The estimation of an LC with 2^K classes, which is 256 classes in the case of the 8 attributes used in this study, is beyond the current capabilities of NLOGIT software used in the estimation, and would make the analysis tedious.

To overcome this problem we use two approaches to investigate AN-A. In the first approach we estimate Model 1 assuming ten latent classes of attribute processing rules. The first seven classes represent non-attendance to a specific attribute (partial non-attendance). Class 8 represents joint non-attendance to the power bill and discount as it is unlikely that a respondent who ignores the power bill attends to the discount. Therefore we assume, for the eight classes, that each of the eight attributes used to describe an alternative in a choice set, except power bill, is ignored on its own. For example classes 1, 2 and 3 represent non-attendance to *Time, Fixed* and *Discount,* respectively. Classes 9 and 10 represent full attendance and non-attendance to all attributes or total non-attendance, respectively. In this model, each vector $\boldsymbol{\beta}_q$ (q = 1, 2, 3, 4, …. 7) consists of only one zero restriction and seven nonzero attribute coefficients representing seven classes which ignored a specific attribute each; vector $\boldsymbol{\beta}_8$ consists of two zeros (for discount and power bill) and six nonzero attribute coefficients; vector $\boldsymbol{\beta}_9$ consists of eight nonzero attributes coefficients representing full attendance; and vector $\boldsymbol{\beta}_{10}$ consists of ten zero coefficients representing total non-attendance where all respondents in class 10 ignored all attributes and therefore made random choices.

Although supplier type is represented by four categorical levels, we assume that non-attendance is at an attribute level, i.e., a respondent either attends to all the levels of supplier type or ignores supplier type altogether. Table 5-15 illustrates the attribute processing rule latent class structure described above. This approach exploits the capability of the latent class model to explore hypothesised attribute processing rules. Including a class assignment model may provide clues as to who applied which attribute processing rule and possibly why.

Table 5-15: Structure of inferred attribute non-attendance classes

Behaviourally defined latent classes	Time	Fix	Dis	Rew	Ren	Own	Supplier Type				Bill
Class 1	0	β_f	β_d	β_{rew}	β_{ren}	β_o	β_{s0}	β_{s1}	β_{s2}	β_{s3}	β_b
Class 2	β_t	0	β_d	β_{rew}	β_{ren}	β_o	β_{s0}	β_{s1}	β_{s2}	β_{s3}	β_b
Class 3	β_t	β_f	0	β_{rew}	β_{ren}	β_o	β_{s0}	β_{s1}	β_{s2}	β_{s3}	β_b
Class 4	β_t	β_f	β_d	0	β_{ren}	β_o	β_{s0}	β_{s1}	β_{s2}	β_{s3}	β_b
Class 5	β_t	β_f	β_d	β_{rew}	0	β_o	β_{s0}	β_{s1}	β_{s2}	β_{s3}	β_b
Class 6	β_t	β_f	β_d	β_{rew}	β_{ren}	0	β_{s0}	β_{s1}	β_{s2}	β_{s3}	β_b
Class 7	β_t	β_f	β_d	β_{rew}	β_{ren}	β_o	0	0	0	0	β_b
Class 8	β_t	β_f	0	β_{rew}	β_{ren}	β_o	β_{s0}	β_{s1}	β_{s2}	β_{s3}	0
Class 9	β_t	β_f	β_d	β_{rew}	β_{ren}	β_o	β_{s0}	β_{s1}	β_{s2}	β_{s3}	β_b
Class 10	0	0	0	0	0	0	0	0	0	0	0

*Fix, Dis, Rew, Ren, and Own denote *Fixed*, *Discount*, *Rewards*, *Renewables*, and *Ownership,* respectively

In the second approach we estimate Model 2A where we investigate a number of possible patterns of AN-A based on suspected attribute processing rules consisting of ignoring subsets of attributes. This differs from Model 1 in that it recognises the possibility that attributes may not have been ignored individually but in pairs or subsets, which is highly likely given the pattern of stated AN-A reported earlier in section 5.4.1 (Table 5-2). Scarpa, Gilbride, et al. (2009) and Hess and Hensher (2010) find evidence that some respondents ignore a subset of attributes. Based on this approach a number of LC models based on different combinations of ignored attributes were estimated and compared, and the best model was selected on the basis of model fit.

The selection of ignored subsets is based on the attributes that respondents reported to have ignored the most. Since *Time* was reported to have been ignored by nearly 60% of the respondents, we include it in each subset of ignored attributes to reflect this high incidence of stated non-attendance to the attribute. A variant of the best-performing model (Model 2B) is estimated with class membership conditioned on respondent's rating of how easy the choice tasks were during the CE. As part of the debriefing process, each respondent was asked to rate how easy it was to make choices in all twelve choice tasks presented to them in the CE. Responses were recorded on a 7-point Likert-type scale with the end points marked as "very difficult", coded as 1, and "very easy" coded as 7. The mid-point of the scale was marked as "neutral", and coded as 4. We create a dummy variable, which we call "*Easy 1*", which takes on the value of 1 if a respondent's score is greater than 4, and zero otherwise. This is the variable used in the class membership model to sharpen class membership. This variable is selected to investigate any link between the attributes attended to and the self-reported cognitive burden.

5.5.3 Results

Table 5-16 presents a summary of the results for three LC models used to infer AN-A. The models are compared to the base MNL model estimated in section 5.4.4. Model 1 assumes ten attribute processing rules, while Model 2A and Model 2B assume five classes. The data fits all the models well, and all significant parameters have the expected signs. Based on R^2, *LL*, AIC and BIC, the models accounting for AN-A perform better than the base MNL which assumes full compensatory behaviour. Model 1 performs better than models 2A and 2B in terms of the above criteria. Visually, the parameter estimates differ across the models, but the signs of significant parameters are robust across the models. However, it should be noted that a direct comparison of parameter estimates between the MNL and the LC models is not possible due to different scaling of the parameter estimates that is related to the scale factor of the random Gumbel error component (Campbell et al., 2011).

The results for Model 1 indicate that the data does not contain evidence of attribute processing rules involving ignoring a single attribute, except *Rewards*, which has a 0.6551 probability of being ignored individually. Finding evidence of an attribute processing rule involving ignoring *Rewards* alone may not be surprising given that this attribute is the third most ignored after *Time* and supplier type. Results of previous analysis of self-reported non-attendance responses indicate that only 20% of respondents may have systematically ignored a single attribute, and these are likely to be included in the class inferred to have ignored *Rewards*. Although *Time*, *Renewables*, *Ownership* and supplier type had the highest self-reported non-attendance rates (60%, 34%, 41% and 47% respectively), inferred AN-A results indicate that they were not ignored individually, which supports the assertion that attributes may be ignored in pairs or subsets (Hess & Hensher, 2010; Scarpa, Gilbride, et al., 2009). Despite the fact that none of the respondents reported having ignored all the attributes, we find evidence supporting total non-attendance by approximately 24% of respondents. This may indicate that respondents who made random choices did not answer the debriefing question honestly. Joint non-attendance to *Discount* and *Bill* is significant and has a probability of 0.0992, which is slightly higher than the self-reported non-attendance to *Bill* (7%). Although 12% of respondents reported full attendance, this is not supported by the results for Model 1.

Given the number of attributes in this study (eight), it may not be surprising that, in the main, a strategy of systematically ignoring a single attribute is not supported by the data. Evidence of systematic non-attendance to a single attribute has been found in previous studies where fewer attributes are used to describe the alternatives in choice sets (e.g., Campbell et al., 2011; Campbell et al., 2008; Scarpa, Gilbride, et al., 2009). In these previous studies, where only four non-price attributes are used, ignoring a single attribute as a coping strategy is more likely to reduce the cognitive burden substantially compared to a situation where eight attributes are used to describe an alternative, as in our study.

Table 5-16: Comparison of attribute processing rules

	MNL (full attendance)	Model 1: 10 classes		Model 2A	Model 2B
	beta (z)	beta (z)	Probability (z)	beta (z)	beta (z)
ASCALT1	0.7221 (6.95)	1.6105 (6.99)	-	0.7524 (3.88)	0.7305 (3.72)
Time	-0.0236 (-4.74)	0.0004 (0.04)	0.0001 (0.00)	-0.1756 (-5.64)	-0.1785 (-5.72)
Fixed	0.0063 (3.16)	0.0034 (0.87)	0.0001 (0.00)	0.0185 (3.55)	0.0182 (3.45)
Discount	0.0110 (4.03)	0.0180 (2.75)	0.0001 (0.00)	0.0014 (0.36)	0.0016 (0.41)
Rewards	0.1226 (2.15)	1.7935 (3.90)	0.6551 (9.79)	0.7640 (2.22)	0.7647 (2.18)
Renewables	0.0085 (7.71)	0.0115 (3.83)	0.0019 (0.02)	0.0494 (12.24)	0.0471 (12.27)
Ownership	0.0036 (2.83)	0.0032 (1.23)	0.0001 (1.00)	0.0386 (7.05)	0.0382 (7.12)
New Electricity Supplier	-0.0942 (-1.05)	0.2828 (1.30)	0.0001 (0.00)	0.1353 (0.93)	0.1093 (0.74)
New non-electricity company	-0.3516 (-3.22)	0.1751 (0.65)	0.0001 (0.00)	-0.3402 (-1.53)	-0.3730 (-1.67)
Well-known non-electricity company	-0.1914 (-1.77)	-0.0191 (-0.07)	0.0001 (0.00)	0.1105 (0.51)	0.0846 (0.38)
Monthly power BILL	-0.0252 (-29.12)	-0.0511 (-22.25)	0.0992 (3.15)	-0.0457 (-25.86)	-0.0454 (-26.32)
Attended to all (TA)			0.0001 (0.00)		
All attributes ignored (TNA)			0.2434 (7.42)		

Class membership models for Model 2A and Model 2B

		Class 1 *(attended to all attributes)*	Class 2 *(ignored Time, Fixed, Discount & Rewards)*	Class 3 *(ignored Time, Fixed, Renewables, & Ownership)*	Class 4 *(ignored Time, Rewards, Renewables & Ownership)*	Class 5 *(ignored all attributes)*
Model 2A	Class probability	0.0612 (2.28)	0.0544 (1.94)	0.1499 (1.91)	0.4522 (5.02)	0.2823 (8.62)
Model 2B	Class probability	0.061	0.06	0.146	0.454	0.279
	Constant	-1.3534 (-2.17)	-1.5776 (-2.21)	-1.5042 (-1.73)	-0.2778 (-0.72)	0.0 (Fixed par)
	Easy 1	-0.2835 (-0.33)	0.08317 (0.10)	1.1905 (1.36)	1.0778 (2.54)	0.0 (Fixed par)

	MNL (full attendance)	Model 1: 10 classes	Model 2A	Model 2B
k	11	20	15	19
Pseudo-R^2	0.266	0.368	0.344	0.346
LL	-2156.66	-1867.74	-1936.4	-1930.4
AIC	4335.3	3775.5	3902.8	3898.9
BIC	4400.2	3893.4	3991.3	4010.9

The five classes in Model 2A and Model 2B have statistically significant probabilities at least at the .1 level. The two models suggest that about 6% of respondents attended to all attributes (class A), and about 28% (class E) ignored all attributes. The use of "*Easy1"* to sharpen class membership in Model 2B improves model fit. Respondents who rated the choice tasks as "easy" have a higher likelihood of belonging to class D. Class D, accounting for about 45% of the sampled population, represents respondents who only considered the discount, fixed rate contract, supplier type, and monthly power bill in making their choices. These attributes are included in standard electricity pricing plans and respondents are likely to be familiar with making trade-offs among them, hence exclusively attending to these attributes made the choice tasks easier. The results based on models 2A and 2B provide evidence that attributes may have been ignored in combinations instead of individually.

Based on inferred AN-A results from the above LC models, the attribute processing rule involving ignoring attributes individually is unlikely to have been adopted by respondents, except for *Renewables*. However, evidence of attribute processing rules involving ignoring subsets of attributes, and ignoring all attributes is supported. Inconsistences between stated and inferred AN-A are observed. A possible explanation is that the differences may be due to errors in self-reporting the attribute processing rules used by respondents. This finding lends support to concerns raised about the reliability of self-reported attribute processing rules (Hensher, 2008; Hensher & Rose, 2009). Previous studies also find inconsistences between stated AN-A and inferred AN-A (e.g., Carlsson et al., 2010; Hess & Hensher, 2010).

The marginal WTP estimates based on the models discussed above are presented in Table 5-17. Where WTP estimates are significant, Model 2A and Model 2B produce values that are between 1.6 and 6.1 times larger than those obtained from the MNL model. In Model 1, only *Discount*, *Rewards*, and *Renewables* have significant WTP estimates. However, the WTP estimate for *Rewards* is more than 7 times the estimate based on the base MNL model. Finding insignificant WTP estimates for most attributes may not be surprising for a model based on attribute processing rules that are not supported by the data.

Table 5-17: WTP estimates for the MNL and LC models ($NZ\$_{(2014)}$/month)

	MNL	Model 1A	Model 2A	Model 2B
	Full attendance	10 classes	5 non-attendance classes	
Time	-0.94[c] (0.20)	*NS*	-3.84[c] (0.64)	-3.93[c] (0.65)
Fixed	0.25[c] (0.08)	*NS*	0.40[c] (0.11)	0.40[c] (0.11)
Discount	0.44[c] (0.11)	0.35[c] (0.13)	*NS*	*NS*
Rewards	4.86[b] (2.25)	35.12[c] (9.01)	16.72[c] (7.50)	16.83[b] (7.66)
Renewables	0.34[c] (0.04)	0.23[c] (0.06)	1.08[c] (0.07)	1.04[c] (0.06)
Ownership	0.14[c] (0.05)	*NS*	0.85[c] (0.11)	0.84[c] (0.11)
New electricity company	*NS*	*NS*	*NS*	*NS*
New non-electricity company	-13.94[c] (4.33)	*NS*	*NS*	-8.21[a] (5.00)
Well-known non-electricity company	-7.58[a] (4.26)	*NS*	*NS*	*NS*

[c], [b], [a] Significant at the .01, .05, and .1 level, respectively. *NS* denotes not statistically significant. Standard errors are in parentheses.

5.6 Hypothetical bias in choice experiments

In this section we explore the influence of respondents' certainty about their choices on model fit and WTP estimates. As stated previously, the main objective of this analysis is to explore how WTP estimates are influenced by the level of certainty of choice responses. At the end of the choice tasks, respondents were asked to rate how sure they were that they would have made the same choices they made in the 12 choice scenarios if they were faced with the same choice situations in real life. A Likert-type scale with endpoints marked as "very unsure" (0) and "very sure" (10), and the midpoint marked as "neither sure or unsure" (5) was used to elicit responses.

5.6.1 Distribution of responses to the certainty statement

We present a summary of the responses in Figure 5-1.

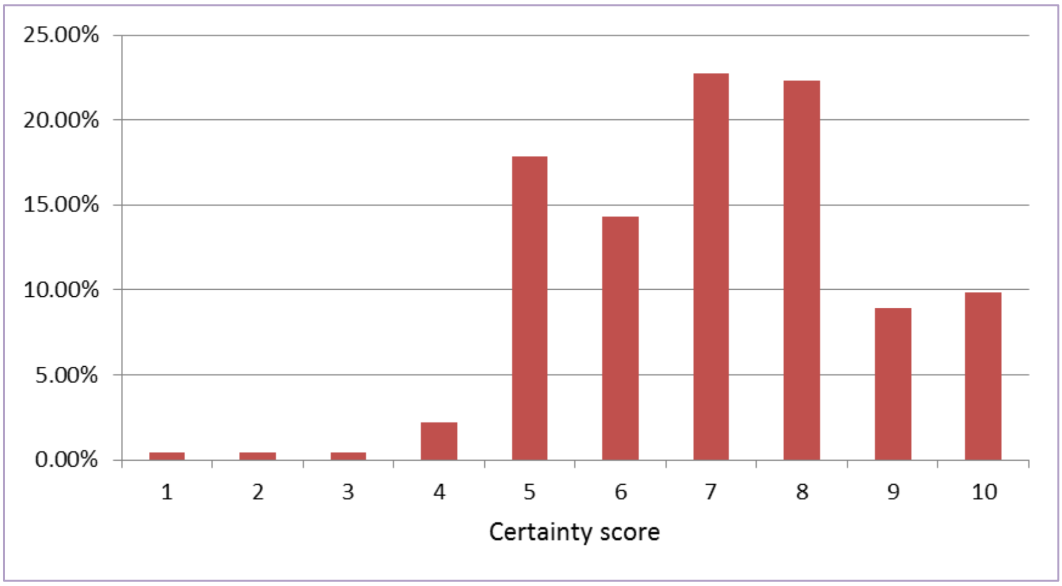


Figure 5-1: Distribution of certainty scores

The sample average score for certainty of 7.07 with a standard deviation of 1.70 indicates that respondents are fairly certain about their choices. Only 3.6% of respondents have certainty scores of less than 5, whilst 63.8% have a score of at least 7, indicating that a majority of respondents in this CE were quite certain about their responses. The sub-sample sizes for individual points of 0 to 4 on the certainty scale are insufficient for model estimation. To overcome this problem, we combine all responses with a score of 5 or less to represent a level we label as 'uncertain', and use this as the reference point in the appropriate models. If respondents who are uncertain about their responses (score of 5 or less) are the source of HB, then we expect to obtain lower average marginal WTP estimates for respondents with higher scores.

5.6.2 Models

To explore the effect of different cut-off points on the certainty scale on model fit and WTP estimates, we estimate a series of MNL models starting with a full sample and then progressively dropping respondents with lower scores, starting with 4 or less. WTP estimates are then computed for each model and the results compared to the base model. In the second round of estimations the MNL and

RPL-EC models are estimated. These models include interaction terms: *Certainty6_Bill, Ceratainty7_Bill, Certainty8_Bill* and *Certainty9&10_Bill* created by interacting the dummy variables indicating the levels of 6, 7, 8, and 9&10, respectively, on the certainty scale with *Bill*. This allows us to explore the effect of the level of certainty on sensitivity to the cost. From this we test the hypothesis that respondents who are less certain about their choices tend to select more expensive alternatives; that is, respondents who are less certain about their choices are less sensitive to the cost of the alternatives chosen.

5.6.3 Regression Results

The results of the MNL models in which we progressively drop respondents with lower certainty scores from the sample are presented in Appendix 5 (see Tables A5-1 to A5-3). The results indicate a general improvement in model fit as we move from the full sample model (M0) to the model estimated for respondents with certainty scores of 9 and above (M5(8)). The normalised AIC and BIC indicate cut-off points of 7 and 8, respectively. This is consistent with the practice in previous studies that have found that these cut-off points result in equivalence between hypothetical and real WTP (e.g., Champ & Bishop, 2001; Ethier et al., 2000; Poe et al., 2002). The main drawback for our study is the lack of external validity criteria against which the WTP estimates can be compared. Therefore we restrict our analysis to comparison of WTP estimates at different cut-off points with estimates from the full sample, which highlights the effect of failing to account for uncertainty in model estimation on WTP estimates.

Figure 5-2 presents a plot of WTP estimates at different cut-off points on the certainty scale. The point 0 corresponds to the model estimated with the full sample. WTP estimates are presented in two groups based on relative magnitudes. Progressively dropping respondents with lower certainty scores seems to have different effects on WTP estimates for groups of attributes. Generally, model M5(8), with a cut-off point of 8, produces some of the highest estimates, but the model suffers from reduced sample size, and three parameter estimates are not significant at the .05 level. This may indicate the effect of reduced sample size and loss of information. The absolute values of WTP estimates for supplier types increase up to the cut-off point of 6 and decline thereafter, whereas WTP for *Rewards* declines initially and rises after the cut-off point of 5. For *Time,* the absolute value of marginal WTP tends to increase throughout. On the other hand, WTP estimates for *Fixed*, *Ownership*, *Renewables* and *Discount* follow different patterns depending on the cut-off point and no general conclusion may be drawn in terms of single direction of the effect. Estimates of WTP for *Discount* rise noticeably after the cut-off point of 4, clearly indicating that respondents with higher certainty scores are more sensitive to the discount rates offered by retailers. This suggests that respondents with higher certainty scores are more sensitive to the cost attribute since the discount directly determines how much a customer actually pays on his/her power bill. *Renewables* follows a somewhat similar but less pronounced upwards increase as *Discount*, where respondents who are more certain about their choices have slightly higher WTP for the attribute.

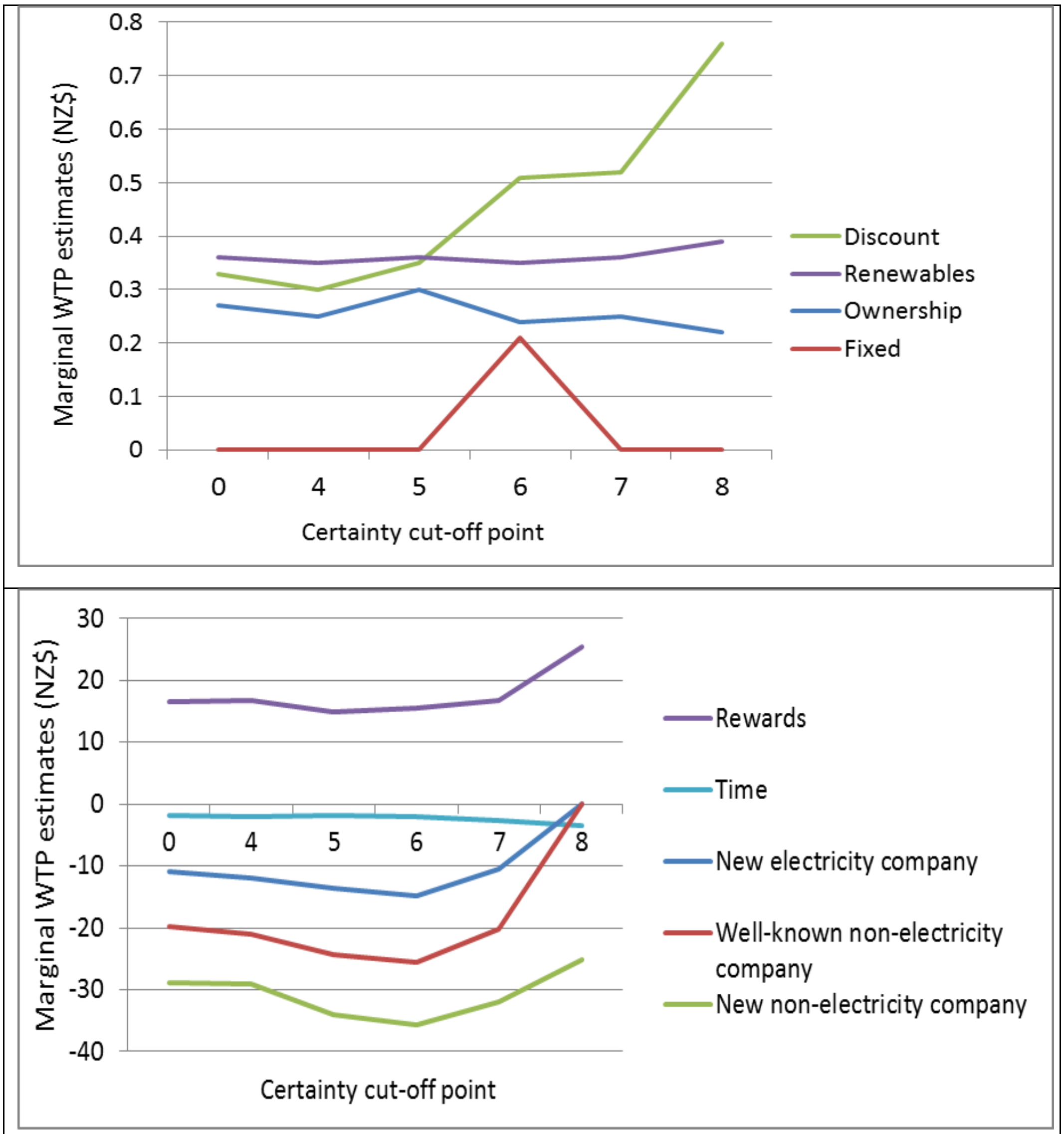


Figure 5-2: WTP estimates at various cut-off points on the certainty scale

WTP estimates for *Ownership* generally fall as the certainty cut-off points increase suggesting that respondents with lower scores are responsible for an upwards bias in WTP, which is consistent with the assertion that respondents who are less certain about their choices are the source of hypothetical bias. However, respondents who are less certain about their choices may have been expressing their concern about local ownership rather than a WTP. WTP for *Fixed* shows a peculiar pattern in that it is only statistically significant at the cut-off point of 6, suggesting a downward bias due to respondents with certainty score below 6, and the effect of sample size after this cut-off point i.e., the number of observations may be insufficient to estimate the independent influence of *Fixed* on choice.

The above results suggest that hypothetical bias may be either positive or negative depending on the nature of the attributes involved. However, we have no theoretical explanation for the differences in the direction of hypothetical bias other than that the differences reflect the underlying preferences for respondents who are more certain about their choices. For example, a comparison of the parameter estimates across the models reveals that sensitivity to all attributes is low when responses of respondents with scores less than 6 are included in model estimation, which may explain the pattern of WTP estimates presented above.

Now we turn to the results of the MNL and RPL-EC models (MNL1 and RPL1) estimated with different coefficients for respondents with different levels of certainty relative to the "uncertain" level, which we have specified as a certainty score of 5 or less. For comparison purposes we also estimate the base models MNL0 and RPL0 where certainty scores are not included in the models. The regression results are presented in Table 5-18. The results indicate that the models incorporating certainty scores perform better than the base models. For example, MNL1 performs better than MNL0 based on AIC, BIC, pseudo-R^2 and an LRT statistic of 43.4 with 4 degrees of freedom, which is greater than the critical value ($\chi^2_{(4,\ .05)}$ = 9.49). RPL1 performs better than RPL0 based on all the criteria and a LRT statistic of 42 with 4 degrees of freedom, which is greater than the critical value ($\chi^2_{(4,\ .05)}$ = 9.49). Furthermore, RPL1 performs better than MNL1 based on AIC, BIC, pseudo-R^2 and an LRT statistic of 502.2 with 5 degrees of freedom, which is greater than the critical value ($\chi^2_{(5,\ .05)}$ = 11.07).

Table 5-18: Regression results for MNL and RPL-EC models

	MNL0	MNL1	PRL0	RPL1
ASCALT1	0.5152[c]	0.5383[c]	0.6690[c]	0.5706[c]
	(7.01)	(7.26)	(4.51)	(3.88)
Time	-0.0484[c]	-0.0458[c]	-0.0541[c]	-0.0512[c]
	(-6.61)	(-6.25)	(-6.12)	(-5.84)
Fixed	0.0030	0.0037[a]	0.0057	0.0055
	(1.41)	(1.72)	(1.64)	(1.62)
Discount	0.0083[c]	0.0089[c]	0.0105[c]	0.0113[c]
	(3.09)	(3.31)	(3.10)	(3.41)
Loyalty Rewards	0.4175[c]	0.4017[c]	0.3628[c]	0.3444[c]
	(6.00)	(5.75)	(4.32)	(4.10)
Renewables	0.0091[c]	0.0093[c]	0.0130[c]	0.0126[c]
	(7.29)	(7.42)	(6.67)	(6.39)
Local Ownership	0.0068[c]	0.0072[c]	0.0090[c]	0.0092[c]
	(5.05)	(5.29)	(3.99)	(4.12)
New electricity company	-0.2758[c]	-0.2678[c]	-0.1879	-0.1846
	(-2.91)	(-2.81)	(-1.50)	(-1.48)
New non-electricity company	-0.7243[c]	-0.7138[c]	-0.8737[c]	-0.8534[c]
	(-5.98)	(-5.86)	(-5.33)	(-5.26)
Well-known non-electricity company	-0.4981[c]	-0.4621[c]	-0.5803[c]	-0.5404[c]
	(-4.35)	(-4.02)	(-3.69)	(-3.47)
Certainty6_Bill		-0.0069[c]		-0.0056[a]
		(-3.33)		(-1.91)
Certainty7_Bill		-0.0086[c]		-0.0091[c]
		(-4.67)		(-3.40)
Certainty8_Bill		-0.0105[c]		-0.0108[c]
		(-5.49)		(-3.97)
Certainty9&10_Bill		-0.0106[c]		-0.0138[c]
		(-5.18)		(-4.50)
Monthly Power Bill	-0.0252[c]	-0.0182[c]	-0.0333[c]	-0.0256[c]
	(-31.13)	(-13.82)	(-29.36)	(-13.65)
Standard deviations of random parameters				
Fixed			0.0275[c]	0.0261[c]
			(6.09)	(6.00)
Discount			0.0191[c]	0.0162[c]
			(3.260	(2.71)
Renewables			0.0149[c]	0.0148[c]
			(6.47)	(6.79)
Ownership			0.0169[c]	0.0165[c]
			(6.83)	(6.65)
ERC (σ)			1.7707[c]	1.5995[c]
			(13.98)	(13.66)
LL	-2165.6	-2143.9	-1913.8	-1892.8
AIC	4353.1	4317.8	3859.6	3825.7
BIC	4418.0	4406.2	3954.0	3943.6
Pseudo R^2	0.2633	0.2708	0.3519	0.3590

[c], [b], [a] Significant at the .01, .05, and .1 level, respectively. z values are in parentheses

All the parameter estimates have the expected signs. Of particular interest are the signs and relative magnitudes of the parameter estimates for the interaction terms *Certainty6_Bill* to *Certainty9&10_Bill*. These parameters measure the sensitivity to the power bill for respondents with the corresponding certainty scores relative to the 'uncertain' level. All these parameters have negative signs indicating that respondents with higher certainty scores have higher disutility of expenditure and are more sensitive to the cost attribute compared to respondents who are uncertain about their choices. Furthermore, the absolute values of the parameter estimates increase with the level of certainty, indicating increasing responsiveness to the cost attribute as certainty increases. This provides empirical evidence in support of the assertion that respondents who are less certain about their choices tend to choose more expensive alternatives. The results of this analysis also show that respondents who are uncertain about their choices are less sensitive to the cost of the alternatives chosen, and are therefore more likely to be the source of hypothetical bias. Certainty levels 9 and 10 were combined in the final models presented here as preliminary estimation revealed no statistical differences in the two parameter estimates. This means that relative to the 'uncertain' level, certainty levels 9 and 10 are the same.

To obtain WTP estimates for the attributes of electricity services, the partial derivative of the systematic component of indirect utility with respect to each non-monetary attribute is divided by the partial derivative with respect to the power bill and its interaction terms. These partial derivatives turn out to be the parameter estimates presented in the previous table (Table 5-18). For each level of certainty, the denominator is the sum of the parameter estimate for the power bill and the parameter estimate for the respective interaction term. For the 'uncertain' level, the denominator is the parameter of the power bill.

The WTP estimates are presented in Table 5-19. The sub-column headings, ≤ C5, C6, ……, ≥ C9, under the MNL1 and RPL1 models indicate the certainty levels for which WTP estimates have been calculated based on these models, while C0 under the MNL0 and RPL0 models indicates that WTP estimates are based on the full sample without accounting for uncertainty. For each model, all marginal WTP estimates fall as certainty scores increase confirming the hypothesis that respondents who are uncertain about their choices tend to choose expensive alternatives or are less sensitive to the cost attribute. The column under "≤ C5" lists marginal WTP estimates for respondents with certainty scores of 5 or less, and clearly shows that the WTP estimates for these respondents are consistently higher; between 1.26 and 1.53 times across the models where the estimates are statistically significant.

In Table 5-20 we present tests of equality between WTP estimates using ≤ C5 as the reference to highlight any significant differences in WTP for respondents with higher certainty scores. Significant differences, at least at the 0.1 level, are observed for all attributes except *Fixed*, *Discount*, and *New Electricity Company*, suggesting that some attributes are more prone to the effects of uncertainty than others. The ANTS increases with the level of certainty for all attributes with significant WTP estimates across the models, indicating that the differences become larger the more certain respondents are about their choices. Comparing the ANTS across the models we observe that the MNL produces a higher number of significant differences in WTP. This suggests that the effect of uncertainty on WTP estimates may be sensitive to model specification. It is interesting to note that the RPL model generally produces lower WTP estimates compared to the MNL, so we conjecture that the lower estimates from the RPL model and the fact that the model estimates a distribution rather than a fixed estimate for WTP attenuates HB.

Table 5-19: WTP for respondents with different levels of certainty about their choices (NZ$$_{(2014)}$ /month)

Attributes	MNL0	MNL1					RPL0	RPL1				
Cut-off points	C0	≤ C5	C6	C7	C8	≥ C9	C0	≤ C5	C6	C7	C8	≥ C9
Time	-1.92[c] (0.29)	-2.52[c] (0.43)	-1.83[c] (0.31)	-1.71[c] (0.29)	-1.60[c] (0.27)	-1.59[c] (0.27)	-1.62[c] (0.26)	-2.00[c] (0.36)	-1.64[c] (0.30)	-1.47[c] (0.26)	-1.40[c] (0.25)	-1.30[c] (0.24)
Fixed	*NS*	0.20[a] (0.12)	0.15[a] (0.09)	0.14[a] (0.08)	0.13[a] (0.08)	0.13[a] (0.08)	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*
Discount	0.33[c] (0.11)	0.49[c] (0.16)	0.35[c] (0.11)	0.33[c] (0.08)	0.31[c] (0.10)	0.31[c] (0.10)	0.32[c] (0.10)	0.44[c] (0.14)	0.36[c] (0.11)	0.33[c] (0.10)	0.31[c] (0.09)	0.29[c] (0.09)
Loyalty Rewards	16.60[c] (2.74)	22.09[c] (4.00)	16.02[c] (2.94)	15.00[c] (2.68)	14.02[c] (2.50)	13.97[c] (2.52)	10.90[c] (2.50)	13.45[c] (3.32)	11.06[c] (2.79)	9.91[c] (2.45)	9.45[c] (2.33)	8.74[c] (2.18)
Renewables	0.36[c] (0.05)	0.51[c] (0.08)	0.37[c] (0.06)	0.35[c] (0.05)	0.32[c] (0.05)	0.32[c] (0.05)	0.39[c] (0.06)	0.49[c] (0.08)	0.41[c] (0.07)	0.36[c] (0.06)	0.35[c] (0.06)	0.32[c] (0.05)
Local Ownership	0.27[c] (0.05)	0.39[c] (0.08)	0.29[c] (0.05)	0.27[c] (0.05)	0.25[c] (0.05)	0.25[c] (0.05)	0.27[c] (0.07)	0.36[c] (0.09)	0.30[c] (0.07)	0.27[c] (0.06)	0.25[c] (0.06)	0.23[c] (0.06)
New electricity company	-10.97[c] (3.71)	-14.73[c] (5.22)	-10.68[c] (3.78)	-10.00[c] (3.52)	-9.34[c] (3.31)	-9.32[c] (3.33)	NS	NS	NS	NS	NS	NS
New non-electricity company	-28.80[c] (4.86)	-39.25[c] (7.19)	-28.47[c] (5.18)	-26.65[c] (4.72)	-24.90[c] (4.42)	-24.83[c] (4.50)	-26.24[c] (4.92)	-33.33[c] (6.64)	-27.40[c] (5.50)	-24.57[c] (4.82)	-23.42[c] (4.62)	-21.66[c] (4.35)
Well-known non-electricity company	-19.81[c] (4.53)	-25.41[c] (6.43)	-18.43[c] (4.69)	-17.25[c] (4.33)	-16.12[c] (4.07)	-16.07[c] (4.10)	-17.43[c] (4.70)	-21.11[c] (6.12)	-17.35[c] (5.10)	-0.51[c] (0.16)	-14.83[c] (4.34)	-13.72[c] (4.05)

[c], [b], [a] Indicate significance at the .01, .05, and .1 level respectively; *NS* denotes not statistically significant even at the .1 level. Standard errors are given in parentheses

Table 5-20: Test of equality of WTP based on the asymptotically normal test statistic (ANTS)[1]

Attributes	MNL0	MNL1				RPL0	RPL1			
	C0	C6	C7	C8	C9&10	C0	C6	C7	C8	C9&10
Time	**1.90**	**2.39**	**2.54**	**2.76**	**2.79**	1.56	**1.86**	**2.17**	**2.33**	**2.60**
Fixed	**1.70**	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*
Discount	1.41	1.22	1.34	1.45	1.46	1.42	0.99	1.23	1.32	1.47
Loyalty Rewards	**1.88**	**2.24**	**2.39**	**2.58**	**2.61**	1.17	1.32	1.58	**1.69**	**1.88**
Renewables	**2.52**	**2.56**	**2.74**	**2.98**	**3.02**	**1.71**	**1.84**	**2.20**	**2.37**	**2.67**
Local Ownership	**2.23**	**2.07**	**2.21**	**2.42**	**2.46**	1.53	1.28	1.54	**1.67**	**1.86**
New electricity company.	1.02	1.12	1.23	1.33	1.35	NS	NS	NS	0.62	0.69
New non-electricity company	**1.97**	**2.16**	**2.32**	**2.53**	**2.57**	1.59	1.60	**1.92**	**2.08**	**2.33**
Well-known non-electricity company	1.23	1.59	**1.72**	**1.87**	**1.89**	0.94	1.11	**3.37**	1.45	1.61

[1] The ANTS is calculated for each level of certainty with ≤ C5 ('uncertain') used as the reference point. Bolded values indicate statistically significant differences at least at the 0.1 level. Absolute values for ANTS are reported

5.7 Summary

In this chapter we investigated attribute non-attendance and hypothetical bias in choice experiments for supplier choice in retail electricity markets. Accounting for AN-A and mitigating HB in CEs enhances the validity and acceptability of welfare estimates derived from SP data. The analysis carried out in this chapter is based on both self-reported and inferred AN-A, and self-reported certainty of choices. Concern has been raised in the literature on AN-A about the reliability of self-reported AN-A as these responses may be subject to reporting error. Furthermore, previous studies have found evidence that points to inconsistences between self-reported AN-A and the choices made by respondents in CEs. Two main approaches to incorporating AN-A in model estimation have been used in previous studies. In the most frequently used approach, the parameters of ignored attributes are restricted to zero, whilst in the other approach different parameters are estimated for ignored attributes. In the case of HB, previous studies have used different cut-off points on the certainty scale in calibrating hypothetical choices to align them with real choices. The main findings of this chapter are summarized below.

Question 2(a): *Are non-price attributes of electricity services ignored in choice experiments on switching or supplier choice? If so, which attributes are ignored? (b) Are attributes ignored individually or in combinations?*

To answer the above questions we relied on both self-reported and inferred AN-A to identify non-price attributes that respondents claim to have ignored, and assumed that the responses were reported without error. The results indicate that no single attribute was considered by all respondents. Based on self-reported AN-A, only 12% of the respondents considered all the attributes in making their choices. About 20% of the respondents claimed to have ignored one out of eight attributes, and about 7% claimed to have ignored 7 attributes. None of the respondents reported total non-attendance; that is, ignored all the attributes. The most- and least-ignored attributes were *Time* (60%) and *Bill* (7%), respectively. Contrary to self-reported AN-A, inferred AN-A analysis suggests that none of the respondents attended to all the attributes; instead, about 24% of the respondents are predicted to have ignored all the attributes. Furthermore, inferred AN-A suggests that none of the respondents who claimed to have considered all the attributes did so. Inferred AN-A results suggest that respondents who ignored all the attributes, and therefore made random choices, and those who claimed to have considered all the attributes did not answer the question truthfully. This indicates inconsistences between self-reported AN-A and the pattern of observed choices as reported in other studies (e.g., Hess & Hensher, 2010). Both self-reported and inferred AN-A results indicate that the attributes were ignored in subsets rather than individually.

Question 2(c): Are the choice responses of respondents who claim to have ignored the cost attribute consistent with their claim? If not, how does this affect model fit and WTP estimates?

Results presented in this chapter suggest that it is worthwhile for researchers to investigate and control for any inconsistences in stated AN-A, particularly self-reported non-attendance to the cost attribute, where the objective is to estimate WTP for non-price attributes. Only 15 respondents (7%) claimed to have ignored the power bill in making their choices. An inspection of the choices of these respondents showed that the cheapest alternatives were selected, on average, 72% of the time. This indicates inconsistences between the respondents' claims and the choices they made. Furthermore, some low income respondents claimed to have ignored the power bill. This is unrealistic given that power bills are a long-term commitment and constitute a significant proportion of weekly income, especially for low income groups in NZ. We find that, in a latent class framework, correcting for inconsistent stated AN-A to the monthly power bill results in improved model fit, expected signs of parameter estimates, and significant differences in class probabilities and WTP estimates. Inconsistent stated AN-A to the power bill was corrected for by assuming full attendance to the attribute.

Question 2(d): Do preferences of respondents who ignore an attribute differ from those who consider it?

Based on MNL and RPL-EC model results, preferences of respondents who claim to have ignored an attribute differ from those who considered it, except *Discount* and *Fixed,* and *Supplier type* in the RPL-EC model. The results from these models do not support the assumption behind assigning zero weights to the attributes that respondents claim to have ignored. For example, there are no significant differences in preferences between respondents who claim to have ignored *Discount* and *Fixed* and those who considered these attributes. For the other attributes, we find that respondents who claim to have ignored an attribute may not have done so, but may have placed less weight on it. All the parameter estimates for ignored attributes were significantly different from zero and had the expected signs. Our results are consistent with the findings by Carlsson et al. (2010) and Gracia et al. (2012). If AN-A to *Discount* and *Fixed* is controlled for by imposing a zero restriction on the parameters of these attributes, significantly lower WTP estimates are obtained, which may indicate that the model is misspecified. Furthermore, the results indicate that restricting the parameters of ignored attributes to zero reduces model fit. On the other hand, controlling for AN-A to the other attributes by restricting the parameters of ignored attributes to zero produces mainly significantly higher (1.07 to 3.42 times) WTP estimates based on the MNL model.

Question 2 (e): What are the effects of attribute non-attendance on WTP?

LC model results show that accounting for AN-A results in significant differences in WTP for some attributes, particularly in Class 2 where most WTP estimates are significantly higher. Based on the MNL and RPL-EC models, except for *Discount* and *Fixed*, failing to account for AN-A results in a downward bias in WTP estimates for most attributes. Accounting for AN-A produces WTP estimates that are between 0.88 and 3.42 times higher based on the MNL model, and between 1.03 and 2.88 times for the RPL-EC model. For *Discount* and *Fixed,* WTP estimates are between 0.48 and 0.78 times lower. The extent of the bias differs across the attributes, with *Discount* and *Fixed* having a positive bias and the rest a negative bias.

Question 3: What are the effects of response uncertainty on WTP estimates?

We find evidence in support of the assertion that respondents who are less certain about their choices are less sensitive to the cost of the alternatives chosen. The results show that respondents with certainty scores less than 6 were willing to pay, on average, 1.26 to 1.53 times more compared to respondents with higher certainty scores. These results are within the range of findings from meta-analysis studies (e.g., List & Gallet, 2001; Little & Berrens, 2004; Murphy et al., 2005). Where respondents with low certainty scores are omitted from the sample in model estimation, WTP estimates are sensitive to the cut-off point selected. However, we find that the cut off points of 7 or 8 results in better model fit for our data. This finding is consistent with previous studies that compare real and hypothetical WTP estimates in various contexts (e.g., Champ & Bishop, 2001; Ethier et al., 2000; Poe et al., 2002).

Chapter 6. Environmental attitudes, altruism and the demand for green electricity

6.1 Introduction

The main objective of this chapter is to estimate WTP for green electricity in the context of supplier choice, and to explain preference heterogeneity using psychological constructs based on the New Ecological Paradigm (NEP) Scale and the norm activation theory (NAT). Unobserved heterogeneity of preferences is captured through the LC model and heterogeneity within and across latent classes is explained using environmental attitudes (EA), which enters the systematic component of the utility function as an interaction with the attribute measuring the proportion of renewables (*Renewable*) in the fuel mix. The RPL-EC model is also used to capture unobserved heterogeneity of preferences for green electricity, and the interaction of the NAT constructs [awareness of a behaviour's consequences (AC), and ascription of responsibility (AR)] with the random parameter for *Renewable* are used to explain heterogeneity around the mean parameter. The sensitivity of WTP estimates to use of the shorter versions of the NEP Scale to measure EA is explored.

Environmental attitudes are defined as a psychological tendency expressed by evaluating the natural environment with some degree of favour or disfavour (Hawcroft & Milfont, 2010). Although the NEP Scale was originally developed to measure environmental concern (Dunlap et al., 2000), it has been used extensively in the social sciences as a measure of EA (Dunlap, 2008). AC and AR activate personal norms which determine altruistic behaviour (Schwartz, 1977). By incorporating psychological constructs in discrete choice models, this chapter contributes to the literature that advances the use of psychological constructs in explaining choice behaviour.

The main questions addressed in this chapter are:

Question 4: (a) How much are electricity consumers willing to pay for green electricity and how can differences in WTP be explained?

(b) Does the use of shorter versions of the NEP Scale influence WTP estimates?

This chapter contributes to the limited literature on preferences for green electricity in the context of supplier choice or switching and extends on these studies by exploring the influence of EA, AC and AR on environmentally-related WTP. Unlike some previous studies that appear to use arbitrary constructs to measure EA, we use the NEP Scale, which is grounded in social psychology theory (Dunlap, 2008; Stern et al., 1995), to measure EA. Furthermore, we use the LC model, which allows us to identify market segments with homogeneous preferences, and the results provide, to the best of our knowledge, the first WTP estimates for green electricity in the New Zealand electricity market based on CEs. We are not aware of any previous studies that have applied the LC model in the context of supplier choice to estimate WTP for green electricity.

Studies that employ the multinomial logit (NML) model focus on the average taste intensity for each attribute, which assumes that respondents have homogeneous preferences with respect to each attribute (e.g., Zhang & Wu, 2012). On the other hand, studies employing the mixed logit or random parameter logit (RPL) model focus on the means and variances of continuous distributions of taste intensities (e.g., Amador et al., 2013; Goett et al., 2000), which assumes that an individual's taste intensity lies somewhere in the estimated distribution. The LC model applied in this chapter estimates a discrete distribution with a small number of support points (Kamakura & Russell, 1989) in which preference heterogeneity is captured by membership in distinct classes with homogeneous preferences or taste intensities. This allows us to identify classes with distinct preferences for green electricity.

Random utility theory and discrete choice experiments are linked to social psychology through the early contributions of Manski (1977) and Thurstone (1994) in the development of the random utility maximization (RUM) model. Despite this link, it would appear that most researchers in environmental economics or non-market valuations in general have failed to look to social psychology for guidance in constructing attitudinal questions that are based on valid attitude-behaviour theories, hence the proliferation of different measures of the same construct. As noted by Dunlap (2008), how EA has been measured in some previous studies is a good case in point.

The next section provides an overview of the background and a literature review. Section 6.3 presents an analysis of responses to the NEP Scale statements used to measure New Zealanders' EA. Section 6.4 presents an analysis of responses to questions measuring the NAT constructs. In sections 6.5 and 6.6 we explain heterogeneity of preferences for green electricity using EA and NAT constructs, respectively. In section 6.7 we explore the effect of using shorter versions of the NEP Scale on WTP. Section 6.8 presents the chapter summary and conclusions

6.2 Background and literature review

Since the mid-1980s, New Zealand (NZ) has embarked on a series of electricity market reforms aimed at promoting a competitive and efficient electricity market. A discussion of the reforms was provided in Chapter 3. Residential consumers are free to choose their preferred retail supplier from the 8 to 18 retail brands available, depending on the region (Electricity Authority, 2013a, 2013c). Although electricity is traded via a "pool" system, most customers should be able to associate their retailers, especially 'gentailers', with the main energy sources used to generate electricity due to the high degree of vertical integration between generation and retail.

In 2014 electricity generation from renewable sources, hydro (57.1%), geothermal (16.2%), wind (5.2%), and bioenergy (1.5%), accounted for nearly 80% of total generation and is set to grow (MBIE, 2015). Although the New Zealand Energy Strategy 2011-2021 sets a target for renewables at 90% by 2025 (Ministry of Economic Development, 2011a), it does not specify how renewables will be supported. The only available support for renewables in NZ is indirect via the emissions trading scheme, which currently provides a negligible level of support as carbon prices are very low. In the absence of direct policy support such as subsidies and feed-in tariffs, consumer-driven renewable energy development through green marketing is one possible future option for NZ. Green marketing has been used in countries like the USA, UK, and Australia to support the development of electricity generation from renewable energy sources. Given a history of some policy alignment with these countries, green marketing is a potential renewable energy development support mechanism in NZ.

According to an NZ study by the Electricity Commission (2008), nearly 50% of respondents indicated that they would consider the environment when choosing an electricity retailer, whilst 17% indicated they would 'very seriously' consider switching to a retailer which promotes itself for using renewable resources. This indicates a potential for green marketing in NZ. Livengood and Bisset (2009) assess the potential of various mechanisms that could be used to facilitate consumer-driven renewable power development in NZ, and identify renewable energy certificates (RECs) as the most appropriate mechanism for the NZ market. They review international literature to identify existing mechanisms for promoting consumer-driven renewable power development, and assess the suitability of each mechanism in terms of ease of implementation and accessibility in the context of NZ electricity markets. The study also notes the scarcity of research on consumer preferences in the NZ electricity markets. This chapter addresses this issue by providing the first in-depth study of consumer preferences for green electricity in the context of supplier choice in NZ using CEs.

Consumer preferences for green electricity have been investigated in a number of international studies (e.g.,Batley, Colbourne, Fleming, & Urwin, 2001; Batley, Fleming, & Urwin, 2000; Bollino, 2009; Borchers et al., 2007; Clark et al., 2003; Ek & Soderholm, 2008; Hansla, Gamble, Juliusson, & Gärling, 2008; Kotchen & Moore, 2007; Oliver, Volschenk, & Smit, 2011; Zarnikau, 2003; Zhang & Wu, 2012; Zoric & Hrovatin, 2012). Studies investigating WTP for green electricity have used SDCs and attitudes to explain differences in WTP. In some studies income has been found to be a significant determinant of WTP (e.g., Batley et al., 2001; Batley et al., 2000; Bollino, 2009; Clark et al., 2003; Kotchen & Moore, 2007; Zoric & Hrovatin, 2012), whilst in others it is not (e.g., Ek & Soderholm, 2008). Other factors that have been found to influence WTP are: social status (Batley et al., 2001); environmental awareness/concern, attitude towards green energy and experience (Batley et al., 2000; Borchers et al., 2007; Kotchen & Moore, 2007; Oliver et al., 2011; Zoric & Hrovatin, 2012); altruism (Kotchen & Moore, 2007), age (Borchers et al., 2007; Zoric & Hrovatin, 2012); and gender (Bollino, 2009). Evidence of the influence of age, income and gender on WTP is inconclusive as the coefficients of these variables are found to be insignificant in some studies (Bollino, 2009; Borchers et al., 2007; Clark et al., 2003; Kotchen & Moore, 2007; Zoric & Hrovatin, 2012), suggesting that these variables may be sensitive to the study context.

Interest in exploring the importance of attitudes and perceptions in explaining heterogeneity of preferences has increased over the years, highlighting increased realization that preference heterogeneity is, at least in part, due to underlying attitudes and convictions (e.g., Alvarez-Daziano & Bolduc, 2009; Ben-Akiva et al., 2002; Ek & Soderholm, 2008; Fielding et al., 2008; Hess & Beharry-Borg, 2011; Johansson, Heldt, & Johansson, 2006; Morey et al., 2008; Nocella et al., 2012). Hess and Beharry-Borg (2011) contend that the guiding philosophy behind this development is that incorporating attitudes in discrete choice models leads to more behaviourally realistic representations of the choice process. This is in contrast with the approach based on neoclassical economic theory which has traditionally used income, price, and other SCDs to explain preference heterogeneity (Aldrich et al., 2007; McFadden, 1999).

However, the growing interest in incorporating attitudes and perceptions in economic models has resulted in the proliferation of different measures of the same latent construct, with studies adopting different approaches in developing survey questions used to elicit attitudinal responses. Dunlap and Jones (2002) estimate the number of different measures of EA to be at least several hundred (Hawcroft & Milfont, 2010). Furthermore, different approaches on how responses to attitudinal questions are treated in the modeling process have been adopted[19]. A concern with this proliferation of different measures of EA is that most of these measures are arbitrarily constructed and are not properly grounded in attitude-behaviour theories such as the NEP Scale. An important question for researchers is to what extent the different measures of the same latent construct influence the results, especially where the objective is to estimate environmentally-related WTP such as WTP for green electricity. Kotchen and Reiling (2000) argue that the unsystematic measurement of EA raises another concern as it limits comparability

[19] See section 2.3.2 of Chapter 2 for a discussion of approaches used to incorporate latent constructs in discrete choice models.

of studies, thereby limiting our understanding of the relationship between EA and environmentally-related WTP responses.

Although the NEP Scale provides a reliable way to assess EA and is one of the instruments most frequently used by social scientists to measure EA (Dunlap, 2008; Hawcroft & Milfont, 2010), only a few studies in non-market valuation and environmental economics have used it. For example, Meyerhoff (2006) notes the limited use of the NEP Scale in contingent valuation studies. Dunlap (2008), and Hawcroft and Milfont (2010) contend that a number of studies that make reference to the NEP Scale do not actually use it, and that some who use it only use a subset of the items. This suggests that, despite awareness among some researchers of the existence of the NEP Scale, for some reason the uptake is very low. One possibility for the low uptake, especially in online CEs surveys, is the length of the scale, which consists of 15 statements.

Long surveys may lead to high drop-out rates and low data quality as respondents rush though the survey, and fatigue may result in respondents making mistakes or inconsistent choices. The length of the survey also determines the cost of the survey, which is an important consideration, especially for research projects with small budgets. For example, for this research the quotations for a sample size of 200 were $1,600 and $1,900 for 10-15 minute and 15-25 minute surveys, respectively. In a trade-off between shorter survey questionnaires and the need to accurately measure EA, some researchers have used shorter versions of the NEP Scale with 5-10, and 12 items instead of the full 15-item NEP Scale (e.g., Bartczak, 2015; Clark et al., 2003; Kotchen & Moore, 2007; Liebe et al., 2011; Meyerhoff, 2006; Stern et al., 1995). To our knowledge the effect of using these subscales or shorter versions of the NEP Scale in model estimation where the objective is to estimate environmentally-related WTP has not been investigated.

6.2.1 The demand for green electricity

Electricity generated from various energy sources such as hydro, gas, coal, wind, geothermal, nuclear, diesel, and solar is perfectly homogeneous in that a kWh generated from one source and delivered to the end user is the same as that generated from any other source. However the generation of electricity from each energy source is associated with specific environmental impacts. For example, electricity generated from non-renewable sources is generally associated with higher negative environmental impacts such as CO_2 pollution and depletion of non-renewable resources compared to generation from renewable sources. Based on environmental impacts associated with generation from each energy source, consumers with preferences for the environment may perceive electricity as a differentiated product. For these consumers electricity generated with relatively low environmental impacts may be preferred to that generated with relatively higher environmental impacts and their “green” preferences may be revealed through a premium paid for electricity generated from preferred “clean” energy sources.

Electricity suppliers in countries such as the USA, Sweden, Spain, and UK offer their customers a choice to buy electricity labelled “green” or electricity generated from specific renewable energy sources such as solar, wind and hydro. A number of international studies have been conducted to estimate the premiums or support for generic “green” or renewable (e.g., Bollino, 2009; Borchers et al., 2007; Kotchen & Moore, 2007; Roe, Teisl, Levy, & Russell, 2001; Zhang & Wu, 2012; Zoric & Hrovatin, 2012), and specific energy sources such as wind (e.g., Borchers et al., 2007; Dimitropoulos & Kontoleon, 2009; Ek, 2005; Gracia et al., 2012; Hanley & Nevin, 1999), solar (e.g., Borchers et al., 2007), and hydro (e.g., Hanley & Nevin, 1999).

Preferences for green electricity may also be revealed in a different manner from the above. For example, in a deregulated market, consumers are free to switch supplier and preferences for the environment may be revealed by switching to a supplier perceived to be supplying electricity generated from renewable sources. In this case, instead of paying a premium without having to switch supplier, which is the target of most studies cited above, respondents make trade-offs between the desired environmental attribute and other attributes of electricity suppliers including the price and switch to the supplier with the highest expected utility. Unlike the previous case, limited literature has estimated WTP for green electricity in the context of switching or choice of electricity supplier (e.g., Amador et al., 2013; Cai et al., 1998; Goett et al., 2000; Kaenzig et al., 2013). Estimating WTP for green electricity in the context of consumer switching provides additional information on the trade-offs or marginal rates of substitution between the attributes of electricity suppliers, and the important determinants of switching. This information may inform competition policy targeted at promoting switching in the retail electricity market, allow retailers to structure their offerings to attract or retain customers, and provide valuable input for new entrants.

In a USA study, Cai et al. (1998) use double bounded questions on price discounts on a sample of 400 residential customers and 400 business customers to estimate the share of customers that would switch to a competitor under various discounts and service attributes such as renewables, reliability, energy conservation assistance and customer service. The double bounded questions were used to estimate threshold discounts at which consumers would switch to a competitor assuming that all other attributes were the same for incumbent and competitor. Follow-up questions were then used to elicit responses that provided information on consumers' preferences for renewables and other attributes. For example, when a respondent indicated they would switch at a certain discount, they were asked if they would still switch if the competitor did not offer renewables. Results from this study show that renewables are not highly rated in terms of importance compared to the other attributes. Only 40% of the respondents stated that they would not switch if the competitor did not offer renewables compared to 76% who would not switch if the competitor had more power outages, and 50% in the case of a competitor offering fewer services.

Another USA study by Goett et al. (2000) uses a sample of small and medium businesses to investigate customers' choice among retail electricity suppliers based on a set of 40 attributes of suppliers, which include the proportion of wind, hydro and generic renewables in the supplier's portfolio of sources of electricity generation. Results suggest that whilst on average consumers were willing to pay an extra \$14.60 per month for a supplier that has 25% hydro compared to a supplier that has no renewables, they would only pay an extra \$1.80 per month for a supplier that has 50% hydro compared to a supplier that has 25% hydro, indicating very limited sensitivity to scope. A similar finding outside the context of green electricity is reported in a contingent valuation study by Desvousges et al. (1993), where the difference in WTP pay to prevent the accidental death of 2000, 20,000, and 200,000 birds was found to be statistically insignificant. This highlights one of the problems in non-market valuation of environmental goods, which involves the lack of scope sensitivity of stated WTP. Under these conditions it has been argued that respondents are merely conveying their concern for the environment instead of stating WTP for the specific change in environmental quality presented in the survey questionnaire (Diamond & Hausman, 1994).

Amador et al. (2013) use a mixed logit panel model with error components to analyse choice responses from a sample of Spanish households to estimate WTP for a number of attributes including the proportion of renewables in the fuel mix. Results indicate that education, concern for greenhouse gas (GHG) emissions, and engaging in energy saving actions have a positive effect on WTP for green electricity. Environmental concern is measured using stated concern about GHG emissions. Systematic heterogeneity in preferences for renewables is investigated by introducing interactions of non-design attributes with the levels of renewables. For average income earners, graduates are willing to pay 10% of their monthly power bill to increase the share of renewables by 10%, compared to 6.6% for non-graduates. Kaenzig et al. (2013) use a hierarchical Bayes model to examine consumer preferences for the attributes of electricity products in German, which included fuel mix. Results indicated that fuel mix is the most important non-price attribute. WTP for green electricity was estimated at €12 per month which was equivalent to about 16% of the average household power bill.

6.2.2 How the NEP Scale has been used in previous studies.

As noted earlier, in much of the previous research on EA and their influence on consumer preferences for products whose production or consumption is associated with environmental outcomes, researchers have constructed measures of EA in a rather arbitrary manner (Hawcroft & Milfont, 2010). In such cases, each study has produced a new measure of EA. Hawcroft and Milfont (2010) review 69 studies from 36 countries that used the NEP Scale. They employ meta-analysis to investigate how the use of various versions of the NEP Scale may have affected the results in terms of measurement of EA. Results show considerable variation in the way the NEP Scale has been used, particularly with regards to the number of items used and the number of points on the Likert scale employed. Their weighted regression analysis reveals that variations in sample type and scale length have a significant effect on NEP scores. Participants scored higher on 6-item versions of the scale than on the revised 15-item version, and lower on other versions of the scale. The study strongly recommends the use of the 15-item scale.

The motives and criteria for selecting a version of the NEP Scale differ across studies. For example, Stern et al. (1995) used 7 items from the original 12-item scale based on item-total correlation – a measure of internal consistency of the scale. Clark et al. (2003) used 10 items based on the same criteria as Stern et al. (1995) to reduce the length of the survey. Kotchen and Moore (2007) used only 5 items, but the motivation behind the use of a shorter version of NEP and the criteria for the selection of items used are not stated. However, an inspection of the items reveals that one item was selected from each of the 5 so-called ‘facets’ of ecological worldview to maintain balance between anti- and pro-NEP statements. Both Stern et al. (1995) and Clark et al. (2003) used item-total correlations from previous studies in selecting their items. The implicit assumption of their approach is that the populations sampled have the same underlying environmental preferences, which might be incorrect, especially across populations with different cultures and traditions. Liebe et al. (2011) combined 3 items from the NEP Scale with 2 other questions to measure environmental concern and provide no reasons for this approach. Meyerhoff (2006) restricts the number of items in a modified version of the NEP Scale to eight due to limited interview time and cites an earlier study that used six items as a basis for the modified scale. Table 6-1 provides a summary of some recent studies that use different versions of the NEP Scale.

Table 6-1: Recent studies that use the NEP Scale

Study	Context	Comments
Dimitris (2015)	Cycling	Only 4 items are used: 2 pro- and 2 anti-NEP to reduce length of survey.
Kaltenborn et al. (2015)	Management of wild reindeer	6 items are used. Argue that studies have shown that it is possible to achieve sufficient inter-item reliability and validity with fewer items. Statements are rephrased.
van Rijnsoever et al. (2015)	Acceptance of energy technologies	Use 11 items excluding items 1, 2, 6 and 9: no reason given for selection of items.
Pienaar et al. (2015)	Context dependence of NEP Scale scores	Use all 15 items.
Cooper et al. (2015)	Hunting, birdwatching	Only 2 items are used and no reasons are given for adopting a short version of the NEP Scale
Rhodes et al. (2015)	Support for a low carbon fuel standard	Authors state that the NEP Scale is used but no details are provided.
Longstaff et al (2015)	Acceptability of renewable fuels policy	Use 6 items and state that for decades shorter versions of the NEP Scale have been used. Items used are not specified.
Ahlheim et al. (2015)	Replacing rubber plantations with rain forest	Mention the use of statements based on NEP Scale but construct their own statements.
Bartczak (2015)	The role of social and environmental attitudes in non-market valuation	To reduce the length of the survey instrument only 9 items tapping 3 facets (eco-crisis, anti-anthropocentrism and balance) are used as they were the most relevant to the topic. Argue that it is common practice to use subscales of NEP or to revise some statements to reflect the particular focus of the study.

6.3 New Zealanders' environmental attitudes

In this section we present the results of the analysis of responses to the NEP Scale used to measure New Zealanders' EA. First, we present and discuss results based on the full NEP Scale to allow for comparison with previous studies. Next, we explore the factors that influence New Zealanders' EA and identify latent classes of EA. Last, we construct sub-scales of the NEP Scale and test them for internal consistency to ensure that they meet the minimum standard criteria recommended in previous studies, and compare them with the full scale. The NEP Scale was discussed in section 2.4.2 of Chapter 2.

6.3.1 Analysis of responses to the NEP Scale statements

During the survey each respondent was asked to indicate on a 5-point scale how far they agreed or disagreed with each item of the NEP Scale. The response categories for each item are "Strongly Agree" (SA), "Mildly Agree" (MA), "Neither Agree Nor Disagree" (NAND), "Mildly Disagree" (MD) and "Strongly Disagree" (SD). Agreement with eight odd-numbered items and disagreement with the seven even-numbered items indicates pro-NEP responses or positive environmental attitudes (Dunlap et al., 2000). Table 6-2 and Figure 6-1 present a summary of the responses to the 15 items of the NEP Scale.

The percentage distribution of responses to the NEP Scale items indicates that respondents tend to have pro-NEP attitudes with respect to most items. For example, 71% of respondents mildly or strongly agree with the statement "When humans interfere with nature it often produces disastrous consequences" (NEP3), 68% mildly or strongly agree that "the balance of nature is very delicate and easily upset" (NEP13), and 79% mildly or strongly agree with the statement "Despite our special abilities humans are still subject to the laws of nature" (NEP9). Only 20% agree with the anti-NEP statement "The balance of nature is strong enough to cope with the impact of modern industrial nations" (NEP8). Despite the tendency for pro-NEP attitude, substantial heterogeneity in environmental attitudes is displayed within the sample as responses are distributed across all response categories. The general pattern of the distribution of responses to the NEP Scale items reported in Table 6-2 is similar to that found in other studies using the NEP Scale such as Aldrich et al. (2007), Clark et al. (2003), Cooper et al. (2004), Dunlap et al. (2000), Ek and Soderholm (2008), and Kotchen and Reiling (2000).

As discussed in Chapter 2, response categories are coded as follows: strongly disagree = 1, mildly disagree = 2, neither agree nor disagree = 3, mildly agree = 4 and strongly agree = 5. All negative statements (even-numbered) are reverse coded. Based on this coding structure, each item or statement has a possible score that ranges from 1 to 5 (see Dunlap et al., 2000). Since an individual's NEP Scale score is the sum of the scores of all 15 NEP Scale items, it ranges from 15 to 75. However, our sample scores range from 23 to 72 and exclude the boundaries for the possible score range. The mean score and standard deviation are 52.2 and 8.3 respectively.

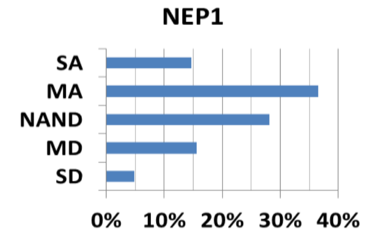
The mean scores for the individual items shown under column three of Table 6-2 indicate that each negative statement is, on average, consistently scored lower than the preceding and subsequent positive (odd numbered) statements except NEP12 (see Figure 6-2). A similar pattern is observed in a USA study by Aldrich et al. (2007) – a plot of the average item scores is included in Figure 6-2 to highlight the similarities. This suggests that respondents evaluate negative environmental statements differently compared to positive ones. In our sample, respondents selected "neither agree nor disagree" more frequently (52.3% of the time) to the negative statements compared to the positive statements. Respondents may have found it relatively difficult to evaluate negative statements and therefore frequently select the neutral midpoint of the scale as a coping strategy. The implication for researchers, especially where researchers formulate their own attitudinal questions, is that caution should be exercised as the way questions are cast may influence the intensity of responses in a particular direction. The full NEP Scale overcomes this problem by the near balance between negative and positive statements.

Table 6-2: Mean scores, percentage distribution of responses and item-total correlations ($r_{i\text{-}t}$) for the NEP Scale items

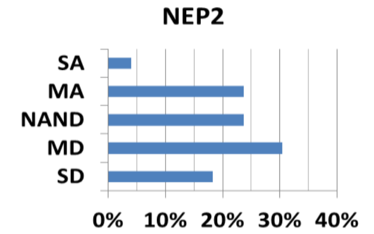
Code	Item or statement*	Mean score**	SA***	MA	NAND	MD	SD	$r_{i\text{-}t}$
NEP1	1. We are approaching the limit of the number of people the earth can support. *(Limits)*	3.41 (1.07)	14.7	36.6	28.1	15.6	4.9	0.35
NEP2	2. Humans have the right to modify the natural environment to suit their needs. *(Anti-anthropocentrism)*	3.35 (1.15)	4.0	23.7	23.7	30.4	18.3	0.51
NEP3	3. When humans interfere with nature it often produces disastrous consequences. *(Balance)*	3.79 (1.07)	26.3	44.6	15.6	8.9	4.5	0.48
NEP4	4. Human ingenuity will ensure that we do not make the earth unlivable. *(Anti-exemptionalism)*	2.94 (1.10)	6.7	33.0	29.5	21.0	9.8	0.41
NEP5	5. Humans are severely abusing the environment. *(Eco-crisis)*	3.88 (1.07)	31.7	40.2	16.5	7.6	4.0	0.49
NEP6	6. The earth has plenty of natural resources if we just learn how to develop them. *(Limits)*	2.30 (1.02)	22.8	39.7	25.4	8.9	3.1	0.10
NEP7	7. Plants and animals have as much right as humans to exist. *(Anti-anthropocentrism)*	4.14 (1.06)	49.1	27.2	14.7	6.3	2.7	0.31
NEP8	8. The balance of nature is strong enough to cope with the impacts of modern industrial nations. *(Balance)*	3.54 (1.05)	1.8	18.3	22.8	37.9	19.2	0.57
NEP9	9. Despite our special abilities humans are still subject to the laws of nature. *(Anti-exemptionalism)*	4.09 (0.83)	33.9	45.5	16.5	3.6	0.4	0.39
NEP10	10. The so-called 'ecological crisis' facing human kind has been greatly exaggerated. *(Eco-crisis)*	3.16 (1.10)	4.9	24.6	34.4	22.3	13.8	0.56
NEP11	11. The earth is like a spaceship with very limited room and resources. *(Limits)*	3.42 (1.00)	11.6	40.2	30.8	12.9	4.5	0.46
NEP12	12. Humans were meant to rule over the rest of nature. *(Anti-anthropocentrism)*	3.54 (1.20)	6.3	14.3	25.0	28.1	26.3	0.39
NEP13	13. The balance of nature is very delicate and easily upset. *(Balance)*	3.85 (0.93)	25.9	42.4	24.1	5.8	1.8	0.42
NEP14	14. Humans will eventually learn enough about how nature works to be able to control it. *(Anti-exemptionalism)*	3.20 (1.13)	5.4	22.8	35.3	19.6	17.0	0.34
NEP15	15. If things continue on their present course we will soon experience a major ecological catastrophe. *(Eco-crisis)*	3.55 (1.04)	18.8	35.7	32.1	8.9	4.5	0.60

*Facet of ecological worldview in parentheses; **standard deviations in parentheses. ***SA, MA, NAND, MD, and SD denote strongly agree, mildly agree, neither agree nor disagree, mildly disagree, and strongly disagree. Note: percentages may not sum to 100 due to rounding

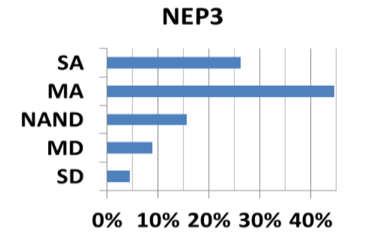
1. We are approaching the limits of the number of people the earth can support.



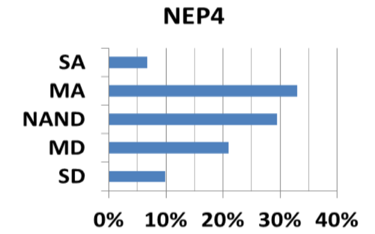
2. Humans have the right to modify the natural environment to suit their needs.



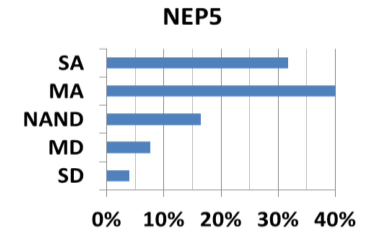
3. When humans interfere with nature it often produces disastrous consequences.



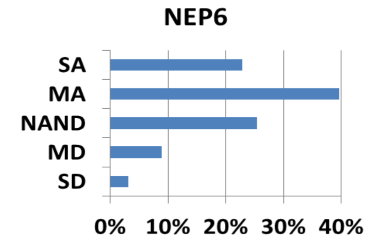
4. Human ingenuity will insure that we do not make the earth unlivable.



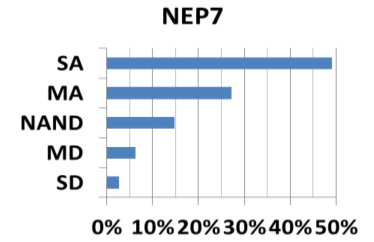
5. Humans are severely abusing the environment.



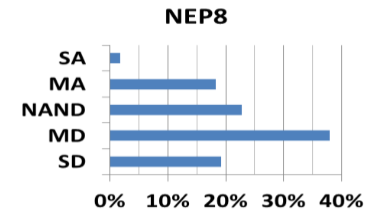
6. The earth has plenty of natural resources if we just learn how to develop them.



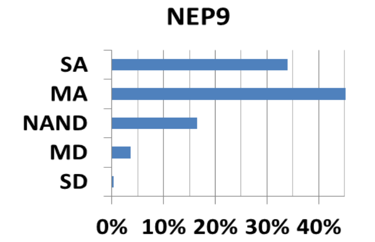
7. Plants and animals have as much right as humans to exist.



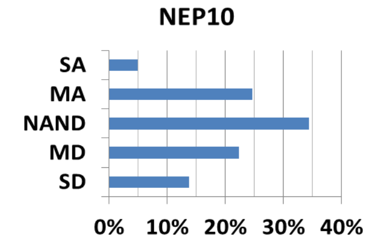
8. The balance of nature is strong enough to cope with the impacts of modern industrial nations.



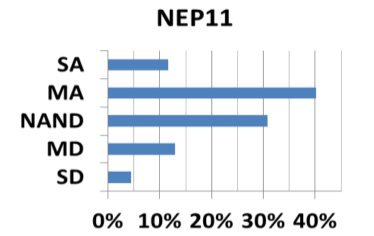
9. Despite our special abilities humans are still subject to the laws of nature.



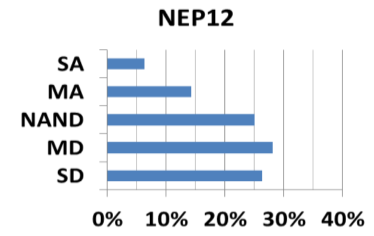
10. The so-called ‘ecological crisis’ facing human kind has been greatly.



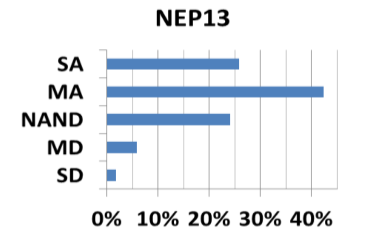
11. The earth is like a spaceship with very limited room and resources.



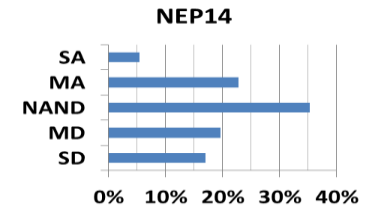
12. Humans were meant to rule over the rest of nature.



13. The balance of nature is very delicate and easily upset.



14. Humans will eventually learn enough about how nature works to be able to control it.



15. If things continue on their present course we will soon experience a major ecological catastrophe.

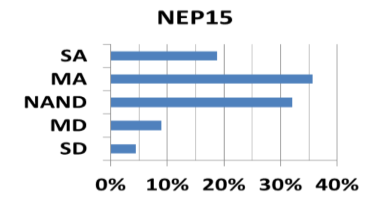


Figure 6-1: Distribution of responses to the NEP Scale statements

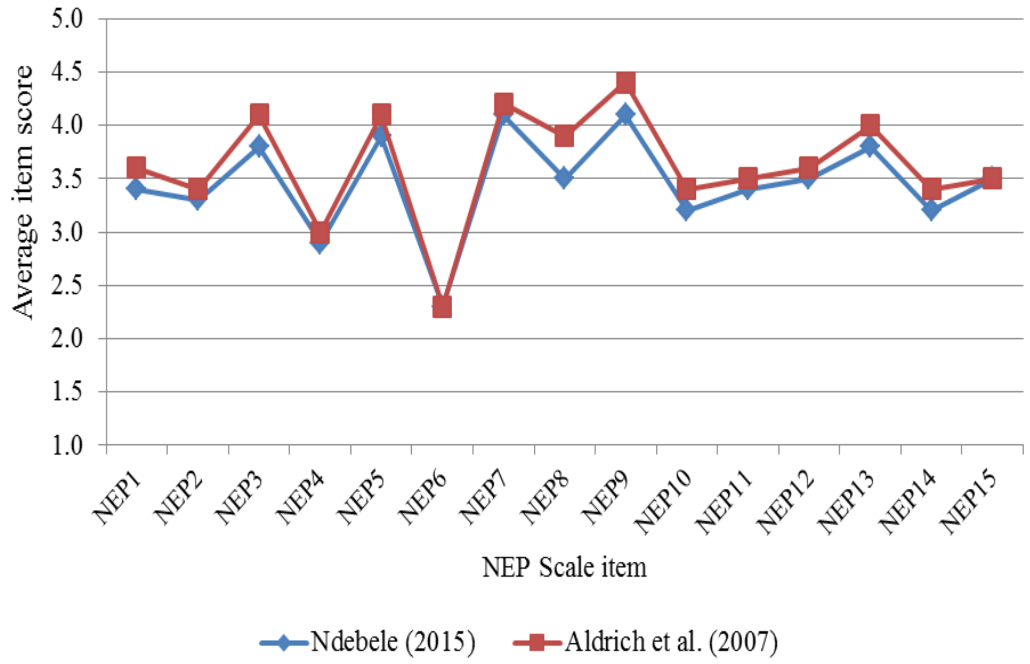


Figure 6-2: Average item scores

6.3.2 Internal consistency of the NEP Scale statements

Before combining the responses to the 15 items of the NEP Scale into a single measure of EA, we establish whether a high degree of internal consistency exists among the items. As indicated in Chapter 2, the internal consistency of the NEP constructs is tested using the corrected item-total correlation (r_{i-t}), Cronbach's coefficient alpha (α), and principal components analysis (PCA) (see, Aldrich et al., 2007; Clark et al., 2003; Dunlap et al., 2000; Ek & Soderholm, 2008). To recap; corrected item-total correlation is the correlation coefficient between each item's score and the sum of the scores of the other 14 items. Cronbach's alpha is a coefficient of reliability used to test whether items are sufficiently inter-related to justify their combination in an index. Previous literature suggests that values of 0.30 for r_{i-t} and $\alpha \geq 0.70$ are acceptable (Aldrich et al., 2007; Clark et al., 2003; Dunlap et al., 2000).

The sample item-total correlation ranges from a low 0.10 for NEP6 (The earth has plenty of natural resources if we just learn how to develop them) to a high of 0.60 for NEP15 (If things continue on their present course we will soon experience a major ecological catastrophe). All but one corrected item-total correlations are higher than 0.30 and statistically significant at the 5% level (see Table 6-2). Cronbach's coefficient alpha is 0.81 and this does not change much (only increases to 0.82) when NEP6 is dropped from the list of items on the scale suggesting that although the correlation of NEP6 with the rest of the items is low, its inclusion does not significantly reduce the reliability of the scale. In Dunlap et al. (2000), 59.2% of the respondents mildly or strongly agreed with NEP6 whilst in this study the corresponding response to this item is 62.5%. The main difference is that in this study only 12% of the respondents mildly or strongly disagreed with the statement and 25.4% neither agreed nor disagreed with it compared to 29.4% and 11% respectively in Dunlap et al. In Kotchen and Reiling (2000), 16.8% of respondents mildly or strongly disagreed with the statement and 15.7% neither agreed nor disagreed with it. This may suggest possible changes in attitudes since then, due to technological advances which have expanded our production possibility frontiers thus reducing the constraints on the limits to economic growth. We note that of all seven anti-NEP statements (NEP2, NEP4, NEP6, NEP8, NEP10, NEP12, and NEP14), only NEP6 has more than 40% of respondents mildly or strongly agreeing with it. However, on the whole our results compare favourably with those of Dunlap et al. (2000) and other previous studies despite a relatively smaller sample size (see Table 6-3).

Table 6-3: Comparison of corrected item-total correlation (r_{i-t}) and Cronbach's alpha

Study and country	N	Target population	r_{i-t} (range)	Cronbach's alpha (α)
Kotchen and Reiling (2000). USA	635	Maine residents	0.38 to 0.71	0.83
Dunlap et al. (2000). USA	676	Washington households	0.33 to 0.61	0.83
Ek and Soderholm (2008). Sweden	655	Swedish households	0.12 to 0.55	0.79
Cooper et al. (2004). USA	200	University students	0.34 to 0.55	0.72
Clark et al. (2003). USA	900	Customers of a retailer	0.32 to 0.59	0.80
This Study (2015). New Zealand	224	Power bill payers in NZ	0.10 to 0.60	0.81

The results of the principal components analysis (PCA) presented in Table 6-4 show that all 15 items of the NEP Scale (except NEP6) load heavily (from 0.42 to

0.71) on the first unrotated factor. The first factor has an eigenvalue of 4.359 and explains 29.06% of the total variance among the items compared to the second factor extracted which has an eigenvalue of 1.724 and only explains 11.49% of the variance among the items. The findings suggest the presence of one major factor which we take to represent environmental attitude or ecological worldview as proposed by Dunlap et al. (2000). The pattern of eigenvalues (4.359, 1.724, 1.351, 1.045 and 0.948), the relatively high item-total correlations, and an alpha equal to 0.81 indicate a high degree of internal consistency for the scale. Consistent with the findings of previous studies these results indicate an adequate level of internal consistency of the NEP Scale and support the assertion that the NEP Scale forms an internally consistent instrument for measuring environmental attitudes.

Table 6-4: Factor loadings for NEP Scale items

Code	Facet of ecological worldview	F1*	F2	F3	F4	F5
NEP 1	Limits to growth	**0.46**	-0.21	**0.60**	-0.08	-0.22
NEP 2	Anti-anthropocentrism	**0.59**	**0.35**	-0.27	0.01	-0.01
NEP 3	Frugality of nature's balance	**0.62**	**-0.32**	0.01	0.25	0.19
NEP 4	Anti-exemptionalism	**0.46**	**0.46**	0.25	**0.50**	-0.04
NEP 5	Possibility of an ecocrisis	**0.62**	-0.27	0.05	-0.23	**0.35**
NEP 6	Limits to growth	0.11	**0.58**	**0.48**	-0.13	-0.22
NEP 7	Anti-anthropocentrism	**0.44**	**-0.30**	**-0.45**	-0.09	**-0.46**
NEP 8	Frugality of nature's balance	**0.66**	0.27	-0.09	-0.07	-0.18
NEP 9	Anti-exemptionalism	**0.49**	-0.20	-0.24	**0.57**	-0.24
NEP 10	Possibility of an ecocrisis	**0.65**	0.26	-0.07	**-0.37**	0.00
NEP 11	Limits to growth	**0.57**	-0.19	**0.44**	0.14	-0.07
NEP 12	Anti-anthropocentrism	**0.46**	**0.43**	**-0.35**	-0.17	-0.15
NEP 13	Frugality of nature's balance	**0.56**	**-0.37**	-0.06	-0.01	0.13
NEP 14	Anti-exemptionalism	**0.42**	**0.39**	-0.13	0.17	0.58
NEP 15	Possibility of an ecocrisis	**0.71**	-0.26	0.13	**-0.31**	0.06
Eigen value		4.359	1.724	1.351	1.045	0.948
Variability (%)		29.06	11.93	9.00	6.97	6.32
Cumulative (%)		29.06	40.54	49.55	56.52	62.84
Cronbach's alpha		0.81	0.45	0.03		
Kaiser-Meyer-Olkin (KMO)**		0.82				

*Unrotated factors, **This is a measure of sampling adequacy: 0.75 represents an adequate sample size.

A summary of the results of the investigation of the dimensionality of the NEP Scale is presented in section 6.1 of Appendix 6. Although evidence suggests the presence of four dimensions of the NEP Scale, we follow Dunlap et al. (2000, p. 435), who argue that they are not inclined to create four NEP subscales "because all 15 items load heavily on the first unrotated factor, have strong item-total correlations and yield an alpha of 0.83 when combined into a single scale." Furthermore, our interest is not in the dimensionality of the NEP Scale but in the use of shorter versions versus the full scale in measuring EA.

6.3.3 Heterogeneity in environmental attitudes

In the previous two sections we analysed and tested responses to the NEP Scale statements for internal consistency, and concluded that the NEP Scale forms an internally consistent instrument for measuring EA. In this section we use the responses to the NEP Scale statements in exploring the factors that influence New Zealanders' EA and identifying latent classes of EA.

6.3.3.1 Methods

A panel ordered probit model, which takes into account the categorical nature of the dependent variable is used to estimate the marginal effects of SDCs on EA. To identify heterogeneity in EA, a panel ordered latent class attitudinal (LCA) model is fitted to the NEP data. We specify a LCA model with covariates in both the class membership model and EA model to allow class probabilities and EA to vary with these variables. A small but growing number of studies have estimated LCA models based on responses to attitudinal questions to identify groups with distinct preferences (e.g., Aldrich et al., 2007; Morey et al., 2006; Morey et al., 2008; Scarpa, Thiene, et al., 2009; Thiene, Galletto, Scarpa, & Boatto, 2013; Ward et al., 2008).

In the LCA model we assume that individuals in the same class have similar EA and that their response patterns to the NEP statements are more correlated within each class than across classes. Conditional on class membership, an individual's responses to all the NEP statements are independent, that is, the correlation is completely induced by the latency of class membership (Breffle et al., 2011). We also assume that an individual's environmental attitude (y_i*) is a continuous latent variable and the scores (y_i) on the NEP Scale items represent indicators of the underlying environmental preference. Following Greene (2008), the link between the observed NEP Scale item responses (y_i) and the latent environmental attitude index (y_i*) is assumed to be of the ordered probit type. We specify a latent regression for y_i* as (Greene, 2008; Greene, 2012):

$$y_i^* = \beta' z_i + \varepsilon_i,\ \varepsilon_i \sim F(\varepsilon_i|\theta),\ E(\varepsilon_i|z_i) = 0,\ Var(\varepsilon_i|z_i) = 1 \tag{6-1}$$

where z_i are the characteristics of respondent i, and y_i takes on the values of the NEP Scale categories 1, 2, 3, 4, 5 (re-coded as 0, 1, 2, 3, 4) according to the following scheme (Greene, 2008):

$$y_i = \begin{cases} 0\ if\ y_i^* \le \mu_{0,} \\ 1\ if\ \mu_0 < y_i^* \le \mu_{1,} \\ 2\ if\ \mu_1 < y_i^* \le \mu_{2,} \\ 3\ if\ \mu_2 < y_i^* \le \mu_{3,} \\ 4\ if\quad y_i^* > \mu_3 \end{cases} \tag{6-2}$$

where μ_j are unknown threshold parameters to be estimated with β. The thresholds (μ_j*'s)* partition the real line into a series of regions corresponding to the ordinal response categories for NEP Scale statements. For identification purposes, μ_0 is normalised to zero and μ_j's for j = 1, 2, 3 are estimated.

The set of probabilities for ordinal outcomes (0, 1, 2, 3, 4) that enter the log likelihood may be expressed as (Greene, 2012):

$$\begin{aligned} Pr(y_i = 0|\boldsymbol{z_i}) &= \Phi(-\boldsymbol{\beta}'\boldsymbol{z_i}) \\ Pr(y_i = 1|\boldsymbol{z_i}) &= \Phi(\mu_1 - \boldsymbol{\beta}'\boldsymbol{z_i}) - \Phi(\mu_0 - \boldsymbol{\beta}'\boldsymbol{z_i}) \\ Pr(y_i = 2|\boldsymbol{z_i}) &= \Phi(\mu_2 - \boldsymbol{\beta}'\boldsymbol{z_i}) - \Phi(\mu_1 - \boldsymbol{\beta}'\boldsymbol{z_i}) \\ Pr(y_i = 3|\boldsymbol{z_i}) &= \Phi(\mu_3 - \boldsymbol{\beta}'\boldsymbol{z_i}) - \Phi(\mu_2 - \boldsymbol{\beta}'\boldsymbol{z_i}) \\ Pr(y_i = 4|\boldsymbol{z_i}) &= 1 - \Phi(\mu_3 - \boldsymbol{\beta}'\boldsymbol{z_i}) \end{aligned} \tag{6-3}$$

For all probabilities to be positive, $0 < \mu_1 < \mu_2 < \mu_3$ (Greene, 2008).

Following Aldrich et al. (2007), Boxall and Adamowicz (2002), Morey et al. (2006), Morey et al. (2008), and Scarpa, Thiene, et al. (2009), the probability of observing an individual's response pattern (x_i) given his/her characteristics (z_i) can be considered as part of a discrete mixture of C multinomials specified as:

$$Pr(x_i : z_i) = \sum_{c=1}^{C} \Pr(c : z_i)\, Pr(x_i|c) = \sum_{c=1}^{C} \Pr(c : z_i) \prod_{q=1}^{15} \prod_{s=0}^{4} \left(\pi_{qs|c}\right)^{x_{iqs}}\ (6-4)$$

where $\Pr(c\colon z_i) = \frac{\exp(\alpha_c' z_i)}{\sum_C \exp(\alpha_c' z_i)}$, $\alpha_C = 0$, is the unconditional probability that individual *i* belongs to class *c* as a function of his/her covariates, q = (1, 2, …. , 15) are the NEP Scale statements (NEP1 to NEP15), s = (0, 1,2, 3, 4) are the re-coded response categories (1, 2, 3, 4, 5), $\pi_{qs|c}$ is the probability that an individual in class *c* selects response category *s* for statement *q*, and x_{iqs} is an indicator variable that takes on the value of 1 if individual *i* answers *s* to statement *q*, and zero otherwise.

With a sample size of 224 respondents, the log-likelihood for a model with *C* classes is specified as:

$$lnL = \sum_{i=1}^{224} ln\,[\sum_{c=1}^{C} P(c\colon z_i) \prod_{q=1}^{15} \prod_{s=0}^{4} (\pi_{qs|c})^{x_{iqs}}] \tag{6-5}$$

subject to $\sum_{s=0}^{4} \pi_{qs|c} = 1$ and, $\sum_{c=1}^{C} P(c\colon z_i) = 1$. The $\pi_{qs|c}$ that maximise the above log likelihood function are now specified as (Morey et al., 2006):

$$\pi_{qs|c} = \frac{\sum_{n=1}^{224} P(c{:}z_i|x_i) x_{iqs}}{\sum_{n=1}^{224} \Pr(c{:}z_i|x_i)} \tag{6-6}$$

The denominator in equation (6-6) estimates the number of individuals in class *c*, whereas the numerator estimates the number of individuals in class *c* that answered *s* to statement *q* (Morey et al., 2006). Since $\pi_{qs|c}$ depends on the conditional membership probabilities, which are unknown, there is insufficient information to maximise the likelihood function. Typically this problem is handled by using the E-M (expectation-maximization) algorithm, an iterative technique that can be used to obtain maximum likelihood estimation in the presence of missing data or incomplete information (Dempster, Laird, & Rubin, 1977), or "when standard procedures are numerically difficult or infeasible" as in the case of the estimation of a large number of parameters (Train, 2009, p. 347). In the E-M algorithm unobserved or missing information is replaced with their expected values which are used as starting values in a search for the maximum of the log likelihood function. The process is reiterated, each time updating the original expectations, until a convergence criterion is reached (Dempster et al., 1977). The LCA model is estimated using NLOGIT 5 software. Although previous studies suggest that the EM method is preferable, Greene (2012, p. 449) advocates for the direct maximisation of the log-likelihood function using

NLOGIT's generalised optimization package. The starting values for iterations are obtained by assuming equal class probabilities and class-specific parameters which differ slightly from the MNL estimates (Greene, 2012).

6.3.3.2 Results

Table 6-5 shows the frequencies of the response categories of the NEP Scale. The response category with the highest frequency is "mildly agree" followed by "neither agree nor disagree" and the least frequently selected category is "strongly disagree", which reflects a tendency by respondents to express pro-NEP attitudes.

Table 6-5: Frequencies and proportions of self-reported levels of environmental concern

Response categories for NEP Scale statements			Frequency*	
Category	Description	Response variable (y)	Count	Percent
1	Strongly disagree	0	177	5.3%
2	Mildly disagree	1	551	16.4%
3	Neither agree nor disagree	2	839	25.0%
4	Mildly agree	3	1077	32.0%
5	Strongly agree	4	716	21.3%

*This is the number of times a specific category is selected

The coefficients and marginal effects for the ordered probit model are presented in Table A6-3 in Appendix 6 and Table 6-6, respectively. The coefficients reported in Table A6-3 are the effects of the covariates on the cumulative normal function of the probabilities that the response variable equals one, and do not show the complete picture implied by the estimated model as in the case of coefficients from OLS regression. Greene (2008, p. 833) suggests caution in interpreting the coefficients of the ordered probit model because "without a fair amount of extra calculation, it is quite unclear how the coefficients in the ordered probit model should be interpreted." Our main interest is in the marginal effects of SDCs, which we report on next.

The marginal effects reported in Table 6-6 measure the partial effects of the covariates on the probabilities of the outcomes (see Table A6-4 in Appendix 6 for full table of regression results). For example, males are more likely to select response categories 1, 2, and 3 compared to females, who are more likely to select categories 4 and 5. Specifically, being male increases the probabilities of response categories 1, 2 and 3 by 1.1%, 1.9%, and 1.0% respectively, and reduces the probabilities of categories 4, and 5 by 1.1% and 2.9% respectively. This implies that, on average, males tend to have lower environmental scores compared to females. An increase in age decreases the probability of response categories 1, 2, and 3 and increases that of 4 and 5, whilst an increase in income has the opposite effect, *ceteris paribus*. Having dependent children in the household and/or belonging to the NZ-European ethnic group have no significant effect on response probabilities. Compared to the "Other" ethnic group, Maori are less likely to select lower categories of the response variable, but are more likely to select response categories 4 and 5. Respondents with higher educational qualifications (at least a bachelor's degree) are more likely to respond 4 and 5 to the NEP statements compared to respondents with lower qualifications.

Table 6-6: Marginal effects of respondents' SDCs on NEP Scale responses[*]

Response category	Gender	Age	Child	*ln*Income	NZ_Euro	Maori	Education
1	0.0107^c	-0.0004^c	0.0027	0.0084^c	0.0003	-0.0176^b	-0.0087^a
	(2.58)	(-3.09)	(0.63)	(3.15)	(0.06)	(–2.24)	(-1.92)
2	0.0186^c	-0.0008^c	0.0047	0.0146^c	0.0006	-0.0342^c	-0.0155^a
	(2.60)	(-3.10)	(0.63)	(3.17)	(0.06)	(-2.01)	(-1.88)
3	0.0104^c	-0.0004^c	0.0026	0.0082^c	0.0003	-0.0229^a	-0.0090^a
	(2.61)	(-3.07)	(0.64)	(3.14)	(0.06)	(-1.72)	(-1.81)
4	-0.0108^b	0.0004^c	-0.0027	-0.0085^c	-0.0003	0.0159^c	0.0086^a
	(-2.56)	(3.06)	(-0.63)	(-3.12)	(-0.06)	(2.71)	(1.94)
5	-0.0289^c	0.0012^c	-0.0073	-0.0227^c	-0.0009	0.0589^a	0.2457^a
	(-2.60)	(3.08)	(-0.63)	(-3.16)	(-0.06)	(1.81)	(1.84)

[a], [b], and [c] denote significance at the 0.1, 0.05, and 0.01 levels respectively. [*]t-values are in parentheses

The results of the LCA model are presented in Table 6-7. Up to three classes of EA - *weak* (10%), *moderate* (61%) and *strong* (29%) environmental groups are supported by the data. A number of models were estimated with different combinations of covariates in the class membership model and the model presented here provided the best fit to the data. Of the covariates used in the class membership sub-model, only age has a significant and positive influence on class membership of the *strong* environmental group compared to the reference group (*weak*). This suggests that on average older respondents have a higher likelihood of belonging to the *strong* group compared to the *weak* group. However, gender and education have no significant influence on the probability of belonging to the *strong* or *moderate* group compared to the *weak* group. Respondents with high incomes are less likely to belong to the *strong* environmental group, whilst Maori and respondents with minor children living at home are more likely to belong to the *moderate* environmental group. Overall, our findings are consistent with previous studies supporting the notion that on average men are less pro-environmental than women and that respondents with higher incomes tend to be less pro-environmental (Clark et al., 2003; Ek & Soderholm, 2008).

Table 6-7: Regression results for the ordered LCA model (N = 224)

Variables	Environmental group					
	Strong		*Moderate*		*weak*	
	Coefficient	z	Coefficient	z	Coefficient	z
Constant	1.7149***	12.06	1.8870***	17.89	2.7859***	3.29
Gender	-0.1438***	-2.58	0.0004	0.01	-0.2479	-0.87
Age	-0.0019	-0.73	-0.0015	-1.10	-0.0079	-0.48
Child	-0.1432**	-2.55	0.0976**	2.43	-0.7399**	-2.18
Income/1000	-0.0042***	-4.37	-0.0008	-1.10	-0.0033	-0.57
NZ_European	-0.1128	-1.34	0.1059*	1.78	0.1014	0.14
Maori	0.4310	0.07	0.3618***	3.13	0.9863	0.07
Education	0.0042	0.07	0.0569	1.35	-0.0828	-0.16
μ1	0.3901***	9.24	1.2061***	22.58	1.0275***	7.36
μ2	0.6406***	12.22	1.9095***	32.91	3.4761***	19.07
μ3	1.2745***	26.21	3.1687***	47.53	4.7644***	6.63
	Class membership model					
Constant	-1.38887	-1.20	1.07081	1.01	0.0 (fixed parameter)	
Age	0.05442**	2.50	0.01670	0.83	0.0 (fixed parameter)	
Gender	-0.30221	-0.39	-0.12089	-0.16	0.0 (fixed parameter)	
Education	0.63508	0.72	0.30534	0.37	0.0 (fixed parameter)	
Class Probability	0.28778		0.61564		0.09659	
LL	-4564.35					
AIC	9201.7					
BIC	9461.6					

***, **, * Significant at the .01, .05, and .1 level, respectively

6.3.4 Constructing and testing subscales of the NEP Scale

To address research *Question 4(b)* we need to construct subscales of the NEP Scale from the responses to the full scale. In constructing the subscales of the NEP Scale we consider important issues addressed by Dunlap et al. (2000) when they revised the old 12-item NEP Scale to form the 15-item NEP Scale. These issues include: (a) an equal number of items or statements measuring each facet of ecological worldview, (b) a balance or near balance between pro-and anti-NEP items - ideally equal numbers but this is not possible even for the full scale with an odd number of items forming the scale, and (c) the internal consistency of the items as measured using the item-total correlation and Cronbach's alpha is sufficiently high to justify combining the items into a single index measuring environmental attitude, and/or factor analysis confirming that all items load heavily on a single factor.

Taking into account the above issues, only subscales with 5 and 10 items meet the condition of equal representation of the five facets. We refer to these as the 5-item and 10-item subscales. There are many combinations of 5 or 10 items that can be drawn from the fifteen items that constitute the full NEP Scale. The 5-item subscale can either have two pro- and three anti-NEP items or vice versa and the 10-item subscale should have an equal number of pro- and anti-NEP items. A convenient strategy that we adopt for drawing items for the 5-item subscales is to take the first five (NEP1 to NEP5), or middle five (NEP6 to NEP10), or last five (NEP10 to NEP15) items of the full NEP Scale as this meets the condition of equal representation and near balance between pro- and anti-NEP items. Using the same strategy of drawing items in blocks of five, there are three possible 10-item subscales that can be constructed by drawing the first ten items (NEP1 to NEP10), the last ten items (NEP6 to NEP15), and combining the first five and the last five items (NEP1 to NEP5 and NEP11 to NEP15). However the latter results in an unbalanced subscale with six pro-NEP and four anti-NEP items. These six subscales are tested for internal consistency to determine which two sub-scales are used in further analysis.

Table 6-8 presents the item-total correlations and Cronbach's alpha for each of the sub-scales. Although Cronbach's alpha and item-total correlation indicate that the 10-item subscale constructed from the first five (first 5) and last five (last 5) items of the NEP Scale has the highest level of internal consistency, it does not meet the condition of balance between pro- and anti-NEP items. The other two 10-item subscales have the same acceptable Cronbach's alpha equal to 0.73, but the subscale constructed from the last ten items is preferred as it has only one item (NEP 6) with an item-total correlation less than 0.30. Of the three 5-item subscales, the one constructed from the first five items of the NEP Scale has the highest Cronbach's alpha (0.61) and is also better in terms of item-total correlation. Therefore, the two sub-scales that we select for use in further analysis are the 5-item (first 5) and the 10-item (last 10) which are mutually exclusive in terms of items as they split the full NEP Scale into two parts. We refer to these subscales as the 5-item NEP Scale and the 10-item NEP Scale from now on.

Table 6-8: Item-total correlations and Cronbach's alpha for the sub-scales of the NEP Scale

Item	15-item NEP Scale	10-item (first 10)	10-item (last 10)	10-item (first 5 plus last 5)	5-item (first 5)	5-item (centre)	5-item (last 5)
NEP 1	0.35	0.32		0.36	0.29		
NEP 2	0.51	0.47		0.44	0.33		
NEP 3	0.48	0.46		0.48	0.47		
NEP 4	0.41	0.40		0.37	0.33		
NEP 5	0.49	0.43		0.50	0.42		
NEP 6	0.10	0.09	0.07			0.03	
NEP 7	0.31	0.28	0.30			0.21	
NEP 8	0.57	0.58	0.53			0.51	
NEP 9	0.39	0.36	0.35			0.26	
NEP 10	0.56	0.52	0.56			0.47	
NEP 11	0.46		0.37	0.48			0.35
NEP 12	0.39		0.41	0.30			0.27
NEP 13	0.42		0.40	0.42			0.38
NEP 14	0.34		0.30	0.35			0.30
NEP 15	0.60		0.55	0.59			0.50
α*	0.81	0.73	0.73	0.86	0.61	0.51	0.60

* Cronbach's alpha

We estimate two LCA models based on equations (6-4) to (6-5) using the preferred subscales described previously, and compare the results with those obtained using the full NEP Scale to determine the accuracy of the subscales in terms of classifying respondents into the same latent classes as the full scale. Table 6-9 presents the results for the subscales alongside those of the full NEP Scale. The models estimated using the subscales suggest, as in the case of the full scale, the presence of up to three classes of environmental attitude which we refer to as *strong, moderate* and *weak* as in the previous estimation. The class sizes obtained using the subscales are different from the respective classes obtained using the full NEP Scale. The 10-item subscale seems to assign more respondents to the *weak* environmental class, and less to the *strong* and *moderate* classes compared to the full scale. The 5-item scale seems to have the opposite effect as it assigns fewer respondents to the *weak* class and more to the *moderate* and *strong* classes compared to the full scale. This is similar to findings by Hawcroft and Milfont (2010), indicating that respondents scored higher on a 6-item subscale and lower on other subscales compared to the full NEP Scale.

Table 6-9: LCA model results for the full NEP Scale and constructed 10- and 5-item sub-scales

	15-item NEP Scale			10-item NEP Scale			5-item NEP Scale		
	Strong	*moderate*	*Weak*	*Strong*	*Moderate*	*Weak*	*Strong*	*Moderate*	*Weak*
		Coefficients			Coefficients			Coefficients	
Constant	1.715^{c}	1.887^{c}	2.786^{c}	1.778^{c}	1.701^{c}	2.159^{c}	1.685^{c}	2.134^{c}	3.717^{b}
Gender	-0.144^{c}	0.001	-0.247	-0.145^{a}	-0.059	-0.204	-0.181	0.055	-0.471
Age	-0.002	-0.002	-0.007	-0.003	-0.001	0.004	0.006	0.000	-0.084^{b}
Child	-0.143^{b}	0.098^{b}	-0.739^{b}	-0.131	0.154^{b}	-0.034	-0.221	0.140	-0.514
Income/1000	-0.004^{c}	-0.001	-0.003	-0.004^{b}	-0.001	-0.005	-0.004	-0.002	0.026
NZ-Euro	-0.113	0.106^{a}	0.101	-0.212	0.198^{a}	-0.097	-0.143	-0.112	0.219
Maori	0.431	0.362^{c}	0.986	0.445	0.664^{b}	0.278	-0.133	0.165	-0.155
Education	0.004	0.057	-0.082	-0.019	0.088	-0.023	-0.017	0.198^{a}	-0.878
$\mu 1$	0.390^{c}	1.206^{c}	1.027^{c}	0.378^{c}	1.087^{c}	1.064^{c}	0.516^{c}	1.470^{c}	0.163
$\mu 2$	0.641^{c}	1.909^{c}	3.476^{c}	0.631^{c}	1.698^{c}	2.850^{c}	0.703^{c}	2.158^{c}	2.822^{c}
$\mu 3$	1.275^{c}	3.169^{c}	4.764^{c}	1.117^{c}	2.940^{c}	3.827^{c}	1.519^{c}	3.596^{c}	3.922^{c}
	Class membership model								
Constant	-1.389	1.071	0.(fixed)	-2.754^{c}	0.(fixed)	-0.536	1.391^{a}	0.(fixed)	-0.682
Age	0.054^{b}	0.017	0.(fixed)	0.040^{b}	0.(fixed)	-0.008	0.016	0.(fixed)	-0.037^{a}
Gender	-0.302	-0.121	0.(fixed)	-0.115	0.(fixed)	-0.238	-0.072	0.(fixed)	0.001
Education	0.635	0.305	0.(fixed)	0.618	0.(fixed)	0.094	0.095	0.(fixed)	0.593
Class Prob.	0.288	0.616	0.097	0.239	0.559	0.202	0.313	0.617	0.070
LL		-4564.35496			-3095.00920			-1529.85154	
AIC		9201.7			6272.0			3141.7	
BIC		9461.6			6506.3			3347.6	
Accuracy[1]		100%			83.93%			81.25%	

[1]We assume that the full or 15-item NEP Scale is 100% accurate since it is used as a reference point.

^{a}, ^{b}, ^{c} Denote significance at 0.1, 0.05, and 0.01 levels respectively

With an appropriate command NLOGIT 5 estimates individual specific posterior or conditional class probabilities. We use these individual posterior class membership probabilities to compare the two sub-scales with the full NEP Scale. We estimate the accuracy of each subscale as the number of times a subscale assigns a respondent to the same class as the full NEP Scale as a percentage of sample size. Based on these criteria, the 10-item scale has an accuracy of 84%, whilst the 5-item sub-scale has and accuracy of 81%. This indicates that the accuracy of the subscales declines as they become shorter.

Table 6-10 presents the characteristics and environmental attitude scores of respondents in the *weak*, *moderate* and *strong* environmental groups for the three scales. For all three scales the *weak* classes have the lowest average age and income, whilst the *strong* classes have the highest average age, implying that the scales are consistent in assigning relatively younger respondents to the *weak* class and relatively older respondents to the *strong* class. For the 5-item scale, the *weak* class is weaker and the moderate class is less moderate than the respective classes based on the longer scales. However, the average item score for the *strong* class is significantly higher for the 5-item NEP Scale compared to the longer scales (the t scores for the differences in means are -2.33 and -2.16 for the 15-item and 10-item NEP Scales, respectively, which are higher the critical value of 1.96 at α = 0.05) . Hawcroft and Milfont (2010) find a similar result from a meta-analysis of studies that used different scale lengths in measuring environmental attitude. The 10-item NEP Scale produces significantly higher average scores for the moderate class compared to the 15-item NEP Scale (t = -2.12).

The conclusion that can be drawn from the results discussed above is that using shorter sub-scales of the NEP scale comes at a cost in the form of reduced accuracy in classifying respondents into groups with homogeneous environmental preferences. If the use of a shorter version of the NEP Scale cannot be avoided, then the 10-item subscale is recommended as no significant differences in the average scores are found in the *strong* and *weak* classes. In section 6.7 we test the effect of using shorter versions of the NEP Scale on WTP for green electricity.

Table 6-10: Characteristics of respondents in the *weak*, *moderate* and *strong* environmental classes

Variable		Weak			Moderate			Strong		
		15-item	10-item	5-item	15-item	10-item	5-item	15-item	10-item	5-item
Class size		10%	20%	8%	60%	54%	63%	30%	26%	29%
Mean NEP Scale score*		43.5	30.0 (45.7)	13.2 (43.0)	50.4	34.6 (51.8)	16.5 (49.8)	58.5	38.9 (58.1)	20.6 (60.1)
mean item score		2.90	3.00	2.64	3.36	3.46	3.29	3.90	3.90	4.12
Gender (male)		45%	39%	42%	46%	47%	47%	49%	53%	48%
Average Income ($000)		39.4	41.0	41.7	46.1	46.1	45.5	44.5	45.8	44.8
Average Age (years)		39	40	36	43	43	44	50	51	49
Ethnicity	NZ Euro	73%	70%	69%	78%	82%	76%	76%	74%	83%
	Maori	9%	9%	5%	5%	3%	4%	3%	4%	5%
	Other	18%	22%	26%	17%	15%	20%	21%	22%	12%
Education **		27%	33%	47%	31%	28%	29%	31%	34%	28%
Dependent children		41%	48%	42%	43%	42%	44%	37%	33%	33%

*Scores in parentheses are based on all 15 items of the NEP Scale. **At least Bachelors

6.4 Analysis of responses to questions based on the norm activation theory

Responses to questions measuring psychological constructs based on the norm activation theory (NAT) are used in section 6.6 to explain heterogeneity in preferences for green electricity. In this section we analyse these responses to determine whether questions measuring the same construct may be combined into a single index. NAT and the construction of statements used to measure the respective psychological constructs were discussed in Chapter 2. Two statements are used to assess respondents' "awareness of consequences" (AC) of switching to a supplier that produces electricity from renewables, and another two statements are used to assess "ascription of responsibility" (AR). Responses are measured on a five-point Likert scale with response categories "Strongly Agree" (SA), "Somewhat Agree" (SWA), "Neither Agree Nor Disagree" (NAND), "Somewhat Disagree" (SWD), and "Strongly Disagree" (SD). These are coded from 1 (SD) to 5 (SA).

Responses to the statements measuring the NAT constructs are spread over all response categories (see Table 6-11). This indicates considerable individual heterogeneity in terms of awareness of the environmental benefits of supporting a supplier that produces electricity from renewable sources, and the feeling of personal responsibility for reducing pollution. However, the percentage distribution of responses shows that respondents have a relatively higher positive evaluation of "awareness of consequences" (AC) compared to "ascription of responsibility" (AR) statements. For example, 66.5% of the respondents believe that switching to a supplier producing electricity from renewable sources is good for the environment, compared to only 27.7% who feel morally obliged to switch to a supplier that generates most of its power from renewable sources. This suggests that, for the majority, other incentives may be required to induce a switch.

Table 6-11: Percentage distribution of responses to AC and AR statements (N = 224)

Statement	Response categories				
	SA	SWA	NAND	SWD	SD
Awareness of the consequences of a behaviour (AC)					
AC1: I believe that switching to a supplier that produces electricity from renewable sources would be good for the environment.	18.30	48.21	28.57	3.57	1.34
AC2: My switching to a supplier that generates electricity from renewable sources will not make a difference to the environment.	4.91	17.86	37.50	26.79	12.95
Ascription of responsibility (AR)					
AR1: I feel personally responsible for helping to reduce carbon dioxide emissions by switching to a supplier that generates electricity from clean energy sources.	7.14	29.91	33.48	22.77	6.70
AR2: I feel morally obliged to switch to a supplier that generates most of its power from renewable sources.	6.25	21.43	39.29	24.11	8.93

Internal consistency of the AC and AR statements is tested using the correlations among the items and the results are presented in Table 6-12. Principal components analysis is not performed as only two statements were used for each construct. Correlation between the AC statements is 0.38 whilst that of the AR statements is 0.71. The relatively low correlation between the AC statements may be due to the fact that AC2 is a negative statement. As we saw in the case of the NEP scale, respondents tend to select the neutral point for negative statements. However, both correlations are significant at the 5% level suggesting that each pair of statements may be combined into a single index measuring the construct.

To obtain an index for each construct, the scores for each pair of statements are averaged. The sample means for the AC and AR scores are 3.52 and 3.00 respectively. The mean score for AR indicates that, on average, respondents are neutral with respect to assigning personal responsibility for engaging in switching behaviour for environmental reasons. Some previous studies have combined AC and AR into a single index measuring altruism (e.g., Clark et al., 2003; Cooper et al., 2004), which may be justified in terms of the high correlations between all items.

Table 6-12: Summary statistics and the correlation matrix (Pearson (n)) for the NAT constructs

Variables	Min	Max	Mean	Std. dev.	AC1	AC2	**AC**	AR1	AR2	**AR**
Awareness of the consequences of a behaviour (AC)										
AC1	1	5	3.79	0.83	1	**0.38**	0.78	0.52	0.48	0.54
AC2	1	5	3.25	1.05	0.38	1	0.87	0.33	0.25	0.31
AC	1	5	3.52	0.78	**0.78**	**0.87**	1	0.50	0.42	0.50
Ascription of responsibility (AR)										
AR1	1	5	3.08	1.04	0.52	0.33	0.50	1	0.71	0.93
AR2	1	5	2.92	1.03	0.48	0.25	0.42	**0.71**	1	0.92
AR	1	5	3.00	0.96	0.54	0.31	0.50	**0.93**	**0.92**	1

In the sections that follow we explore the effect of the psychological constructs on WTP for green electricity.

6.5 Environmental attitudes and WTP for green electricity

Although our hypothesis is that respondents expressing higher environmental concern are expected to consider renewables in choosing their power company, and that their choices would reflect a willingness to pay for green electricity, there are a number of reasons why higher environmental scores may not translate to a WTP. First, responses to the NEP Scale statements tell us nothing about an individual's ability to pay, but only about their environmental attitude. Second, an individual's WTP for green electricity may depend on a number of factors such as income, current electricity prices (or monthly power bill), environmental attitude, beliefs and perceptions about whether supporting electricity generation from renewable energy sources by paying more for green electricity would be an effective way of reducing CO_2 emissions, and the perceived property rights. Therefore, it is possible for a respondent to express high concern for the environment and a zero WTP for green electricity if they cannot afford, or don't believe that paying for green electricity is an effective strategy for addressing CO_2 emission and resource depletion by the electricity sector, or that electricity generators have no right to pollute and the government is responsible for ensuring that electricity generators pay for their CO_2 emissions.

The analysis that follows addresses research *Question 4: (a) How much are electricity consumers willing to pay for green electricity and how can differences in WTP be explained?*

6.5.1 Methods

To find the model that best fits the data, the MNL, RPL-EC and LC models described in Chapter 2 are estimated. EA enters the utility function as an interaction with *Renewable*. We recognise the three classes of environmental attitudes identified in section 6.4.2 and also follow an approach adopted in previous studies by coding the NEP scores using a dummy coding structure with three levels representing *weak*, *moderate* and *strong* environmental attitudes (e.g., Aldrich et al., 2007; Cooper et al., 2004; Kotchen & Reiling, 2000). Each level is interacted with *Renewable* to form *WNEP_Renewable*, *MNEP_Renewable* and *SNEP_Renewable*, but only the last two interaction terms enter the utility functions of alternatives as *weak* is used as a reference level.

We use the Wald test for linear restrictions to test whether the slopes of the dummy interaction terms described above are equal in the MNL model (Hensher et al., 2005a). Details of how the dummy variables are created under each version of the NEP Scale are provided in Table 6-13. The dummy variables created for the subscales of the NEP Scale are used in estimation at a later stage. The sample sizes differ slightly across the scales as we avoid splitting respondents with the same score. All the attributes including interaction terms enter the systematic component of utility linearly in all the models estimated.

Table 6-13: Description of NEP score levels

Scales	WNEP (*weak NEP*)	MNEP (*moderate NEP*)	SNEP (*strong NEP*)
15-item NEP Scale	= 1 if score < 47, otherwise 0. (n = 70)	= 1 if 48 ≤ score ≤ 55, otherwise 0. (n = 77)	= 1 if score >55, otherwise 0. (n = 77)
10-item NEP Scale	= 1 if score ≤ 31, otherwise 0. (n = 69)	= 1 if 32 ≤ score ≤ 36, otherwise 0. (n = 72)	= 1 if score > 36, otherwise 0. (n = 83)
5-item NEP Scale	= 1 if score ≤ 15, otherwise 0. (n = 66)	= 1 if 16 ≤ score ≤ 18, otherwise 0. (n = 78)	= 1 if score > 18, otherwise 0. (n = 80)

The models that include interaction terms described above are suffixed with a number indicating the number of items in each version of the NEP Scale used. For example for the MNL we have MNL_15, MNL_10, and MNL_5 for the models using 15, 10, and 5 items of the NEP Scale. The specification of random parameters in the RPL-EC model is tested through alternative specifications. Only parameters with significant standard deviations are specified as random in the final models. For example, preliminary estimation of the RPL-EC model suggested that the parameters for *Renewable*, *Loyalty Rewards* and the dummies indicating supplier type should be treated as non-random. A random parameter specification for these variables turned out insignificant estimates of the standard deviations.

To avoid the complications associated with estimating WTP as a ratio of two random parameters with the same or different distributions, we assume a non-random (fixed) parameter for *Monthly Power Bill*. This allows the distribution of marginal WTP to take the same form as that assumed for the respective parameters scaled by the parameter for *Monthly Power Bill* (Goett et al., 2000; Hensher et al., 2005a; Revelt & Train, 1998). Revelt and Train (1998) and Goett et al. (2000) mention that using a fixed parameter for the cost attribute allows an easy derivation and interpretation of the distribution of WTP. Hensher et al. (2005a) and Goett et al. (2000) discuss problems such as unreasonable and extremely high WTP estimates associated with applications in which a random parameter is specified for the cost attribute, where the cost parameter takes on a value arbitrarily close to zero. To allow for comparability of results, we follow the practice in most previous studies estimating WTP for the attributes of electricity services by assuming that random parameters or taste intensities are normally distributed in the sampled population (e.g., Goett et al., 2000; Gracia et al., 2012; Hensher et al., 2014). Specifying a normal distribution, which has support on each side of zero, implies that for each attribute some respondents would like it, whilst others would dislike it (Goett et al., 2000).

6.5.2 Results

Preliminary estimations of the LC model with covariates and/or EA in the class membership model revealed that these variables are poor predictors of membership of preference class in the context of supplier choice based on our choice dataset. For EA, this finding is not surprising since the NEP scores are only expected to affect preferences for *Renewable*, yet the identified classes are based on preferences for all the attributes used in describing the alternatives in choice sets. To ovoid over-parameterisation, the class membership model in the final LC model is specified as a base model suggested by Heckman and Singer (1984), in which class verification is based on class-specific constants.

As discussed in Chapter 2, we rely on information criteria, pattern of significant parameters and relative signs, ease of interpreting the results and the need for parsimony in determining the number of classes to retain. In all estimations of the LC model, we start with a single class and progressively increase the number of classes, each time observing changes in information criteria and parameter estimates.

Information criteria presented in Table 6-14 indicate the presence of up to three or five preference classes, and Figure 6-3 presents a visual display of changes in information criteria as the number of classes is increased. Based on CAIC and BIC, only three classes should be retained compared to five indicated by AIC, and AIC3[20]. The performance of CAIC and BIC in identifying fewer classes compared to AIC and AIC3 is consistent with findings in previous studies investigating the performance of information criteria (e.g., Andrews & Currim, 2003a). Therefore, we retain three classes for the LC model. The LC model with three classes identifies market segments with clearly distinct preferences for the attributes.

[20] HQC and crAIC (not reported in Table 6-14) also indicate up to five preference classes.

Table 6-14: Information criteria used to determine the number of latent classes

Number of classes	CAIC	BIC	AIC3	AIC
1	4423	4410	4346	4333
2	4011	3984	3851	3824
3	**3863**	**3822**	3621	3580
4	3929	3874	3604	3549
5	3986	3917	**3579**	**3510**
6	4084	4001	3595	3512

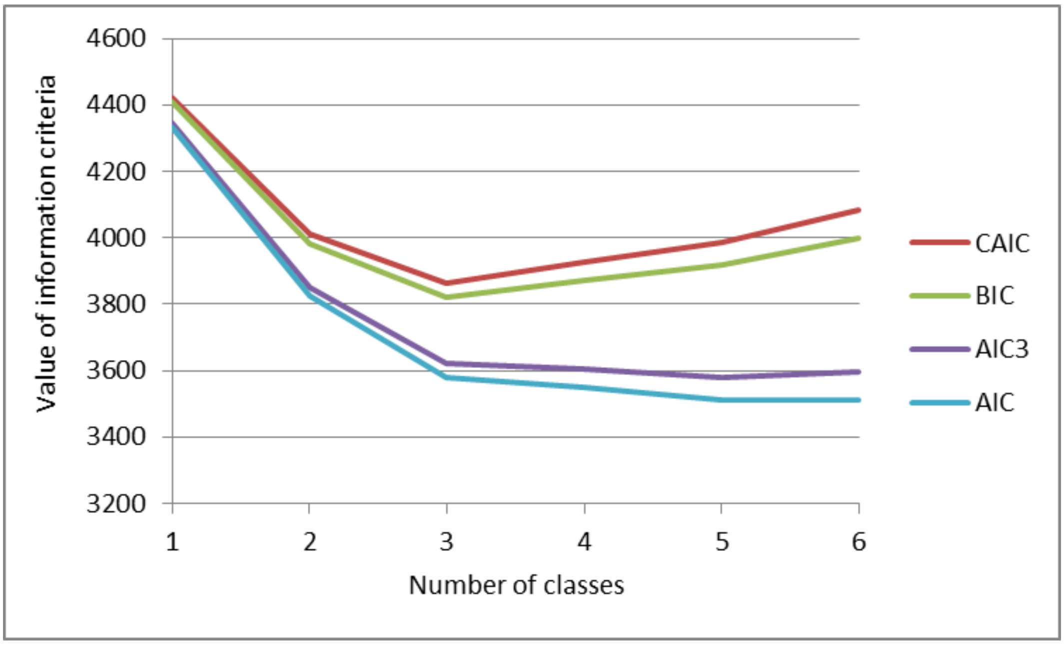


Figure 6-3: Information criteria used to determine the number of classes

Regression results for the final models are presented in Table 6-15. Overall the data fits all the models well with pseudo-R^2 values ranging from 0.267 for MNL_15 and 0.408 for the LC_15. All significant parameters have the expected signs across the three models, indicating the robustness of the results.

Table 6-15: Regression results

Variable	MNL_15	RPL_15	LC_15		
			Class 1	Class 2	Class 3
ASCALT1	0.5759^{c}	0.6171^{c}	0.5170^{c}	0.0956	3.2536^{c}
	(0.0744)	(0.1503)	(0.1887)	(0.1276)	(0.4867)
Time	-0.0431^{c}	-0.0479^{c}	-0.0385^{b}	-0.0342^{c}	-0.0419
	(0.0074)	(0.0101)	(0.0175)	(0.0118)	(0.0351)
Fixed	0.0046^{b}	0.0079^{b}	0.0056	0.0104^{b}	-0.0033
	(0.0021)	(0.0035)	(0.0066)	(0.0045)	(0.0129)
Discount	0.0096^{c}	0.0127^{c}	0.0054	0.0158^{c}	0.0516^{c}
	(0.0027)	(0.0033)	(0.0057)	(0.0044)	(0.0188)
Loyalty Rewards	0.3696^{c}	0.2907^{c}	0.2720^{a}	0.3601^{c}	0.4899
	(0.0695)	(0.0839)	(0.1527)	(0.1222)	(0.3833)
Renewable	0.0031	0.0061^{b}	0.0019	0.0079^{b}	-0.0042
	(0.0024)	(0.0030)	(0.0061)	(0.0036)	(0.0106)
MNEP_Renewable	0.0066^{b}	0.0068^{a}	0.0074	0.0055	0.0230^{a}
	(0.0030)	(0.0039)	(0.0067)	(0.0051)	(0.0136)
SNEP_Renewable	0.0105^{c}	0.0125^{c}	0.0144^{a}	0.0099^{b}	-0.0002
	(0.0029)	(0.0047)	(0.0081)	(0.0045)	(0.0141)
Local Ownership	0.0082^{c}	0.0112^{c}	0.0134^{c}	0.0122^{c}	0.0056
	(0.0014)	(0.0022)	(0.0029)	(0.0022)	(0.0095)
New Electricity Company	-0.3333^{c}	-0.2742^{b}	-0.0889	-0.1842	-0.4429
	(0.0953)	(0.1259)	(0.2089)	(0.1620)	(0.5264)
New Non-electricity Company	-0.7405^{c}	-0.8812^{c}	-0.3076	-0.8090^{c}	-1.5438^{a}
	(0.1223)	(0.1647)	(0.2793)	(0.1957)	(0.8389)
Well-known Non-electricity Company	-0.4248^{c}	-0.4993^{c}	-0.0572	-0.3968^{b}	-0.2898
	(0.1146)	(0.1568)	(0.2946)	(0.1796)	(0.5048)
Monthly Power Bill	-0.0255^{c}	-0.0337^{c}	-0.0569^{c}	-0.0138^{c}	-0.0147^{b}
	(0.0008)	(0.0011)	(0.0039)	(0.0017)	(0.0061)
Class Probabilities			0.5382^{c}	0.3471^{c}	0.1148^{c}
			(0.0435)	(0.0429)	(0.0219)
Standard Deviations of Random Parameters					
Time		0.0416^{c} (0.0150)			
Fixed		0.0266^{c} (0.0045)			
Discount		0.0152^{b} (0.0069)			
MNEP_Renewable		0.0074^{a} (0.0044)			
SNEP_Renewable		0.0204^{c} (0.0036)			
Local Ownership		0.0165^{c} (0.0025)			
Error component		1.5979^{c} (0.1329)			
LL	-2153.59	-1887.98		-1748.95	
AIC	4333.2	3818.0		3579.9	
BIC	4409.8	3933.9		3821.7	
Pseudo-R^2	0.2669	0.3607		0.4078	

^{c}, ^{b}, ^{a} Significant at the .01, .05 and .1 level, respectively. Standard errors are in parentheses

A comparison of the models in terms of model fit shows that LC_15 performs best with highly significant LRT statistics of 809.28 and 278.06 against MNL_15 and RPL-15, respectively. An LRT statistic of 12.02 for MNL_15 versus the base MNL model against a χ^2 critical value of 5.99 ($\chi^2_{(2)\ 0.05}$) confirms that including the interaction terms between *Renewable* and the NEP Scale score in model estimation improves goodness-of-fit. Furthermore, the Wald test for linear restrictions ($\chi^2_{(3)} = 2.19$) in the MNL model has a p-value of .139, which is greater than .05. The null hypothesis that the slopes of the interaction terms are equal is rejected at the 95% level of confidence. This suggests that the NEP score has a non-linear effect on the utility of *Renewable,* that is, a unit increase in the NEP score does not have a constant effect on utility at all levels of the NEP score.

Although all the parameter estimates in Table 6-15 provide considerable insight into the preferences for the attributes, we focus mainly on the parameter estimates for the *Renewable, MNEP_Renewable SNEP_Renewable*, and *Monthly Power Bill* variables which are most relevant to the research *Question 4 (a)*. The coefficient of *Renewable* is insignificant at the .05 level in MNL_15 and in classes 1 and 2 of LC_15, suggesting indifference towards *Renewable* by respondents in the *weak* environmental group. The coefficients of *MNEP_Renewable*, and *SNEP_Renewable,* which capture the systematic effect of moderate and high NEP scores on the utility of *Renewable* are significant, at least at the .1 level in MNL_15 and RPL-15 indicating heterogeneity in preferences for *Renewable.* These significant coefficients indicate that, on average, respondents belonging to the *moderate* and *strong* environmental groups have stronger preferences for *Renewable* compared to respondents in the *weak* environmental group.

In LC_15, *MNEP_Renewable* is insignificant in class 2 indicating that respondents in the *weak* and *moderate* environmental groups have similar preferences for *Renewable*. The significance of *SNEP_Renewable* varies across the three classes in LC_15, indicating heterogeneity of preferences for *Renewable* across the classes. Significant heterogeneity exists within class 2 at the .05 level, with respondents in the *strong* environmental group exhibiting higher sensitivity to *Renewable* than the groups with lower NEP Scale scores. All standard deviations of random parameters including the error component are significant at least at the .1 level, indicating heterogeneity around the sampled population mean parameters for the variables and significant correlations in the error structure of the non-status quo alternatives.

WTP estimates

Estimates of marginal WTP for the non-price attributes of electricity services are presented in Appendix 6 (Table A6-5), and a summary of WTP for green electricity is presented separately in Table 6-16. Based on MNL_15, respondents in the *weak* environmental group are not willing to pay any significant amount for green electricity, whist those belonging to the *moderate* and *strong* environmental groups are willing to pay on average \$2.60 (\$0.26x10) and \$4.10 (\$0.41x10) per month, respectively, to secure a 10% increase in green electricity. WTP for respondents with high NEP Scale scores is about 1.6 times that of respondents with moderate or average scores. Estimates based on RPL_15 reveal no significant differences in WTP between respondents in the *weak* and *moderate* environmental groups at the .05 level. However, respondents belonging to the *strong* environmental group are willing to pay, on average, \$5.50 per month to secure a 10% in green electricity, which is about 3 times that of respondents in the *weak* and *moderate* environmental groups.

Table 6-16: WTP for a 1% increase in generation from renewable energy sources (NZ$_{(2014)}$ / month)

Environmental group	MNL_15	RPL_15	LC_15		
			Class 1	Class 2	Class 3
Weak	*NS*	0.18[b]	*NS*	0.57[b]	*NS*
		(0.089)		(0.27)	
Moderate	0.26[b]	0.18[b1]	*NS*	0.57[b]	*NS*
	(0.118)	(0.089)		(0.27)	
Strong	0.41[c]	0.55[c]	0.25[a]	1.29[c]	*NS*
	(0.117)	(0.109)	(0.14)	(0.26)	
Class size			53.82%	34.70%	11.48%

[c], [b], [a] Significant at the .01, .05 and .1 level, respectively. Standard errors are in parentheses. *NS* denotes not statistically different from zero. [1]WTP increases to \$0.38 (0.077) if the estimate of \$0.20 which is only significant at 0.1 level is included.

WTP varies both within and across the three latent classes identified in LC_15, except class 3 where WTP is zero for all environmental groups. Respondents in class 3, representing about 11% of the sampled population, have a zero WTP for green electricity; hence EA does not influence WTP in this class. In classes 1 and 2, EA helps in explaining differences in WTP for green electricity. For example, in class 2 which accounts for about 35% of the sample, respondents belonging to the *weak* and *moderate* environmental groups are willing to pay on average $5.70 per month for a 10% increase in green electricity, whilst respondents belonging to the *strong* environmental group are willing to pay on average $12.90 per month to secure the same increase. On the other hand, for respondents in class 1, representing about 54% of the sampled population, WTP differences between environmental groups are only discernible at the .1 level. Respondents in the weak and moderate environmental groups have a zero WTP, whilst those in the strong environmental group have a WTP of $2.50 per month for a 10% increase in green electricity.

Based on LC_15, there is a potential for green marketing in New Zealand, where electricity retailers may be able to sell green electricity to about 35% of the retail customers. In this market segment, WTP to secure a 10% increase in green electricity represents between 3 and 7% of the sample average monthly power bill ($174) depending on the environmental group. Although the WTP estimates discussed above are not directly comparable to those in the studies reviewed in section 6.2.1 due to differences in the framing of the choice questions, they are however, of the same order.

The next section extends on the analysis conducted so far in addressing research *Question 4 (a)* by exploring the influence of the psychological constructs based on the norm activation theory (NAT) on WTP for green electricity.

6.6 Altruism and the demand for green electricity

In this section we estimate a model of supplier choice that integrates the psychological constructs based on the NAT with Lancaster's characteristic theory of demand and random utility theory. The general framework for integrating psychological constructs with stated choice was described in detail in Chapter 2, and a summary of the analysis of responses to the questions measuring the NAT constructs, '*awareness of a behaviour's consequences'* (AC), and *'beliefs about personal responsibility or ascription of responsibility'* (AR), was presented earlier in section 6.6. The main objective of this analysis is to determine whether AC and AR, the antecedents of altruistic behaviour, play any systematic role in explaining heterogeneity of preferences for *Renewable* (green electricity). We test the null hypothesis that AC and AR do not explain heterogeneity of preferences for green electricity.

To achieve the above objective we utilize the mixed logit model's ability to determine possible sources of heterogeneity by revealing preference heterogeneity around the mean of a random parameter (Hensher et al., 2005a). Specifically, we use a panel mixed logit model with error components to determine whether AC and AR are possible sources of heterogeneity around the mean of the random parameter for *Renewable*, and estimate WTP for green electricity at different levels of AC and AR. The random parameter for *Renewable* is interacted with AC and AR in a RPL-EC model estimated using NLOGIT 5 software. The interaction terms decompose any heterogeneity observed within the parameter of *Renewable*, and offer an explanation for differences in preferences for the attribute (Hensher et al., 2005a). A significant standard deviation parameter for *Renewable* confirms heterogeneity in respondents' preferences for green electricity. On the other hand, statistically significant interaction terms confirm that differences in the marginal utilities for *Renewable* may be explained, in part, by differences in AC and AR scores. For example, respondents reporting higher AC and AR scores are expected to be more sensitive to *Renewable*, hence the parameter estimates for the interaction terms are expected to be positive and significant when the null hypothesis does not hold.

Following Hensher et al. (2005a), heterogeneity around the mean parameter for *Renewable* explained by AC and AR is included in the marginal utility (MU) of *Renewable* as follows:

$$MU_{Renew} = \beta_{meanRenew} + \beta_{AC} * AC + \beta_{AR} * AR + \sigma_{Renew} * N \qquad (6\text{-}7)$$

were, $\beta_{meanRenew}$ and σ_{Renew} are the mean and standard deviation parameter estimates for *Renewable*, β_{AC} and β_{AR} are the heterogeneity in mean parameter estimates for AC and AR, respectively, and *N* is a random variate with a standard normal distribution. The MU of *Renewable* is then included in the utility function of an alternative i for respondent n, defined in equation 5.1, as shown in the following equation.

$$U_{in} = \sum_k \beta_{nk} X_{ink} + (\beta_{meanRenew} + \beta_{AC} AC_n + \beta_{AR} AR_n + \sigma_{Renew} N_n) Renew_{in} + \alpha_{sq} + \mu_n' z_{in} + \varepsilon_{in} \quad (6\text{-}8)$$

6.6.1 Regression results

Regression results presented in Table 6-17 show that the overall model is statistically significant with a χ^2 statistic of 2142.67 against a χ^2 critical value of 28.87 (with 18 degrees of freedom at alpha equal to 0.05). A pseudo-R^2 of 0.36 is acceptable for a choice model. This model performs better than the base RPL-EC model estimated in the previous chapter (Table 5-12 on page 178) in terms of a LRT ($\chi^2_{(df\ =\ 2)}$ = 64.20), log likelihood, information criteria and pseudo-R^2. This indicates that a model accounting for heterogeneity around the mean parameter for *Renewables* provides a better fit for the data. All parameter estimates are significant at the 0.05% level. Given the objective of this analysis, we focus on the mean and standard deviation parameters for *Renewable*, and the heterogeneity in mean parameter estimates for AC and AR reported under the sub-heading '*Heterogeneity in mean (Parameter:Variable)'* in the results table.

The heterogeneity in mean parameter estimates for AC and AR are positive and statistically significant, which confirms that the variations in respondents' preferences for *Renewable* or green electricity are, in part, explained by personal norms. Furthermore, these estimates indicate a stronger influence of AR on preferences compared to AC. This implies that the feeling of personal responsibility for considering the environment in choosing a supplier explains more variation in preferences for green electricity than awareness of the consequences of doing so.

Since the heterogeneity in mean parameter estimates are all significant at the 0.05% level, we reject the null hypothesis that AC and AR do not play any systematic role in explaining differences in preferences for green electricity.

Table 6-17: RPL-EC model regression results

Variables	Coefficient	Std. Error	| z |	p-value	95% CI LB	95% CI UB
Random parameters in utility functions						
Time	-0.0458[c]	0.0086	5.29	.0000	-0.0627	-0.0288
Fixed	0.0079[b]	0.0035	2.26	.0239	0.0010	0.0147
Discount	0.0128[c]	0.0034	3.75	.0002	0.0061	0.0194
Renewable	-0.0353[c]	0.0088	3.99	.0001	-0.0527	-0.0179
Ownership	0.0106[c]	0.0023	4.61	.0000	0.0061	0.0151
ERC	0.0	……. (Fixed Parameter)…..				
Nonrandom parameters in utility functions						
ASCALT1	0.6768[c]	0.1511	4.48	.0000	0.3806	0.9730
Rewards	0.2934[c]	0.0843	3.48	.0005	0.1282	0.4586
New electricity company	-0.2664[b]	0.1269	2.10	.0358	-0.5151	-0.0177
New non-electricity company	-0.8925[c]	0.1651	5.41	.0000	-1.2162	-0.5689
Well-known non-electricity company	-0.5038[c]	0.1574	3.20	.0014	-0.8122	-0.1953
Monthly power Bill	-0.03401[c]	0.00116	29.35	.0000	-0.0363	-0.0317
Heterogeneity in mean (Parameter:Variable)						
Renewable:AC	0.0062[b]	0.0026	2.36	.0182	0.0011	0.0114
Renewable:AR	0.0082[c]	0.0023	3.47	.0005	0.0035	0.0128
Standard deviations of random parameters						
NsTime	0.0458[c]	0.0086	5.29	.0000	0.0288	0.0627
NsFixed	0.0268[c]	0.0043	6.29	.0000	0.0184	0.0351
NsDiscount	0.0187[c]	0.0059	3.18	.0015	0.0072	0.0303
NsRenewable	0.0102[c]	0.0024	4.18	.0000	0.0054	0.0149
NsOwnership	0.0171[c]	0.0024	6.99	.0000	0.0123	0.0219
NsERC	1.6995[c]	0.1259	13.50	.0000	1.4528	1.9462
LL	-1881.73					
AIC	3799.5					
BIC	3905.6					
Pseudo-R^2	0.3628					
$\chi^2_{(18\ d.f)}$ [p-value]	2142.67 [.00001]					

[c], [b], [a] Denote significance at the .01, .05, and .1 level, respectively

6.6.2 WTP for green electricity

WTP for green electricity is estimated by dividing the marginal utility of *Renewable* expressed in equation (6-7) by the parameter estimate for *Monthly power bill* (β_{Bill}) as follows.

$$WTP_{Renewable} = (\beta_{meanRenew} + \beta_{AC}AC + \beta_{AR}AR + \sigma_{Renew} * N)/-\beta_{Bill} \quad (6\text{-}9)$$

The parameter estimates in the expression for MU of *Renewable* are the unconditional parameter estimates that are representative of the entire sampled population. Unconditional individual-specific parameter estimates are simulated by creating a hypothetical sample of 10,000 individuals, and randomly assigning each to a point on the distribution of the random parameter for *Renewable* by taking random draws (*rnn*) from a standard normal distribution. For each hypothetical individual, *rnn* replaces *N* in equation (6-9), and individual-specific WTP estimates are computed. The distribution of the random draws used and the simulated WTP distribution are presented in Figure 6-4 and Figure 6-5, respectively. Additional WTP estimates are calculated at different combinations of the AC and AR scores to highlight sensitivity to the scores. The estimated mean and standard deviation of the WTP distribution are reported in Table 6-18. When evaluated at the sample mean scores for AC and AR, average WTP for a 10% increase in *Renewable* is \$3.20 per month. When AC is high (5) and AR is low (1), WTP is predicted to be low, highlighting the strong influence of AR on preferences for *Renewable.*

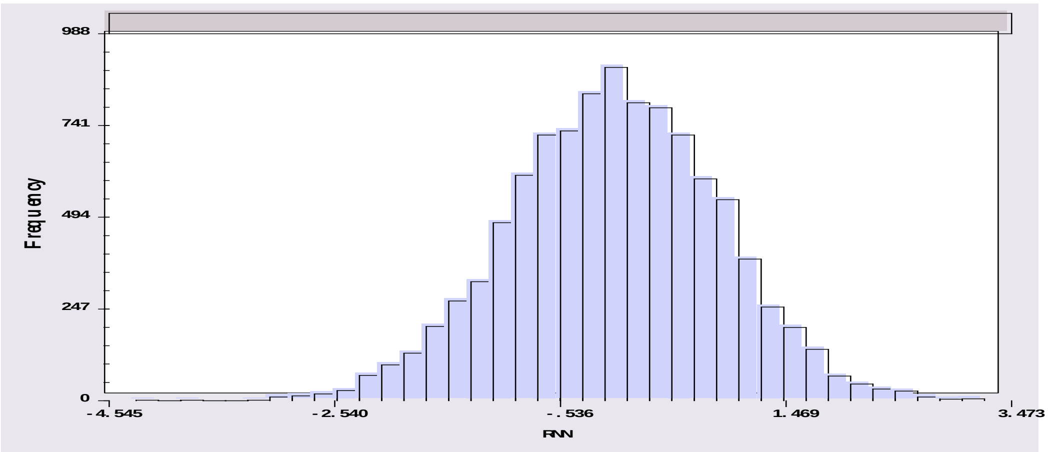


Figure 6-4: Histogram of randomly drawn normal distribution with mean zero and standard deviation one

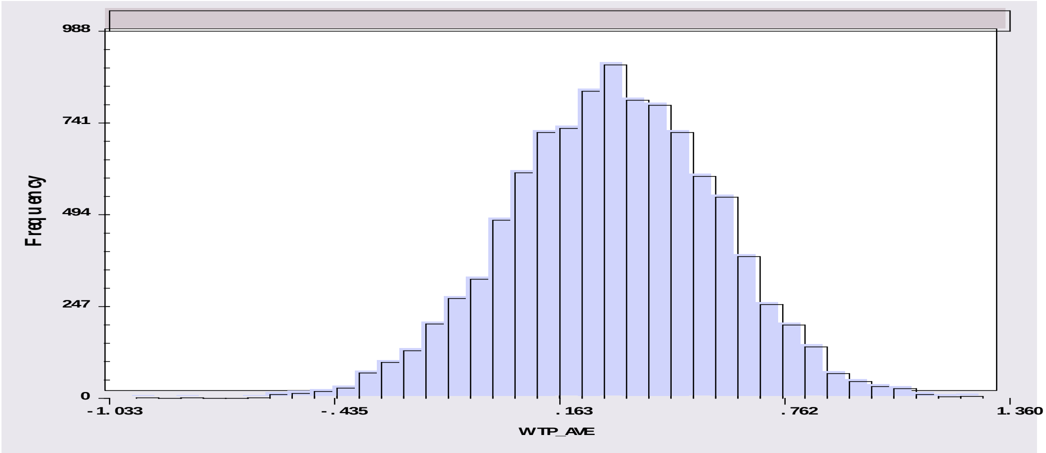


Figure 6-5: Histogram of the sampling distribution of WTP for green electricity

Table 6-18: WTP to secure a 1% increase in green electricity (NZ$$_{(2014)}$ /month)

Scores		Mean	Std. Dev
AC = 3.52, AR =3	(average)	0.32	0.29
AC = 3, AR =3	(neutral)	0.22	0.29
AC = 4, AR = 4	(high)	0.65	0.29
AC =5, AR =1	(mixed: high AC, low AR)	0.12	0.29

6.7 The influence of shorter versions of the NEP Scale on WTP estimates

In this section we conduct the econometric analysis required to answer research *Question 4 (b): Does the use of shorter versions of the NEP Scale influence WTP estimates?* In models estimated in section 6.5, EA was measured using the full NEP Scale. The latent class model LC_15 was identified as the best model. To achieve our objective, two additional LC models, LC_10 and LC_5, are estimated and the results compared with LC_15.The additional models, LC_10 and LC_5, use EA scores based on the 10- and 5-item subscales of the NEP Scale, respectively. The subscales were discussed in detail in section 6.5. The variables used in LC_10 and LC_5 are the same as those defined previously for LC_15. We also estimate MNL_10, MNL_5, RPL_10, and RPL_5 to allow for more precise comparison of WTP estimates since the sample sizes are the same for all pairs of WTP estimates that are compared for each logit specification.

6.7.1 Regression results

The regression results and discussion for MNL_10, MNL_5, RPL_10, and RPL_5 are presented in Appendix (6.4). As in the previous estimation of the LC model we use information criteria to determine the number of classes. Based on the more stringent CAIC and BIC, and the pattern of significant parameters we retain three preference classes across all the models. The information criteria used to determine the number of preference classes are presented in Table 6-19. The bolded values indicate the minimum values for the criteria.

Table 6-19: Criteria for the number of classes

No. of	LCM_15				LCM_10				LCM_5			
Classes	AIC	AIC3	CAIC	BIC	AIC	AIC3	CAIC	BIC	AIC	AIC3	CAIC	BIC
1	4333	4346	4423	4410	4332	4345	4422	4409	4329	4342	4418	4406
2	3824	3851	4011	3984	3820	3847	4006	3979	3813	3840	4000	3973
3	3580	3621	**3863**	**3822**	3592	3633	**3875**	**3834**	3596	3637	**3879**	**3838**
4	3549	3604	3929	3874	3540	3595	3920	3865	3568	3623	3947	3892
5	**3510**	**3579**	3986	3917	3509	3577	3984	3915	3535	3604	4011	3942
6	3512	3595	4084	4001	**3475**	**3558**	4048	3965	**3505**	**3588**	4078	3995

The LC model regression results are presented in Table 6-20. All significant parameters have the expected signs, and the parameter for *Monthly Power Bill* is highly significant in all classes, indicating sensitivity to the cost element. The model using the full NEP Scale (LC_15) performs better than the models using shorter versions of the NEP Scale in terms of LL, CAIC, BIC and pseudo-R^2. LC_5 performs worse than the other two models.

The significance of the coefficients of *Renewable*, and the interaction terms *MNEP_Renewable* and *SNEP_Renewable* varies across classes and models revealing both homogeneity and heterogeneity of preferences for renewables both within and across classes among respondents with *weak*, *moderate* and *strong* NEP scores. For example, under LC_15, all candidate coefficients are insignificant at the .05 level in classes 1 and 3 irrespective of the NEP score level, revealing homogeneity within and across classes, whilst in class 2 the coefficients of *Renewable* and *SNEP_Renewable* are significant at the .05 level, revealing heterogeneity within the class. In LC_10 none of the candidate coefficients in class 2 are significant at the .05 level but instead *SNEP_Renewable* is significant in class 3, which represents a much smaller segment. This implies that the use of the 10-item scale instead of the 15-item scale would lead to the prediction of a significantly smaller market segment (9% versus 35%) in which only respondents with *strong* NEP scores have positive and significant taste intensities for green electricity. On the other hand, the use of the 5-item scale leads to the prediction of two market segments, classes 2 and 3, in which respondents with *strong* and *moderate* NEP scores respectively, have a positive preference for renewables.

Table 6-20: LC model results for supplier choice with dummy coded levels for NEP scores

	LCM_15			LCM_10			LCM_5		
Attribute	Class1	Class2	Class3	Class1	Class2	Class3	Class1	Class2	Class3
ASCALT1	0.5170[c]	0.0956	3.2536[c]	0.4454[b]	0.1552	4.8890[c]	0.4513[b]	0.2471[a]	3.5267[c]
Time	-0.0385[b]	-0.0342[c]	-0.0419	-0.0442[c]	-0.0355[c]	-0.0902	-0.0411[b]	-0.0330[c]	-0.0715
Fixed	0.0056	0.0104[b]	-0.0033	0.0112[b]	0.0038	-0.0079	0.0082	0.0102[b]	-0.0174
Discount	0.0054	0.0158[c]	0.0516[c]	0.0055	0.0178[c]	-0.0183	0.0054	0.0165[c]	0.0487[b]
Loyalty Rewards	0.2720[a]	0.3601[c]	0.4899	0.3210[b]	0.4458[c]	1.7674[b]	0.2976[b]	0.4249[c]	0.7215
Renewable	0.0019	0.0079[b]	-0.0042	0.0037	0.0069[a]	0.0147	0.0078	0.0035	0.0024
MNEP_Renewable	0.0074	0.0055	0.0230[a]	0.0103	0.0041	-0.0043	0.0002	0.0058	0.1462[c]
SNEP_Renewable	0.0144[a]	0.0099[b]	-0.0002	0.0088	0.0082[a]	0.0460[b]	0.0064	0.0167[c]	-0.0016
Ownership	0.0134[c]	0.0122[c]	0.0056	0.0140[c]	0.0104[c]	0.0603[c]	0.0135[c]	0.0106[c]	0.0206[b]
New electricity company	-0.0889	-0.1842	-0.4429	-0.0641	-0.2446	-1.2673	-0.0955	-0.1153	-0.2708
New non-electricity company	-0.3076	-0.8090[c]	-1.5438[a]	-0.2524	-0.8876[c]	-0.9128[a]	-0.3065	-0.7863[c]	-1.0780
Well-known non-electricity company	-0.0572	-0.3968[b]	-0.2898	-0.0864	-0.4486[c]	0.2016	-0.1064	-0.3243[a]	-0.0892
Monthly Power Bill	-0.0569[c]	-0.0138[c]	-0.0147[b]	-0.0560[c]	-0.0132[c]	-0.0244[b]	-0.0550[c]	-0.0125[c]	-0.0163[b]
Estimated latent class probabilities	0.5382[c]	0.3471[c]	0.1148[c]	0.5476[c]	0.3635[c]	0.0889[c]	0.5558[c]	0.3392[c]	0.1050[c]
Model Fit									
LL		-1748.95			-1755.05			-1757.10	
Pseudo R-squared		0.4078			0.4057			0.4049	
AIC		3579.9			3592.1			3596.2	
BIC		3821.7			3833.9			3838.0	

[c], [b], [a] Significant at the .01, .05 and .1 level, respectively. Standard errors are in parentheses

WTP estimates are presented in Table 6-21. Based on LC_15, respondents in classes 1 and 3 are not willing to pay any significant amount for renewables, at least at the .05 level of confidence, whilst respondents in class 2 are willing to pay \$5.70 (0.57x10) or \$12.90 (1.29x10) per month to secure a 10% increase in renewables depending on the level of NEP score. In LC_10, only class 2 respondents with *strong* NEP scores are willing to pay \$11.40 (1.14x10) per month to secure a 10% increase in renewables whilst the rest are predicted to have zero WTP at the .05 level of significance. LC_5 is the only model producing two classes with statistically significant WTP estimates for renewables at the .05 level. However, the WTP estimate of \$89.90 (8.99x10) per month for a 10% increase in renewables by respondents with *moderate* NEP scores in class 3 is rather high, but this only applies to a subgroup in a small market segment of less than 11% of the market. It is interesting to note that this subgroup belongs to a class that considered *Renewable*, *Ownership*, *Discount* and *Monthly power bill* in making their choices. This suggests that these respondents may have been expressing strong support for renewables by selecting alternatives offering higher levels for *Renewable*, and placed less weight on other non-price attributes or ignored them altogether.

WTP estimates based on the MNL and RPL-EC models are presented in Table 6A-7 in Appendix (6.4).

Table 6-21: WTP with Dummy coded levels for NEP score

Attribute		LCM_15 Class 1	LCM_15 Class2	LCM_15 Class 3	LCM_10 Class 1	LCM_10 Class2	LCM_10 Class 3	LCM_5 Class 1	LCM_5 Class2	LCM_5 Class 3
Time		-0.68^{b}	-2.47^{c}	*NS*	-0.79^{c}	-2.68^{c}	*NS*	-0.75^{b}	-2.63^{c}	*NS*
		(0.31)	(0.90)		(0.29)	(0.85)		(0.31)	(0.96)	
Fixed		*NS*	0.75^{b}	*NS*	0.20^{b}	*NS*	*NS*	NS	0.81^{b}	*NS*
			(0.35)		(0.10)				(0.38)	
Discount		*NS*	1.14^{c}	*NS*	*NS*	1.35^{c}	*NS*	NS	1.31^{c}	*NS*
			(0.38)			(0.39)			(0.44)	
Loyalty Rewards		4.78^{a}	26.05^{c}	*NS*	5.74^{b}	33.68^{c}	72.31^{a}	5.41^{b}	33.96^{c}	*NS*
		(2.68)	(9.23)		(2.47)	(9.28)	(38.48)	(2.56)	(10.45)	
	(Weak NEP)	*NS*	0.57^{b}	*NS*	*NS*	0.52^{a}	*NS*	*NS*	*NS*	*NS*
			(0.27)			(0.31)				
Renewable	*(Moderate NEP)*	*NS*	0.57^{b}	*NS*	*NS*	0.52^{a}	*NS*	*NS*	*NS*	8.99^{b}
			(0.27)			(0.31)				(3.72)
	(Strong NEP)	0.25^{a}	1.29^{c}	*NS*	*NS*	1.14^{c}	1.88^{a}	*NS*	1.33^{c}	*NS*
		(0.14)	(0.26)			(0.25)	(1.02)		(0.49)	
Ownership		0.24^{c}	0.89^{c}	*NS*	0.25^{c}	0.79^{c}	2.47^{c} (0.76)	0.25^{c}	0.84^{c}	1.27^{a}
		(0.05)	(0.17)		(0.05)	(0.16)		(0.05)	(0.19)	(0.68)
New electricity company		*NS*	*NS*	*NS*	*NS*	-18.48^{a}	*NS*	*NS*	*NS*	*NS*
						(11.19)				
New non-electricity company		*NS*	-58.53^{c}	*NS*	*NS*	-67.05^{c}	*NS*	*NS*	-62.85^{c}	*NS*
			(15.27)			(15.77)			(17.71)	
Well-known non-electricity company		*NS*	-28.71^{b}	*NS*	*NS*	-33.89^{b}	*NS*	*NS*	-25.92^{a}	*NS*
			(13.39)			(13.24)			(14.87)	
Market segment size		53.82%	34.70%	11.48%	54.76%	36.35%	8.89%	55.58%	33.92%	10.50%

^{c}, ^{b}, ^{a} Significant at the .01, .05 and .1 level, respectively. *NS* denotes not statistically significant. Standard errors are in parentheses

We compare WTP for green electricity across the three models using the asymptotically normal test statistic (ANTS)[21] and present the results in Table 6-22. There are no significant differences in WTP for green electricity for class 1 across all models since none of the WTP estimates are significant at the .05 level. For class 2, LC_15 and LC_10 only produce WTP estimates that are not significantly different for *weak* and *moderate* NEP score levels when WTP estimates that are significant at the .1 level are considered for LC_10. The difference is also significant at the .1 level for the *strong* NEP score level. Significant differences are found between WTP estimates based on LC_15 and LC_5 at *weak* and *moderate* NEP score levels. For class 3, significant differences exist between WTP estimates based on LC_15 and LC_5 at *moderate* and *strong* NEP score levels, and also between LC_10 and LC_5 at *moderate* NEP scores. These results suggest that the choice of the version of the NEP Scale used in model estimation matters depending on the level of the NEP score at which WTP for green electricity is evaluated. However, the 10-item subscale is preferred to the 5-item scale based on the ANTS results, at least at the .1 level.

Table 6-22: Test for equality of WTP for green electricity using ANTS[1]

		Class 1		Class 2		Class 3	
		Ratio[2]	| ANTS |	Ratio	| ANTS |	Ratio	| ANTS |
Weak NEP score level	LC_15 vs. LC_10	-	*NS*	1.11	**216**	-	*NS*
	LC_15 vs. LC_5	-	*NS*	-	**2.16**	-	*NS*
	LC_10 vs. LC_5	-	*NS*	-	0.52	-	*NS*
Moderate NEP score level	LC_15 vs. LC_10	-	*NS*	1.11	**2.16**	-	NS
	LC_15 vs. LC_5	-	*NS*	-	**2.16**	-	**-2.42**
	LC_10 vs. LC_5	-	*NS*	-	**1.69**	-	**2.42**
Strong NEP score level	LC_15 vs. LC_10	-	**1.80**	1.13	**1.94**	**-**	**1.85**
	LC_15 vs. LC_5	**-**	**1.80**	0.97	0.11	-	**2.74**
	LC_10 vs. LC_5	-	*NS*	0.85	0.47	-	0.61

[1] ANTS = 1.96 indicates statistically significant differences between each pair of WTP estimates. All bolded values are significant at the .1 level. [2]This is the ratio of WTP estimates obtained from the two competing models. '–'Dashes indicate that the ratio cannot be estimated as at least one of the estimates is equal to zero. *NS* denotes not statistically significant.

[21] The formula for the ANTS is presented in Chapter 2 as: $ANTS = \frac{(WTP_k^1 - WTP_k^2)}{\sqrt{(Var(WTP_k^1) - Var(WTP_k^2))}}$

A comparison of class probabilities for corresponding classes across the models indicates that LC_10 and LC_5 produce statistically different class probabilities for class 1 and that LC_15 and LC_10 also produce statistically different class probabilities for class 3, which further supports the assertion that the choice of the version of the NEP Scale matters as it affects the sizes of the market segments.

Table 6-23: Comparison of estimated prior probabilities

	Class 1		Class 2		Class 3	
	Ratio[2]	| ANTS |[1]	Ratio	| ANTS |	Ratio	| ANTS |
LC_15 vs. LC_10	0.98	-0.55	0.95	-0.93	1.29	**2.45**
LC_15 vs. LC_5	0.97	**-1.70**	1.02	0.97	1.09	0.92
LC_10 vs. LC_5	0.99	**-40.51**	1.07	1.54	0.85	**-1.92**

[1] ANTS = 1.96 indicates statistically significant differences between each pair of WTP estimates. All bolded values are significant at the .1 level. [2]This is the ratio of WTP estimates obtained from the two competing models.

A summary of the marginal WTP for *Renewable* based on the MNL and RPL-EC models is presented in Table 6-24. The results show that respondents with *weak* NEP scores are not willing to pay any significant amount for power generated from renewable energy sources except under model RPL_15 where the estimated WTP is $1.80 per month for a 10% increase in *Renewable*. Based on RPL_15, respondents with *weak* and *moderate* NEP scores have the same WTP for *Renewable*. Estimates based on the other models indicate that respondents with *moderate* NEP scores are willing to pay amounts ranging from $2.60 to $4.10 for a 10% increase in *Renewable* depending on the model, while respondents with *strong* NEP scores have even higher WTP, ranging from $4.10 to $4.50 to secure the same increase in *Renewable.*

In Table 6-25 we provide a comparison and tests for differences in WTP estimates obtained using the three versions of the NEP Scale. Although WTP estimates based on the MNL model are not statistically different across all the scales for respondents with *weak* NEP scores, estimates based on RPL_15 are significantly different from those obtained using RPL_10 and RPL_5 for this score level. For *moderate* NEP scores, models using shorter versions of the NEP scale produce higher WTP estimates as all ratios are less than 1; e.g., the 5- and 10-item scales produce WTP estimates that are 1.58 and 1.19 times that of the full NEP Scale, respectively, based on the MNL model and 1.56 and 1.50 times based on the RPL model. However, the RPL model produces higher WTP estimates with longer scales for *strong* NEP scores. Tests for equality show significant statistical differences in WTP estimates with the 5-item scale in the MNL model compared to the longer scales. The MNL model produces higher WTP estimates at *moderate* and *strong* NEP scores with the 5-item scale compared to the longer scales, while the RPL model produces higher and lower WTP estimates with longer scales for *strong* and *moderate* NEP scores respectively. Specifically, MNL_15 and RPL_15 produce significantly different WTP estimates at the .05 level than MNL_5 and RPL_5, respectively, for *strong* NEP scores.

Table 6-24: WTP for a 1% increase in green electricity (NZ$$_{(2014)}$ /month)

Environmental attitude group	MNL_15	MNL_10	MNL_5	RPL_15	RPL_10	RPL_5
Weak	*NS*	*NS*	*NS*	0.18^{b} (0.089)	*NS*	*NS*
Moderate	0.26^{b} (0.118)	0.31^{b} (0.120)	0.41^{c} (0.118)	0.18^{b1} (0.089)	0.27^{b} (0.123)	0.28^{b} (0.124)
Strong	0.41^{c} (0.117)	0.43^{c} (0.119)	0.45^{c} (0.118)	0.55^{c} (0.109)	0.45^{c} (0.138)	0.41^{c} (0.132)

^{c}, ^{b}, ^{a} Significant at the .01, .05 and .1 level, respectively. [1]This increases to 0.38 (0.077) if the estimate of 0.20 significant at 10% is included. Standard errors are in parentheses

Table 6-25: Comparison and test for equality of WTP estimates

Comparison	Environmental attitude group					
	Weak NEP		Moderate NEP		Strong NEP	
	Ratio	| ANTS |	Ratio	| ANTS |	Ratio	| ANTS |
MNL_15 vs. MNL_10	-	NS	0.83	**2.29**	0.95	1.06
MNL_15 vs. MNL_5	-	NS	0.63	**97.11**	0.92	**4.13**
MNL_10 vs. MNL_5	-	NS	0.76	**4.22**	0.96	0.91
RPL_15 vs. RPL_10	-	**2.03**	0.67	1.05	1.23	1.19
RPL_15 vs. RPL_5	-	**2.03**	0.65	1.14	1.36	**1.97**
RPL_10 vs. RPL_5	-	NS	0.97	0.60	1.11	1.07

6.8 Chapter summary

The main objective of this chapter was to estimate WTP for green electricity and explain preference heterogeneity using EA and constructs based on the NAT. We also assessed the implications of measuring EA using shorter versions of the NEP Scale on environmentally-related WTP.

Three classes of environmental attitudes, *weak*, *moderate* and *strong* were identified for New Zealanders. The average EA scores for the three groups were 43, 50, and 58 respectively; whilst the sample mean score was 52 (standard deviation = 8). Gender, age, income, ethnicity and education were found to be significant determinants of EA. These results provide insight into New Zealanders' EA. A conclusion drawn from these results was that SDCs of respondents explain differences in EA.

Based on the MNL and RPL-EC models using the full NEP Scale, EA was found to be a significant determinant of WTP for green electricity. Results from these models showed that respondents with *strong* EA are willing to pay more for green electricity compared to respondents with *weak* and *moderate* EA. The LC model identified three preference classes for the attributes of electricity services. Respondents in classes 1 and 2, accounting for 65% of the sampled population, were predicted to have a zero WTP for green electricity. For these respondents, EA scores are irrelevant as there is no relationship between EA and WTP. However, EA helps in explaining differences in WTP among respondents in class 2. WTP for respondents with *strong* EA was estimated to be $12.90 per month for a 10% increase in green electricity compared to $5.70 for respondents with *weak* and *moderate* EA. These estimates represent, on average, between 3 and 7% of monthly power bills, which indicates a potential for green marketing in New Zealand. Furthermore, these estimates are within the range of premiums paid for green electricity reported in the literature.

Results for the RPL-EC model indicated that both AC and AR play a systematic role in explaining heterogeneity of preferences for green electricity. The positive and significant heterogeneity in mean parameters for AC and AR indicate that respondents who are aware of the consequences of supporting renewables and feel responsible for supporting renewables have stronger preferences for green electricity than those who are not. When evaluated at the sample mean scores for AC and AR, WTP for green electricity is estimated to be \$3.20 per month for a 10% increase in green electricity.

Two short versions of the NEP Scale were constructed from the 15 statements constituting the revised NEP Scale. The construction of the short scales or subscales consisting of 5 and 10 statements was based on equal representation of the five facets of ecological worldview (*Limits, Balance, Eco-crisis, Anti-anthropocentrism, and Anti-exemptionalism*), balance between pro- and anti-NEP statements, principal components analysis, and generally accepted levels of internal consistency of the scales, such as 0.3 for item-total correlations and $\alpha \geq 0.7$ for Cronbach's alpha. The subscales were first tested for accuracy in classifying respondents into groups with homogeneous environmental preferences before being applied to the demand for green electricity. The internal consistency of the NAT constructs was tested using correlations among the items. All the scales for the psychological constructs used in this chapter met the minimum internal consistency criteria recommended in the literature.

The subscales were found to be less accurate in classifying respondents into groups with homogeneous environmental preferences. The 5-item NEP Scale had the least accuracy, and produced significantly higher average scores for the *strong* EA group and lower average scores for the *weak* and *moderate* environmental attitude groups compared to the longer scales. Although the 10-item NEP Scale produced significantly higher average scores for the *moderate* environmental group compared to the 15-item NEP Scale, no significant differences in the mean scores were found across the two scales for the *weak* and *strong* environmental groups. These findings suggest that the use of shorter versions of the NEP Scale compromises precision in the measurement of EA. However, where the use of a shorter version of the NEP Scale is unavoidable, the 10-item NEP Scale is recommended over the 5-item NEP Scale.

A comparison of models estimated using different versions of the NEP Scale revealed significant differences, mainly between the 5-item scale and the longer scales, in terms of predicted class probabilities and WTP estimates. The model using the full NEP Scale also produced the best fit for the data. However, the 10-

item NEP Scale tended to produce similar results as the full NEP Scale, except for *strong* EA. These findings demonstrate that the version of the NEP Scale used, particularly the 5-item NEP Scale, affects the estimates of marginal WTP for green electricity. As such the use of the 5-item scale should be avoided as its use may produce misleading results.

Chapter 7. Summary and conclusion

This thesis has described and analysed consumer preferences for the various attributes of electricity services with a particular emphasis on non-price attributes. The findings improve our understanding of the demand for green electricity and consumer switching behaviour in retail electricity markets and offer valuable insights for policy and marketing decisions.

A choice experiment was designed and used to generate the data for the MNL, RPL-EC and LC models that were used to analyse the choice data to provide answers to the research questions. These questions were addressed in chapters 4 to 6 of this thesis, and the main findings and conclusions are summarized in this chapter. The first research question challenged the notion that consumers perceive all suppliers to be the same except for the price. This idea appears to have had a pervasive influence on the way switching is promoted, as price differences are the main focus of switching campaigns. Evidence from most jurisdictions indicates reluctance by most consumers to switch supplier despite the availability of price comparison websites, suggesting that other factors are at play. The second and third research questions dealt with methodological issues concerning attribute non-attendance and hypothetical bias (HB), which have been shown, in the stated preference literature, to influence model fit and WTP estimates. The fourth research question investigated the potential for green marketing in NZ and the ways in which the use of shorter versions of the NEP Scale to measure environmental attitude may influence estimates of WTP for green electricity.

Chapter 3 contributes to the debate on the competitiveness of retail electricity markets in NZ by providing evidence that, based on the benchmark of price conversion (see, Electricity Authority, 2010), some retail electricity markets in NZ are not competitive. For a selected number of markets, we showed that over the period 2012-2015, most new entrants were not the lowest-priced as expected under a competitive market model. Given that promoting retail competition was the main objective of the Electricity Authority's *"What's My Number"* consumer switching campaign over the period 2011-2014, our findings suggest that the success of the campaign was limited, at least in the markets covered by this analysis.

The importance of non-price attributes. In this thesis we have demonstrated that non-price attributes are important determinants of supplier choice; hence, consumers do not perceive suppliers to be the same except for price – *Research Questions (RQ) 1 & 1a*. We identified three distinct consumer types based on their preferences for the attributes of electricity services, and found that non-price attributes were important for all classes. Although respondents in class 3 (41%), described as "bargain hunters," had the strongest preference for price, they also had: strong preferences for the status quo, fixed price guarantees and local ownership of supplier; and the strongest dislike for call waiting time. Therefore, they did not make their choices based on price alone. The other two preference classes exhibited less sensitivity to price and valued most non-price attributes, suggesting that their choices were also not based on price alone.

WTP estimates showed considerable heterogeneity of preferences across the three preference groups. Respondents with higher sensitivities to power bill savings were predicted to have higher WTP for the non-price attributes both within and across preference groups. Overall, "bargain hunters" had the lowest WTP for non-price attributes, while the "captive and loyal customers" had the highest. WTP estimates presented in Chapter 4 are reasonable and of the same order of magnitude as those obtained in other studies, which lends validity to the results.

Determinants of WTP for non-price attributes. We found that estimates of WTP for most attributes were sensitive to age, income, and behavioural intention and that environmental attitude had a significant influence on WTP for *Renewables*. Overall, socio-demographic characteristics (SDCs) of respondents were found to be poor predictors of WTP for the non-price attributes (*RQ 1b*).

Individual-specific WTP estimates from the LC model were regressed on SDCs and attitudes using OLS to identify the determinants of WTP. As expected, the model fit for this secondary regression was poor since the information on choices that was used to derive the WTP estimates was omitted from the regression.

Preferences for power bill savings. We found that respondents had different bill savings thresholds at which they would switch supplier (*RQ 1c*). Tests for linear restrictions showed that the taste intensities of respondents with different bill savings thresholds were not represented by the same slope, indicating significant differences in preferences. Respondents with lower bill savings thresholds were more likely to switch to a new supplier from another sector. For example, the minimum bill savings ($10.46/month) required to induce indifference among "bargain hunters" between staying with their incumbent traditional supplier and switching to a well-known company from another sector was within the range currently available in the market. The implication of these findings is that policies targeted at lowering the thresholds may be used to promote switching. Furthermore, 62% of respondents indicated that they would switch if they could save $100 per year, yet only 31% actually switched supplier when average bill savings of $150 per year were attainable. This suggests that convincing consumers that the advertised bill savings are real may increase switching rates in NZ.

Attitudes towards switching and preference heterogeneity. Respondents who expressed positive behavioural intentions towards switching were predicted to be more likely to belong to the "discerning and mobile" preference group (class 2) or the "bargain hunters" group (class 1) compared to the "captive and loyal" customer group (class 3). These groups had distinct preferences for the attributes that behavioural intention helps to explain.

WTP estimates obtained from stated choice experiments have been shown to be affected by attribute non-attendance (AN-A) and HB. The effects of these methodological issues on model fit and WTP estimates were specifically addressed in *Question 2,* which is discussed next.

Attribute non-attendance. Based on both self-reported and inferred AN-A, we showed that respondents ignored subsets of attributes, and that attribute-processing rules involving ignoring individual attributes were not supported by the choice data, except for *Rewards,* which had a 65% probability of being ignored individually (*RQ 2a*).

Attributes which are normally not specified in standard electricity plans were the most ignored, e.g., call waiting time, loyalty rewards and supplier type. However, none of the attributes were exempt from AN-A, as only 12% of respondents claimed to have considered all the attributes, while inferred AN-A suggested that 24% of the respondents made random choices. Thus we found evidence suggesting inconsistencies between self-reported and inferred AN-A, which casts doubt on the reliability of self-reported AN-A. Similar inconsistencies have been noted in previous studies investigating AN-A in different contexts (e.g., Hess & Hensher, 2010). An important issue when using self-reported AN-A is whether or not respondents accurately report their attendance to the cost attribute, since its coefficient is included as the denominator in all computations of WTP.

Only 15 respondents (7%) reported that they ignored the cost of the alternatives when making their choices. Compared to other studies that investigate AN-A, the proportion of respondents ignoring the cost attribute in this study was relatively small. We found inconsistencies between stated AN-A and the choices that these respondents made (*RQ 2c*).

For example, the cheapest alternative was selected 72% of the time, suggesting that the cost of the alternatives may not have been ignored, and that some reporting errors may have been made. Furthermore, some respondents with low incomes reported having ignored the power bill, which would be unrealistic in real choice situations, given that the power bill in NZ constitutes a significant proportion of weekly income for these respondents. Ignoring self-reported AN-A for the power bill but preserving stated non-attendance to the other attributes resulted in improved model fit, expected signs of parameter estimates, and significant differences in class probabilities and WTP estimates. These results suggest that it is important to inspect stated AN-A for inconsistencies, particularly for the cost attribute, and ignore any claims that are found to be inconsistent with the choices. A related question that we address next is whether respondents who claimed to have ignored an attribute had different preferences from those who considered it.

Preferences of respondents who attend to or ignore attributes. We found that the preferences of respondents who attended to an attribute differed from those who ignored it, except for *Discount* and *Fixed*. We note that because these two attributes are included in standard electricity plans in NZ, respondents were more likely to have prior experience making trade-offs involving these attributes and therefore should have found it relatively easy to process this information. It is possible, therefore, that non-attendance could have been reported to signify that less effort was involved in processing information on the levels of these attributes (*RQ 1d*).

We reached the above finding by fitting MNL and RPL-EC models to the choice data and testing whether preferences differed between respondents who claimed to have ignored an attribute and those who attended to it. The systematic component of the indirect utility function was specified with an additional term for each candidate attribute to capture the marginal utility for respondents who claimed to have ignored it relative to respondents who considered the attribute.

Although significant differences in preferences were found for the other attributes, none of the estimated parameters suggested zero taste intensities for the attributes that respondents claimed to have ignored. This questions the validity of the standard practice of restricting the parameters of attributes to zero for respondents who claim to have ignored the attributes. Our results suggest that respondents may have placed lower weights on the attributes reported as having been ignored, rather that completely ignoring them. These results are consistent with findings in previous studies (e.g., Carlsson et al., 2010; Gracia et al., 2012). Restricting the parameters of ignored attributes to zero produced significantly higher WTP estimates except for *Discount* and *Fixed,* which had significantly lower WTP estimates. The direction of the bias seems to depend on the nature of the attributes involved. The next question explored the effect of AN-A on WTP.

The effects of attribute non-attendance on WTP. Failing to account for AN-A in the latent class model produced significantly lower estimates of WTP for some attributes, particularly in Class 2. The MNL and RPL-EC models produced similar results to the LC model except that WTP estimates for *Discount* and *Fixed* were significantly higher when AN-A was not accounted for in model estimation. Compared to the MNL and RPL-EC models, the LC model produced mixed results with significantly lower WTP for *Fixed* and lower but no significant difference for *Discount* in class 2. For significant WTP estimates, AN-A resulted in significantly higher estimates in class 1 and significantly lower estimates in class 2. The direction of the bias seems to depend on the preference class, suggesting that the LC model is able to capture the differential effect of AN-A across groups with heterogeneous preferences. Since respondents in class 1 only care about a few attributes and therefore put more weight on these attributes in making their choices, the bias is positive. On the other hand, respondents in class 2 care about all the attributes and considered them in making their choices leading to negative bias because assuming full attendance in model estimation includes choices of respondents with lower or zero WTP for the ignored attributes. Accounting for AN-A produced WTP estimates that were between 0.88 and 3.42 times higher under the MNL model, and between 1.03 and 2.88 times higher under the RPL-EC model. The direction of the bias seemed to depend on the nature of the attributes. For *Discount* and *Fixed* the bias caused by AN-A was positive while for the rest of the attributes it was negative (*RQ 2e*).

These findings were reached by estimating WTP using MNL, RPL-EC and LC models with and without accounting for AN-A. In the first instance original data was used, which assumed full attendance to all attributes. In the second, the standard practice of restricting parameters of ignored attributes to zero was employed and the estimates were tested for differences using the ANTS.

Approaches to accounting for AN-A. The results presented in Chapter 5 show that the taste intensities of respondents who claimed to have ignored an attribute were significantly different to zero, indicating that the 'ignored' attributes influenced the choice probabilities. This finding does not support the standard practice of assumption zero weights for 'ignored' attributes, which implies that 'ignored' attributes have no influence on choice probabilities. Assuming non-zero taste intensities for 'ignored' attributes in model estimation improves model fit. To the extent that these results may be generalised to other contexts, we recommend that researchers should avoid the standard practice of assuming zero weights for 'ignored' attributes, and estimate different parameters for these attributes.

The effect of response uncertainty on WTP estimates. We found that respondents who were less certain about their choices tended to select more expensive alternatives, which induced an upwards bias in WTP. Respondents with certainty scores less than 6 are predicted to have WTP that is 1.26 to 1.53 times higher compared to respondents with higher scores. The results indicated that the responses of respondents with lower certainty scores were the likely source of hypothetical bias, as generally held in the literature. This justifies the standard practice of omitting responses for respondents with certainty scores below 7 or 8. At these cut-off points we obtained better model fit for our data. Our findings are consistent with previous studies, suggesting that the certainty statements were properly applied in the analysis carried out for this thesis (*RQ 3*).

This question was addressed using respondents' responses to certainty statements. Instead of recoding or omitting responses of respondents reporting certainty scores below an arbitrary cut-off point, we avoided this criticism and the issue of how to recode these responses by estimating parameters for each level of certainty. Respondents with a certainty score less than 6 were grouped together and used as the reference point for the other levels.

The last research question that was addressed in this thesis relates to consumer demand for green electricity and how differences in WTP among respondents can be explained.

Willingness to pay for 'green' electricity. The 35% of New Zealanders in the "discerning and mobile class" were willing to pay, on average, \$5.70 to \$12.90 per month to secure a 10% increase in electricity generated from renewable energy sources (based on latent class analysis). We argue that this indicates the potential for green marketing in New Zealand, which could be used as a mechanism for promoting consumer-driven renewable power development. Based on these results we assert that gentailers could attract and retain these consumers by providing information on the proportion of renewables in their fuel mix.

The RPL-EC model produced WTP estimates that ranged from \$1.80 to \$5.50 per month for a 10% increase in green electricity, depending on environmental attitudes (EA) group. Based on the RPL-EC model results, aggregate WTP for a 10% increase in electricity generated from renewable energy sources was estimated at \$54.7 million per year. This was obtained by multiplying WTP for each EA group, weighted by predicted EA class probability, by the total number of residential power bill accounts to obtain an annual estimate (*RQ 4a*).

Environmental attitudes and norm activation theory explain preference heterogeneity. Based on the sample NEP Scale scores, we showed that New Zealanders tend to express positive EA. Gender (male) and income had a negative influence on environmental attitudes, while age had a positive influence. Having dependent children and higher educational qualifications (at least a university degree) had no significant influence on EA.

New Zealanders can be classified into three EA groups – *weak*, *moderate* and *strong*, accounting for 10%, 61% and 29% of the sampled population, respectively. The average EA scores for these groups were 44, 50 and 58, where the possible scores ranged from 15 to 75. We also showed that the NAT constructs (awareness of the consequences [AC] and ascription of responsibility [AR]) played a systematic role in explaining heterogeneity of preferences for green electricity. Respondents with higher AC and AR had a higher WTP for green electricity. However, AR had a stronger influence on WTP than AC, which makes intuitive sense as consumers who feel morally obliged to support green electricity would be expected to express a higher WTP than respondents with higher AC and lower AR scores (*RQ 4a*).

Use of shorter versions of the NEP Scales influences WTP estimates. When shorter versions of the NEP Scale were used to measure EA, estimates of WTP for green electricity were sensitive to the version of the scale (*RQ 4b*). Significant differences in WTP estimates and class probabilities were obtained when EAs measured using shorter versions of the NEP Scale were used in model estimation. The 5-item NEP Scale generally produced WTP estimates that were consistently significantly different from those obtained with longer versions of the NEP Scale. The 10-item NEP Scale produced WTP estimates that were statistically different from those obtained with the full NEP Scale less often compared to the 5-item NEP Scale. Based on our findings we recommend that researchers use the full NEP Scale to measure EA. However, where shorter versions cannot be avoided, we recommend the use of the 10-item NEP Scale.

Use of information criteria in determining the number of preference classes. Of the six information criteria (IC) used to determine the number of classes in the LC models estimated in this thesis, AIC, and crAIC consistently indicated more preference classes compared to the other IC. Specifically, we find that CAIC and BIC consistently identify the smallest number of preference classes, while AIC3 and HQC mostly identify an intermediate number of classes. These findings are consistent with the literature investigating the performance of IC (e.g., Andrews & Currim, 2003a; Lin & Dayton, 1997; Yang & Yang, 2007).

Promoting switching and future research. Given the results summarized in this chapter, we conclude that New Zealanders do value the non-price attributes of electricity services. Our findings on the importance of these attributes can be used to increase switching rates, the uptake of 'green electricity' and potentially the level of competition in the retail electricity sector. Future areas of research may be extended to include CEs involving real choices, where respondents are presented with real supplier choice situations and asked to complete a switch if a competitor is preferred to the incumbent retailer. The results from such research would provide external validity for the results presented in this thesis. On the question of green marketing, a future area of research worth pursuing would be the estimation of WTP for electricity generated from specific energy sources. This would provide more accurate measures of consumer support for specific renewables than for the generic *Renewable* estimated in this thesis.

References

Abdullah, S., & Mariel, P. (2010). Choice experiment study on the willingness to pay to improve electricity services. *Energy Policy, 38*(8), 4570-4581. doi:10.1016/j.enpol.2010.04.012

Adamowicz, W., Boxall, P., Williams, M., & Louviere, J. (1995). *Stated preference approaches for measuring passive use values: Choice experiments versus contingent valuation*. Staff Paper 95-03. Staff Paper. University of Alberta. Edmonton. Retrieved from http://core.ac.uk/download/pdf/6671381.pdf

Ajzen, I. (1988). *Attitudes, personality and behavior*. Milton Keynes, UK: Open University Press.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-179.

Ajzen, I. (2001). Nature and operation of attitudes. *Annual Review of Psychology, 52*, 27-58.

Ajzen, I. (2005). *Attitudes, personality and behaviour* (2nd ed.). Berkshire, UK: McGraw-Hill Professional Publishing.

Ajzen, I., Brown, T. C., & Rosenthal, L. H. (1996). Information bias in contingent caluation: Effects of personal relevance, quality of information, and motivational orientation. *Journal of Environmental Economics and Management, 30*(1), 43-57. doi:http://dx.doi.org/10.1006/jeem.1996.0004

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Aldrich, G. A., Grimsrud, K. M., Thacher, J. A., & Kotchen, M. J. (2007). Relating environmental attitudes and contingent values: how robust are methods for identifying preference heterogeneity? *Environmental & Resource Economics, 37*(4), 757-775. doi:10.1007/s10640-006-9054-7

Alvarez-Daziano, R., & Bolduc, D. (2009). *Canadian consumers' perceptual and attitudinal responses toward green automobile technologies: an application of hybrid choice models*. 2009 EAERE-FEEM-VIU European Summer School in Resources and Environmental Economics: Economics, Transport and Environment, Economics. Venice International University. Retrieved from http://www.feem-web.it/ess/files/alvarez-daziano.pdf

Amador, J. F., Gonzalez, R. M., & Ramos-Real, J. F. (2013). Supplier choice and WTP for electricity attributes in an emerging market: The role of perceived past experience, environmental concern and energy saving behavior. *Energy Economics, 40*, 953-966. doi:10.1016/j.eneco.2013.06.007

Andrews, R. L., & Currim, I. S. (2003a). A comparison of segment retention criteria for finite mixture logit models. *Journal of Marketing Research, 40*(2), 235-243. doi:10.2307/30038851

Andrews, R. L., & Currim, I. S. (2003b). Retention of latent segments in regression-based marketing models. *International Journal of Research in Marketing, 20*(4), 315-321. doi:http://dx.doi.org/10.1016/j.ijresmar.2003.04.001

Arrow, K., Solow, A., Portney, P. R., Leamer, E. E., Radnner, R., & Schuman, H. (1993). Report of the NOAA panel on contingent valuation. *Federal Register, 58*(10), 4601 - 4614.

Bartczak, A. (2015). The role of social and environmental attitudes in non-market valuation: An application to the Bialowieza Forest. *Forest Policy and Economics, 50*, 357-365. doi:10.1016/j.forpol.2014.09.011

Batley, S. L., Colbourne, D., Fleming, P. D., & Urwin, P. (2001). Citizen versus consumer: Challenges in the UK green power market. *Energy Policy, 29*(6), 479-487. doi:doi: 10.1016/S0301-4215(00)00142-7

Batley, S. L., Fleming, P. D., & Urwin, P. (2000). Willingness to pay for renewable energy: Implications for UK green tariff offerings. *Indoor and Built Environment, 9*(3-4), 157-170. doi:10.1159/000057504

Ben-Akiva, M., Walker, J., Bernardino, A. T., Gopinath, D. A., & Morikawa, T. (2002). Integration of choice and latent variable models. In H. Mahmassani (Ed.), *In perpetual motion: travel behavior research opportunities and application challenges* (pp. 431-470). Amsterdam, Netherlands: Elsevier Science.

Bennett, J., & Adamowicz, W. (2001). Some fundamentals of environmental choice modelling. In J. Bennett & R. Blamey (Eds.), *The choice modelling approach to environmental valuation* (pp. 37-72). Cheltenham, Uk: Edward Elgar.

Bertram, G. (2006). Restructuring the New Zealand electricity sector 1984-2005. In F. P. Sioshansi & W. Pfaffenberger (Eds.), *Electricity market reform: An international perspective*. Amsterdam: Elsevier.

Bertram, G. (2014). *Asset values, rents, and the single buyer proposal for the New Zealand electricity sector*. Paper for Auckland University Economics Department seminar. Institute for Governance and Policy Studies, Victoria University of Wellington. Retrieved from http://www.geoffbertram.com/fileadmin/publications/Auckland%20seminar%2011%20April%202014.pdf

Blass, A. A., Lach, S., & Manski, C. F. (2010). Using elicited choice probabilities to estimate random utility models: Preferences for electricity reliability. *International Economic Review, 51*(2), 421-440.

Bliemer, M. (2013). Efficient design for a latent class model. NGENE Forum. Retrieved from http://www.choice-metrics.com/forum/viewtopic.php?f=2&t=164&sid=3c8b6fa16afb7e738cb1cf31d41308c8.

Bliemer, M. C. J., & Rose, J. M. (2011). Experimental design influences on stated choice outputs: An empirical study in air travel choice. *Transportation Research Part A-: Policy and Practice, 45*(1), 63-79. doi:10.1016/j.tra.2010.09.003

Blumenschein, K., Blomquist, G. C., Johannesson, M., Horn, N., & Freeman, P. (2008). Eliciting willingness to pay without bias: Evidence from a field experiment. *Economic Journal, 118*(525), 114-137.

Blumenschein, K., Johannesson, M., Blomquist, G. C., Liljas, B., & O'Conor, R. M. (1998). Experimental results on expressed certainty and hypothetical bias in contingent valuation. *Southern Economic Journal, 65*(1), 169-177. doi:10.2307/1061360

Bollino, C. A. (2009). The willingness to pay for renewable energy sources: The case of italy with socio-demographic determinants. *Energy Journal, 30*(2), 81-96.

Borchers, A. M., Duke, J. M., & Parsons, G. R. (2007). Does willingness to pay for green energy differ by source? *Energy Policy, 35*(6), 3327-3334. doi:10.1016/j.enpol.2006.12.009

Börjesson, M., & Algers, S. (2011). Properties of internet and telephone data collection methods in a stated choice value of time study context. *Journal of Choice Modelling, 4*(2), 1-19. doi:http://dx.doi.org/10.1016/S1755-5345(13)70055-1

Boxall, P., Adamowicz, W. L., & Moon, A. (2009). Complexity in choice experiments: choice of the status quo alternative and implications for welfare measurement*. *Australian Journal of Agricultural and Resource Economics, 53*(4), 503-519. doi:10.1111/j.1467-8489.2009.00469.x

Boxall, P. C., & Adamowicz, W. L. (2002). Understanding heterogeneous preferences in random utility models: A latent class approach. *Environmental and Resource Economics, 23*(4), 421-446.

Breffle, W. S., Morey, E. R., & Thacher, J. A. (2011). A joint latent-class model: Combining Likert-scale preference statements with choice data to harvest preference heterogeneity. *Environmental & Resource Economics, 50*(1), 83-110. doi:10.1007/s10640-011-9463-0

Brennan, T. J. (2007). Consumer preference not to choose: Methodological and policy implications. *Energy Policy, 35*(3), 1616-1627. doi:10.1016/j.enpol.2006.04.023

Browne, O., Poletti, S., & Young, D. (2012). Simulating market power in the New Zealand electricity market. *New Zealand Economic Papers, 46*(1), 35-50. doi:10.1080/00779954.2011.649566

Brownstone, D., & Small, K. A. (2005). Valuing time and reliability: assessing the evidence from road pricing demonstrations. *Transportation Research Part a-Policy and Practice, 39*(4), 279-293.

Brownstone, D., & Train, K. (1999). Forecasting new product penetration with flexible substitution patterns. *Journal of Econometrics, 89*(1-2), 109-129.

Burgess, L., & Street, D. J. (2003). Optimal designs for 2(k) choice experiments. *Communications in Statistics-Theory and Methods, 32*(11), 2185-2206. doi:10.1081/sta-120024475

Burgess, L., & Street, D. J. (2005). Optimal designs for choice experiments with asymmetric attributes. *Journal of Statistical Planning and Inference, 134*(1), 288-301. doi:10.1016/j.jspi.2004.03.021

Burke, R. R., Harlam, B. A., Kahn, B. E., & Lodish, L. M. (1992). Comparing dynamic consumer choice in real and computer-simulated environments. *Journal of Consumer Research, 19*(1), 71-82. doi:10.2307/2489189

Cai, Y., Deilami, I., & Train, K. (1998). Customer retention in a competitive power market: Analysis of a 'double-bounded plus follow-ups' questionnaire. *The Energy Journal, 19*(2), 191-215.

Campbell, D. (2007). Willingness to pay for rural landscape improvements: Combining mixed logit and random-effects models. *Journal of Agricultural Economics, 58*(3), 467-483. doi:10.1111/j.1477-9552.2007.00117.x

Campbell, D., & Doherty, E. (2012). Combining discrete and continuous mixing distributions to identify niche markets for food. *European Review of Agricultural Economics, 40*(2), 287-311. doi:10.1093/erae/jbs018

Campbell, D., Hensher, D. A., & Scarpa, R. (2011). Non-attendance to attributes in environmental choice analysis: a latent class specification. *Journal of Environmental Planning and Management, 54*(8), 1061-1076. doi:10.1080/09640568.2010.549367

Campbell, D., Hutchinson, W. G., & Scarpa, R. (2008). Incorporating discontinuous preferences into the analysis of discrete choice experiments. *Environmental and Resource Economics, 41*(3), 401-417. doi:10.1007/s10640-008-9198-8

Carlsson, F., Kataria, M., & Lampi, E. (2009). *Dealing with ignored attributes in choice experiments on valuation of Sweden's environmental quality objectives*. Jena Economic Research Papers. Economic research papers. Friedrich Schiller University and the Max Planck Institute of Economics, Jena, Germany. Retrieved from http://www.wiwi.uni-jena.de/papers/jerp2009/wp_2009_089.pdf

Carlsson, F., Kataria, M., & Lampi, E. (2010). Dealing with ignored attributes in choice experiments on valuation of Sweden's environmental quality objectives. *Environmental & Resource Economics, 47*(1), 65-89. doi:10.1007/s10640-010-9365-6

Carlsson, F., & Martinsson, P. (2001). Do hypothetical and actual marginal willingness to pay differ in choice experiments? Application to the valuation of the environment. *Journal of Environmental Economics and Management, 41*(2), 179-192.

Carlsson, F., Martinsson, P., & Akay, A. (2011). The effect of power outages and cheap talk on willingness to pay to reduce outages. *Energy Economics, 33*(5), 790-798. doi:10.1016/j.eneco.2011.01.004

Carson, R. T., Flores, N. E., Martin, K. M., & Wright, J. L. (1996). Contingent valuation and revealed preference methodologies: Comparing the estimates for quasi-public goods. *Land Economics, 72*(1), 80-99. doi:10.2307/3147159

Carson, R. T., Louviere, J. J., Anderson, D. A., Arabie, P., Bunch, D. S., Hensher, D. A., et al. (1994). Experimental analysis of choice. *Marketing Letters, 5*(4), 351-367. doi:10.1007/bf00999210

Champ, P. A., & Bishop, R. C. (2001). Donation payment mechanisms and contingent valuation: An empirical study of hypothetical bias. *Environmental and Resource Economics, 19*(4), 383-402.

Champ, P. A., Bishop, R. C., Brown, T. C., & McCollum, D. W. (1997). Using donation mechanisms to value nonuse benefits from public goods. *Journal of Environmental Economics and Management, 33*(2), 151-162. doi:10.1006/jeem.1997.0988

Champ, P. A., Moore, R., & Bishop, R. C. (2009). A comparison of approaches to mitigate hypothetical bias. *Agricultural and Resource Economics Review, 38*(2), 166-180.

ChoiceMetrics. (2012). *Ngene 1.1.1 User Manual & Reference Guide*.

Clark, C. F., Kotchen, M. J., & Moore, M. R. (2003). Internal and external influences on pro-environmental behavior: Participation in a green electricity program. *Journal of Environmental Psychology, 23*(3), 237-246.

Cooper, P., Poe, G. L., & Bateman, I. J. (2004). The structure of motivation for contingent values: a case study of lake water quality improvement. *Ecological Economics, 50*(1-2), 69-82. doi:10.1016/j.ecolecon.2004.02.009

Costanza, R., dArge, R., deGroot, R., Farber, S., Grasso, M., Hannon, B., et al. (1997). The value of the world's ecosystem services and natural capital. *Nature, 387*(6630), 253-260.

Cummings, R. G., & Taylor, L. O. (1999). Unbiased value estimates for environmental goods: A cheap talk design for the contingent valuation method. *The American Economic Review, 89*(3), 649-665.

Daglish, T. (2015). *Consumer governance in electricity markets*. Research Paper, New Zealand Institute for the Study of Competition and Regulation. Wellington. Retrieved from http://researcharchive.vuw.ac.nz/bitstream/handle/10063/4183/MP4.pdf?sequence=1

Defeuilley, C. (2009). Retail competition in electricity markets. *Energy Policy, 37*(2), 377-386. doi:http://dx.doi.org/10.1016/j.enpol.2008.07.025

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via EM algorithm. *Journal of the Royal Statistical Society Series B-Methodological, 39*(1), 1-38.

Denscombe, M. (2006). Web-based questionnaires and the mode effect - An evaluation based on completion rates and data contents of near-identical questionnaires delivered in different modes. *Social Science Computer Review, 24*(2), 246-254. doi:10.1177/0894439305284522

DeShazo, J. R., & Fermo, G. (2004). *Implications of rationally-adaptive pre-choice behavior for the design and estimation of choice models*. Working paper. School of Public Policy and Social Research, University of California at Los Angeles.

Desvousges, W., Johnson, F., Dunford, R., Boyle, K., Hudson, S., & Wilson, K. (1993). Measuring natural resource damages with contingent valuation : Tests of validity and reliability. In J. A. Hausman (Ed.), *Contingent valuation: A critical assessment*. Amsterdam: Elsevier.

Diamond, P. A., & Hausman, J. A. (1994). Contingent valuation - Is some number better than no number. *Journal of Economic Perspectives, 8*(4), 45-64.

Dimitropoulos, A., & Kontoleon, A. (2009). Assessing the determinants of local acceptability of wind-farm investment: A choice experiment in the Greek Aegean Islands. *Energy Policy*, *37*(5), 1842-1854.

Dolnicar, S., Laesser, C., & Matus, K. (2009). Online versus paper: Format effects in tourism surveys. *Journal of Travel Research, 47*(3), 295-316. doi:10.1177/0047287508326506

Dunlap, R. E. (2008). The New Environmental Paradigm Scale: From Marginality to Worldwide Use. *Journal of Environmental Education, 40*(1), 3-18. doi:10.3200/joee.40.1.3-18

Dunlap, R. E., Van Liere, K. D., Mertig, A. G., & Jones, R. E. (2000). Measuring endorsement of the New Ecological Paradigm: A revised NEP scale. *Journal of Social Issues, 56*(3), 425-442.

Ek, K. (2005). Public and private attitudes towards "green" electricity: the case of Swedish wind power. *Energy Policy*, *33*(13), 1677-1689.

Ek, K., & Soderholm, P. (2008). Norms and economic motivation in the Swedish green electricity market. *Ecological Economics, 68*(1-2), 169-182. doi:10.1016/j.ecolecon.2008.02.013

Electricity Authority. (2010). *Customer switching fund reseach report*. Castalia Strategic Advisors, New Zealand. Retrieved from https://www.ea.govt.nz/dmsdocument/8887

Electricity Authority. (2011a). *Consumer switching: A qualitative and quantitative study; Final report* Wellington, New Zealand: UMR Research. Retrieved from http://www.ea.govt.nz/search/?q=2011+baseline+national+survey

Electricity Authority. (2011b). *Electricity in New Zealand*. Wellington. Retrieved from https://www.ea.govt.nz/dmsdocument/12292

Electricity Authority. (2012a). *Consumer switching: A quantitative study supplemented by qualitative research*. Wellington, New Zealand: UMR Research. Retrieved from https://www.ea.govt.nz/dmsdocument/12694

Electricity Authority. (2012b). *What's My Number: A changing landscape for New Zealand electricity consumers*. Wellington, New Zealand: Electricity Authority. Retrieved from www.ea.govt.nz/dmsdocument/12828

Electricity Authority. (2013a). *Consumer switching fund*. Wellington, New Zealand. Retrieved from http://www.ea.govt.nz/consumer/csf/#survey

Electricity Authority. (2013b). *Shopping around for electricity retailers: A quantitative study among the general public*. Wellington, New Zealand: UMR Research. Retrieved from http://www.ea.govt.nz/consumer/csf/

Electricity Authority. (2013c). *What's My Number: Competition and choice - a review of the 2013 campaign*. Wellington, New Zealand: Electricity Authority. Retrieved from http://www.ea.govt.nz/dmsdocument/18331

Electricity Authority. (nd). *History of government involvement in electricity*. Retrieved from https://www.ea.govt.nz/about-us/what-we-do/our-history/

Electricity Commission. (2008). *Retail competition: A qualitative and quantitative study*. Wellington, New Zealand: UMR Research

Electricity Technical Advisory Group. (2009). *Improving electricity market perfomance*. Wellington, New Zealand: Ministry of Economic Development. Retrieved from http://www.med.govt.nz/sectors-industries/energy/pdf

Ethier, R. G., Poe, G. L., Schulze, W. D., & Clark, J. (2000). A comparison of hypothetical phone and mail contingent valuation responses for green-pricing electricity programs. *Land Economics, 76*(1), 54-67.

Evans, L. (2013). *Cost shifting: the single buyer model with price discrimination*. Wellington: New Zealand Institute for the Study of Competition and Regulation. Retrieved from http://www.iscr.org.nz/f869,22851/3._Cost_Shifting_-_The_Single_Buyer_Model_With_Price_Discrimination.pdf

Evans, L., & Guthrie, G. (2012). An examination of Frank Wolak's model of market power and its application to the New Zealand electricity market. *New Zealand Economic Papers, 46*(1), 25-34. doi:10.1080/00779954.2011.647504

Evans, L., Hogan, S., & Jackson, P. (2012). A critique of Wolak's evaluation of the NZ electricity market: Introduction and overview. *New Zealand Economic Papers, 46*(1), 1-10. doi:10.1080/00779954.2011.645223

Evans, L. T., & Meade, R. B. (2005). *Alternating currents or counter-revolution? Contemporary electricity reform in New Zealand*. Wellington, New Zealand: Victoria University Press.

Ferrini, S., & Scarpa, R. (2007). Designs with a priori information for nonmarket valuation with choice experiments: A Monte Carlo study *Journal of Environmental Economics and Management 53*(3), 342-363.

Fiebig, D. G., Keane, M. P., Louviere, J., & Wasi, N. (2010). The generalized multinomial logit model: Accounting for scale and coefficient heterogeneity. *Marketing science, 29*(3), 393-421. doi:10.1287/mksc.1090.0508

Fielding, K. S., McDonald, R., & Louis, W. R. (2008). Theory of planned behaviour, identity and intentions to engage in environmental activism. *Journal of Environmental Psychology, 28*(4), 318-326. doi:10.1111/j.1559-1816.1998.tb01685.x.

Fleming, C. M., & Bowden, M. (2009). Web-based surveys as an alternative to traditional mail methods. *Journal of Environmental Management, 90*(1), 284-292. doi:10.1016/j.jenvman.2007.09.011

Gamble, A., Juliusson, E. A., & Gärling, T. (2007). Barriers to consumer switching in the Swedish electricity market *Proceedings of Nordic Consumer Policy Research Conference* (Helsinki, Finland:

Gamble, A., Juliusson, E. A., & Gärling, T. (2009). Consumer attitudes towards switching supplier in three deregulated markets. *Journal of Socio-Economics, 38*(5), 814-819. doi:10.1016/j.socec.2009.05.002

Gärling, T., Gamble, A., & Juliusson, E. A. (2008). Consumers' switching inertia in a fictitious electricity market. *International Journal of Consumer Studies, 32*(6), 613-618. doi:10.1111/j.1470-6431.2008.00728.x

Garner, D. (2012, February 21). Poll shows asset sales unpopular. *TV3 News*. Retrieved from http://www.3news.co.nz/Poll-shows-asset-sales-unpopular/tabid/1607/articleID/243681/Default.aspx

Giulietti, M., Grossi, L., & Waterson, M. (2010). Price transmission in the UK electricity market: Was NETA beneficial? *Energy Economics, 32*(5), 1165-1174. doi:http://dx.doi.org/10.1016/j.eneco.2010.01.008

Giulietti, M., Price, C. W., & Waterson, M. (2005). Consumer choice and competition policy: A study of UK energy markets. *Economic Journal, 115*(506), 949-968. doi:10.1111/j.1468-0297.2005.01026.x

Goett, A. A. (1998). *Estimating customer preferences for new pricing products*. Electric Power Research Institute Report TR-111483, Palo Alto

Goett, A. A., Hudson, K., & Train, K. E. (2000). Customers' choice among retail energy suppliers: The willingness-to-pay for service attributes. *Energy Journal, 21*(4), 1-28.

Gracia, A., Barreiro-Hurle, J., & Perez y Perez, L. (2012). Can renewable energy be financed with higher electricity prices? Evidence from a Spanish region. *Energy Policy, 50*, 784-794. doi:10.1016/j.enpol.2012.08.028

Greene, W. H. (2008). *Econometric analysis* (6th ed.). Upper Saddle River, NJ: Pearson Prentice Hall

Greene, W. H. (2012). NLOGIT Version 5 Reference Guide. Plainview, NY: Econometrics Software, Inc.

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: contrasts with mixed logit. *Transportation Research Part B: Methodological, 37*(8), 681-698. doi:10.1016/s0191-2615(02)00046-2

Greene, W. H., & Hensher, D. A. (2013). Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. *Applied Economics, 45*(14), 1897-1902. doi:10.1080/00036846.2011.650325

Hanley, N., Mourato, S., & Wright, R. E. (2001). Choice modelling approaches: A superior alternative for environmental valuation? *Journal of Economic Surveys, 15*(3), 435-462.

Hanley, N., & Nevin, C. (1999). Appraising renewable energy developments in remote communities: the case of the North Assynt Estate, Scotland. *Energy Policy, 27*(9), 527-547. doi:10.1016/s0301-4215(99)00023-3

Hansen, C. (2014). *Enhancing electricity industry performance*. Presentation to Business NZ Energy Council. Electricity Authority. Wellington. Retrieved from https://www.ea.govt.nz/dmsdocument/17879

Hansla, A., Gamble, A., Juliusson, A., & Gärling, T. (2008). Psychological determinants of attitude towards and willingness to pay for green electricity. *Energy Policy, 36*(2), 768-774. doi:http://dx.doi.org/10.1016/j.enpol.2007.10.027

Hausman, J., & McFadden, D. (1984). Specification tests for the multinomial logit model. *Econometrica, 52*(5), 1219-1240. doi:10.2307/1910997

Hawcroft, L. J., & Milfont, T. L. (2010). The use (and abuse) of the new Environmental Paradigm Scale over the last 30 years: A meta-analysis. *Journal of Environmental Psychology, 30*(2), 143-158. doi:10.1111/j.1464-0597.1999.tb00047.x. 10.1037/0003-066x.54.2.93

Heckman, J., & Singer, B. (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica, 52*(2), 271-320. doi:10.2307/1911491

Hensher, D. (2004). *Information processing strategies in stated choice studies: The implications on willingness to pay of respondents ignoring specific attributes*. Working Paper, Instutute of Transport Studies. University of Sydney. Australia. Retrieved from http://ws.econ.usyd.edu.au/itls/wp-archive/itls_wp_04-01.pdf

Hensher, D. (2008). Joint estimation of process and outcome in choice experiments and implications for willingness to pay. *Journal of Transport Economics and Policy, 42*(2), 297-322.

Hensher, D. A. (2010). Hypothetical bias, choice experiments and willingness to pay. *Transportation Research Part B-Methodological, 44*(6), 735-752. doi:doi: 10.1016/j.trb.2009.12.012

Hensher, D. A., & Greene, W. H. (2010). Non-attendance and dual processing of common-metric attributes in choice analysis: a latent class specification. *Empirical Economics, 39*(2), 413-426. doi:doi: 10.1007/s00181-009-0310-x

Hensher, D. A., & Rose, J. M. (2009). Simplifying choice through attribute preservation or non-attendance: Implications for willingness to pay. *Transportation Research Part E: Logistics and Transportation Review, 45*(4), 583-590. doi:10.1016/j.tre.2008.12.001

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005a). *Applied choice analysis: A primer*. Cambridge, UK: Cambridge University Press.

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005b). The implications on willingness to pay of respondents ignoring specific attributes. *Transportation, 32*(3), 203-222. doi:doi: 10.1007/s11116-004-7613-8

Hensher, D. A., Rose, J. M., & Greene, W. H. (2012). Inferring attribute non-attendance from stated choice data: implications for willingness to pay estimates and a warning for stated choice experiment design. *Transportation, 39*(2), 235-245. doi:10.1007/s11116-011-9347-8

Hensher, D. A., Shore, N., & Train, K. (2014). Willingness to pay for residential electricity supply quality and reliability. *Applied Energy, 115*, 280-292. doi:10.1016/j.apenergy.2013.11.007

Herriges, J. A., & Kling, C. L. (1999). Nonlinear income effects in random utility models. *Review of Economics and Statistics, 81*(1), 62-72. doi:10.1162/003465399767923827

Hess, S., & Beharry-Borg, N. (2011). Accounting for latent attitudes in willingness-to-pay studies: The case of coastal water quality improvements in Tobago. *Environmental and Resource Economics, 2*(1), 109-131. doi:doi: 10.1007/s10640-011-9522-6

Hess, S., & Hensher, D. A. (2010). Using conditioning on observed choices to retrieve individual-specific attribute processing strategies. *Transportation Research Part B: Methodological, 44*(6), 781-790. doi:10.1016/j.trb.2009.12.001

Hogan, S., & Jackson, P. (2012). A critique of Wolak's evaluation of the NZ electricity market: The incentive to exercise market power with elastic demand and transmission loss. *New Zealand Economic Papers, 46*(1), 11-23. doi:10.1080/00779954.2011.646671

Hole, A. R. (2011). A discrete choice model with endogenous attribute attendance. *Economics Letters, 110*(3), 203-205.

Holmes, T. P., & Adamowicz, W. L. (2003). Attribure-based methods. In P. A. Champ, K. J. Boyle & T. C. Brown (Eds.), *A primer on nonmarket valuation* (pp. 171-220). Dordrecht, Netherlands: Kluwer Adademic Publishers.

Hortaçsu, A., Madanizadeh, S. A., & Puller, S. L. (2015). *Power to choose? An analysis of choice frictions in the residential electricity market*. Texas A&M University.

Texas, USA. Retrieved from http://econweb.tamu.edu/puller/AcadDocs/HMP_retail_latest.pdf

Huber, J., & Zwerina, K. (1996). The Importance of utility balance in efficient choice designs. *Journal of Marketing Research, 33*(3), 307-317.

Internet World Stats. (2012). *Top 50 countries with the highest internet penetration rate.* Retrieved from http://www.internetworldstats.com/top25.htm

Isacsson, G. (2007). *The trade off between time and money: Is there a difference between real and hypothetical choices?* , Transport Economics Research Unit. Swedish National Road and Transport Research Institute. Retrieved from https://ideas.repec.org/p/hhs/vtiwps/2007_003.html

Johansson, M. V., Heldt, T., & Johansson, P. (2006). The effects of attitudes and personality traits on mode choice. *Transportation Research Part a-Policy and Practice, 40*(6), 507-525. doi:10.1016/j.tra.2005.09.001

Johnson, E. J., & Meyer, R. J. (1984). Compensatory Choice Models of Noncompensatory Processes: The Effect of Varying Context. *Journal of Consumer Research, 11*(1), 528-541.

Johnson, F. R., Lancsar, E., Marshall, D., Kilambi, V., Muhlbacher, A., Regier, D. A., et al. (2013). Constructing experimental designs for discrete-choice experiments: Report of the ISPOR conjoint analysis experimental design good research practices task force. *Value in Health, 16*(1), 3-13.

Kaenzig, J., Heinzle, S. L., & Wuestenhagen, R. (2013). Whatever the customer wants, the customer gets? Exploring the gap between consumer preferences and default electricity products in Germany. *Energy Policy, 53*, 311-322. doi:10.1016/j.enpol.2012.10.061

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies - the endowment effect, loss aversion, and status-quo bias. *Journal of Economic Perspectives, 5*(1), 193-206.

Kahneman, D., & Tversky, A. (1979). Prospect theory - Analysis of decision under risk. *Econometrica, 47*(2), 263-291. doi:10.2307/1914185

Kamakura, W. A., & Russell, G. J. (1989). A probabilistic choice model for market segmentation and elasticity structure. *Journal of Marketing Research, 26*(4), 379-390.

Kanninen, B. J. (2002). Optimal design for multinomial choice experiments. *Journal of Marketing Research, 39*(2), 214-227. doi:10.1509/jmkr.39.2.214.19080

Kessels, R., Jones, B., Goos, P., & Vandebroek, M. (2009). An efficient algorithm for constructing Bayesian optimal choice designs. *Journal of Business & Economic Statistics, 27*(2), 279-291. doi:10.1198/jbes.2009.0026

King, G. W. (1975). An analysis of attitudinal and normative variables as predictors of intentions and behavior. *Speech Monographs, 42*(3), 237-244.

Klojgaard, M. E., & Hess, S. (2014). Understanding the formation and influence of attitudes in patients' treatment choices for lower back pain: Testing the benefits of a hybrid choice model approach. *Social Science & Medicine*, *114*, 138-150. doi:10.1016/j.socscimed.2014.05.058

Kontoleon, A., & Yabe, M. (2003). Assessing the impacts of alternative 'opt-out' formats in choice experiment studies: Consumer preferences for genetically modified content and production information in food. *Journal of Agricultural Policy and Research*, *5*, 1-43.

Kotchen, M. J., & Moore, M. R. (2007). Private provision of environmental public goods: Household participation in green-electricity programs. *Journal of Environmental Economics and Management*, *53*(1), 1-16.

Kotchen, M. J., & Reiling, S. D. (2000). Environmental attitudes, motivations, and contingent valuation of nonuse values: a case study involving endangered species. *Ecological Economics*, *32*, 93-107.

Ladenburg, J., Dahlgaard, J. O., & Bonnichsen, O. (2010). *Testing the effect of a short cheap talk script in choice experiments*. FOI Working Paper 2010 / 11. Institute of Food and Resource Economics, University of Copenhagen. Copenhagen. Retrieved from http://okonomi.foi.dk/workingpapers/WPpdf/WP2010/WP_2010_11_testing_effect.pdf

Ladenburg, J., Olsen, S., & Nielsen, R. (2007). *Reducing hypothetical bias in choice experiments: Testing an opt-out reminder*. Powerpoint Presentation. Institute of Food and Resource Economics University of Copenhagen, Denmark. Retrieved from www.eftec.co.uk/docman/envecon-2007/economic.../download

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, *74*(2), 132.

Lancsar, E., & Louviere, J. (2006). Deleting 'irrational' responses from discrete choice experiments: a case of investigating or imposing preferences? *Health Economics*, *15*(8), 797-811. doi:10.1002/hec.1104

Layton, B. (2013). *The economics of electricity*. Wellington: Electricity Authority. Retrieved from https://www.ea.govt.nz/dmsdocument/15066

Layton, B. (2014). *Progress with improving electricity industry performance*. Presentation to the Commerce Committee. Electricity Authority. Wellington. Retrieved from https://www.ea.govt.nz/dmsdocument/17439

Layton, D. F., & Lee, S. T. (2006). Embracing model uncertainty: Strategies for response pooling and model averaging. *Environmental & Resource Economics*, *34*(1), 51-85. doi:10.1007/s10640-005-3784-9

Liebe, U., Preisendoerfer, P., & Meyerhoff, J. (2011). To pay or not to pay: Competing theories to explain individuals' willingness to pay for public environmental goods. *Environment and Behavior*, *43*(1), 106-130. doi:10.1177/0013916509346229

Lin, T. H., & Dayton, C. M. (1997). Model selection information criteria for non-nested latent class models. *Journal of Educational and Behavioral Statistics, 22*(3), 249-264. doi:10.3102/10769986022003249

Lindhjem, H., & Navrud, S. (2011). Are Internet surveys an alternative to face-to-face interviews in contingent valuation? *Ecological Economics, 70*(9), 1628-1637. doi:http://dx.doi.org/10.1016/j.ecolecon.2011.04.002

List, J. A. (2001). Do explicit warnings eliminate the hypothetical bias in elicitation procedures? Evidence from field auctions for sportscards. *American Economic Review, 91*(5), 1498-1507.

List, J. A., & Gallet, C. A. (2001). What experimental protocol influence disparities between actual and hypothetical stated values? *Environmental and Resource Economics, 20*(3), 241.

List, J. A., Sinha, P., & Taylor, M. H. (2006). Using choice experiments to value non-market goods and services: Evidence from field experiments *Advances in Economic Analysis & Policy 6* (2)

Little, J., & Berrens, R. (2004). Explaining disparities between actual and hypothetical stated values: Further investigation using meta-analysis. *Economics Bulletin, 3* (6), 1-13.

Littlechild, S. (2009). Retail competition in electricity markets — expectations, outcomes and economics. *Energy Policy, 37*(2), 759-763. doi:http://dx.doi.org/10.1016/j.enpol.2008.09.089

Livengood, E., & Bisset, S. (2009. *Sustainable development in the power sector: Options for consumer choice in the New Zealand electricity market*. Paper presented at the ANZSEE 2009, Green Mileage in the Global Meltdown: An Ecological Economics Way Forward, Darwin, Northern Territory, Australia

Lockwood, M. (1996). Non-compensatory preference structures in non-market valuation of natural area policy. *Australian Journal of Agricultural Economics, 40*(2), 85-101.

Lockwood, M. (1999). Preference structures, property rights, and paired comparisons. *Environmental & Resource Economics, 13*(1), 107-122. doi:10.1023/a:1008239616998

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: Analysis and application*. Cambridge, UK: Cambridge University Press.

Louviere, J. J., Islam, T., Wasi, N., Street, D., & Burgess, L. (2008). Designing discrete choice experiments: Do optimal designs come at a price? *Journal of Consumer Research, 35*(2), 360-375.

Lusk, J. L. (2003). Effects of cheap talk on consumer willingness-to-pay for golden rice. *American Journal of Agricultural Economics, 85*(4), 840-856.

Lusk, J. L., & Norwood, F. B. (2005). Effect of experimental design on choice-based conjoint valuation estimates. *American Journal of Agricultural Economics, 87*(3), 771-785. doi:10.1111/j.1467-8276.2005.00761.x

Lusk, J. L., & Schroeder, T. C. (2004). Are choice experiments incentive compatible? A test with quality differentiated beef steaks. *American Journal of Agricultural Economics, 86*(2), 467-482. doi:10.1111/j.0092-5853.2004.00592.x

MacKerron, G. (2011). Implementation, implementation, implementation: old and new options for putting surveys and experiments online. *Journal of Choice Modelling, 4*(2), 20-48. doi:http://dx.doi.org/10.1016/S1755-5345(13)70056-3

Manski, C. F. (1977). Structure of random utility models. *Theory and Decision, 8*(3), 229-254.

Manski, C. F., & Lerman, S. R. (1977). Estimation of choice probabilities from choice based samples. *Econometrica, 45*(8), 1977-1988.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics* (pp. 104-142). New York, NY: Accademic Press.

McFadden, D. (1994). Contingent valuation and social choice. *American Journal of Agricultural Economics, 76*(4), 689-708.

McFadden, D. (1999). Rationality for economists? *Journal of Risk and Uncertainty, 19*(1), 73-105.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics, 15*(5), 447-470.

McLachlan, G., & Peel, D. (2000). *Finite mixture models*. New York: John Wiley & Sons, Inc.

Meldrum, J. R. (2015). Comparing different attitude statements in latent class models of stated preferences for managing an invasive forest pathogen. *Ecological Economics, 120*, 13-22. doi:10.1016/j.ecolecon.2015.09.024

Meyerhoff, J. (2006). Stated willingness to pay as hypothetical behaviour: Can attitudes tell us more? *Journal of Environmental Planning and Management, 49*(2), 209-226. doi:10.1080/09640560500507959

Milon, J. W., & Scrogin, D. (2006). Latent preferences and valuation of wetland ecosystem restoration. *Ecological Economics, 56*(2), 162-175. doi:10.1016/j.ecolecon.2005.01.009

Ministry of Business Innovation & Employment. (2010). *Chronology of New Zealand electricity reform*. Wellington, New Zealand. Retrieved from http://www.med.govt.nz/sectors-industries/energy/pdf-docs-library/electricity-market/electricity-industry/chronology-of-electricity-reform/Chronology%20of%20NZ%20electricity%20reform.pdf

Ministry of Business Innovation & Employment. (2013). *Energy in New Zealand*. Wellington, New Zealand. Retrieved from http://www.mbie.govt.nz/info-services/sectors-industries/energy/energy-data-modelling/publications/energy-in-new-zealand/previous-editions/Energy-in-New-Zealand-2013.pdf

Ministry of Business Innovation & Employment. (2015). *Energy in New Zealand 2015*. Wellington, New Zealand. Retrieved from www.med.govt.nz/sectors-industries/energy/energy-modelling/publications

Ministry of Economic Development. (2011a). *New Zealand Energy Strategy 2011–2021 and the New Zealand Energy Efficiency and Conservation Strategy 2011-2016*. Wellington: Retrieved from www.med.govt.nz/energy-strategy.

Ministry of Economic Development. (2011c). *New Zealand Energy Data File 2011*. Retrieved from http://www.med.govt.nz/sectors-industries/energy/pdf-docs-library/energy-data-and-modelling/energydatafile-2011.pdf.

Ministry of Economic Development. (2012). *New Zealand Energy Data File 2012*. Wellington, New Zealand. Retrieved from www.med.govt.nz/sectors-industries/energy/energy-modelling/publications/energy-data-file

Morey, E., Thacher, J., & Breffle, W. (2006). Using angler characteristics and attitudinal data to identify environmental preference classes: A latent-class model. *Environmental & Resource Economics, 34*(1), 91-115. doi:10.1007/s10640-005-3794-7

Morey, E., Thiene, M., De Salvo, M., & Signorello, G. (2008). Using attitudinal data to identify latent classes that vary in their preference for landscape preservation. *Ecological Economics, 68*(1-2), 536-546. doi:10.1016/j.ecolecon.2008.05.015

Morey, E. R., Sharma, V. R., & Karlstrom, A. (2003). A simple method of incorporating income effects into logit and nested-logit models: Theory and application. *American Journal of Agricultural Economics, 85*(1), 248-253. doi:10.1111/1467-8276.00116

Murphy, J. J., Allen, P. G., Stevens, T. H., & Weatherhead, D. (2005). A meta-analysis of hypothetical bias in stated preference valuation. *Environmental & Resource Economics, 30*(3), 313-325.

Nocella, G., Boecker, A., Hubbard, L., & Scarpa, R. (2012). Eliciting consumer preferences for certified animal-friendly foods: Can elements of the theory of planned behavior improve choice experiment analysis? *Psychology & Marketing, 29*(11), 850-868.

Norwood, F. B. (2005). Can calibration reconcile stated and observed preferences? *Journal of Agricultural and Applied Economics, 37*(1), 237-248.

Norwood, F. B., Lusk, J. L., & Boyer, T. (2008). Forecasting hypothetical bias: A tale of two calibrations. In T. L. Cherry, S. Kroll & J. F. Shogren (Eds.), *Environmental economics, Experimental methods* (pp. 447-465). London and New York: Routledge.

NZX Ltd. (2014). Understanding electricity markets*: Training Course, 13th and 14th March 2014* (Wellington: NZX Energy).

Oliver, H., Volschenk, J., & Smit, E. (2011). Residential consumers in the Cape Peninsula's willingness to pay for premium priced green electricity. *Energy Policy, 39*(2), 544-550. doi:http://dx.doi.org/10.1016/j.enpol.2010.10.012

Oppewal, H., Louviere, J. J., & Timmermans, H. J. P. (1994). Modeling hierarchical conjoint processes with integrated choice experiments. *Journal of Marketing Research, 31*(1), 92-105.

Poe, G. L., Clark, J. E., Rondeau, D., & Schulze, W. D. (2002). Provision point mechanisms and field validity tests of contingent valuation. *Environmental and Resource Economics, 23*(1), 105-131. doi:10.1023/a:1020242907259

Price, C. W. (2004). *Reforming household energy markets: Some welfare effects in the United Kingdom* CCR Working Paper CCR 04-2. Working paper, Centre for Competition and Regulation University of East Anglia. UK. Retrieved from http://competitionpolicy.ac.uk/documents/8158338/8199514/ccp4-2.pdf/9b053939-1661-4093-b3b3-47a7148bf56b

Ready, R. C., Champ, P. A., & Lawton, J. L. (2010). Using respondent uncertainty to mitigate hypothetical bias in a stated choice experiment. *Land Economics, 86*(2), 363-381.

Retail Advisory Group. (2013, April 9). *Review of options for promoting retail competition by increasing consumers' propensity to compare and switch retailers*. Discussion paper. Electricity Authority. Wellington, New Zealand. Retrieved from https://www.ea.govt.nz/dmsdocument/14617

Revelt, D., & Train, K. (1998). Mixed logit with repeated choices: Households' choices of appliance efficiency level. *The Review of Economics and Statistics, 80*(4), 647-657.

Revelt, D., & Train, K. (2000). *Customer-specific taste parameters and mixed logit: Households' choice of electricity supplier*. Working Paper No. E00-274. Department of Economics. University of California, Berkeley, CA. Retrieved from http://escholarship.org.ezproxy.waikato.ac.nz/uc/item/1900p96t

Roe, B., Teisl, M. F., Levy, A., & Russell, M. (2001). US consumers' willingness to pay for green electricity. *Energy Policy, 29*(11), 917-925. doi:10.1016/s0301-4215(01)00006-4

Rose, J., & Hensher, D. A. (2010). *Latent class model (LCM)*. Excecutive Course February 2010, Faculty of Economics and Business. The University of Sydney.

Rose, J. M. (2013). Efficient design for a latent class model. NGENE Forum. Retrieved from http://www.choice-metrics.com/forum/viewtopic.php?f=2&t=164&sid=3c8b6fa16afb7e738cb1cf31d41308c8.

Rose, J. M., & Bliemer, M. C. J. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews, 29*(5), 587-617. doi:10.1080/01441640902827623

Rose, J. M., Bliemer, M. C. J., Hensher, D. A., & Collins, A. T. (2008). Designing efficient stated choice experiments in the presence of reference alternatives. *Transportation Research Part B-Methodological, 42*(4), 395-406. doi:10.1016/j.trb.2007.09.002

Rowlands, I. H., Parker, P., & Scott, D. (2004). Consumer behaviour in restructured electricity markets. *Journal of Consumer Behaviour, 3*(3), 272-283. doi:10.1002/cb.140

Saelensminde, K. (2002). The impact of choice inconsistencies in stated choice studies. *Environmental & Resource Economics, 23*(4), 403-420.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty, 1*(1), 7-59. doi:10.1007/bf00055564

Sandor, Z., & Wedel, M. (2001). Designing conjoint choice experiments using managers' prior beliefs. *Journal of Marketing Research, 38*(4), 430-444. doi:10.1509/jmkr.38.4.430.18904

Scarpa, R., Ferrini, S., & Willis, K. G. (2005). Performance of error component models for status-quo effects in choice experiments. In R. Scarpa & A. Alberini (Eds.), *Applications of simulation methods in environmental and resource economics* (pp. 247-273). Dordrecht, The Netherlands: Kluwer Academic Publishers.

Scarpa, R., Gilbride, T. J., Campbell, D., & Hensher, D. A. (2009). Modelling attribute non-attendance in choice experiments for rural landscape valuation. *European Review of Agricultural Economics, 36*(2), 151-174. doi:10.1093/erae/jbp012

Scarpa, R., & Rose, J. M. (2008). Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why. *Australian Journal of Agricultural and Resource Economics, 52*(3), 253-282.

Scarpa, R., & Thiene, M. (2005). Destination choice models for rock climbing in the Northeastern Alps: A latent-class approach based on intensity of preferences. *Land Economics, 81*(3), 426-444. doi:10.2307/4129695

Scarpa, R., Thiene, M., & Galletto, L. (2009). Consumers WTP for wine with certified origin: Preliminary results from latent classes based on attitudinal responses. *Journal of Food Products Marketing, 15*(3), 231-248.

Scarpa, R., Thiene, M., & Hensher, D. A. (2010). Monitoring choice task attribute attendance in nonmarket valuation of multiple park management services: Does It matter? *Land Economics, 86*(4), 817-839.

Schwartz, S. H. (1977). Normative influences on altruism. In B. Leonard (Ed.), *Advances in Experimental Social Psychology* (Vol. 10, pp. 221-279). New York, NY: Academic Press.

Spash, C. L. (1997). Ethics and environmental attitudes with implications for economic valuation. *Journal of Environmental Management, 50*(4), 403-416. doi:10.1006/jema.1997.0017

Spash, C. L. (2000). Ecosystems, contingent valuation and ethics: the case of wetland re-creation. *Ecological Economics, 34*(2), 195-215. doi:10.1016/s0921-8009(00)00158-0

Stern, P. C., Dietz, T., & Guagnano, G. A. (1995). The New Ecological Paradigm in social-psychological context. *Environment and Behavior, 27*(6), 723-743.

Street, D. J., & Burgess, L. (2004). Optimal and near-optimal pairs for the estimation of effects in 2-level choice experiments. *Journal of Statistical Planning and Inference, 118*(1-2), 185-199. doi:10.1016/s0378-3758(02)00399-3

Swait, J., & Louviere, J. (1993). The role of the scale parameter in the estimation and comparison of multinomial logit-models. *Journal of Marketing Research, 30*(3), 305-314. doi:10.2307/3172883

Taylor, L., Morrison, M., & Boyle, K. (2010). Exchange rules and the incentive compatibility of choice experiments. *Environmental and Resource Economics, 47*(2), 197-220. doi:10.1007/s10640-010-9371-8

Thiene, M., Galletto, L., Scarpa, R., & Boatto, V. (2013). Determinants of WTP for Prosecco wine: A latent class regression with attitudinal responses. *British Food Journal, 115*(2-3), 279-299. doi:10.1108/00070701311302249

Thiene, M., & Scarpa, R. (2008). Hiking in the Alps: exploring substitution patterns of hiking destinations. *Tourism Economics, 14*(2), 263-282.

Thurstone, L. L. (1994). A law of comparative judgment (reprinted from psychological review, vol 34, pg 273, 1927). *Psychological Review, 101*(2), 266-270. doi:10.1037//0033-295x.101.2.266

Tonsor, G. T., & Shupp, R. S. (2011). Cheap talk scripts and online choice experiments: "Looking beyond the mean". *American Journal of Agricultural Economics, 93*(4), 1015.

Train, K. E. (2009). *Discrete choice methods with simulation* (2nd ed.). Cambridge, UK: Cambridge University Press.

VaasaETT. (2013). *The most active energy markets in 2013 revealed.* Retrieved from http://www.utilitycustomerswitching.eu/424/

Walker, J., & Ben-Akiva, M. (2002). Generalized random utility model. *Mathematical Social Sciences, 43*(3), 303-343.

Walker, J. L. (2001). *Extended discrete choice models: Integrated framework, flexible error structures, and latent variables* (PhD). Massachusetts Institute of Technology. Retrieved from https://its.mit.edu/sites/default/files/documents/WalkerPhD.pdf

Wall, R., Devine-Wright, P., & Mill, G. A. (2007). Comparing and combining theories to explain proenvironmental intentions. The case of commuting-mode choice. *Environment & Behavior, 39*(6), 731-753.

Ward, K. J., Stedman, R. C., Luloff, A. E., Shortle, J. S., & Finley, J. C. (2008). Categorizing deer hunters by typologies useful to game managers: A latent-class model. *Society & Natural Resources, 21*(3), 215-229. doi:10.1080/08941920701831913

Willis, K. G. (2006). Assessing public preferences: The use of stated-preference experiments to assess the impact of varying planning conditions *The Town Planning Review 77*(4), 485-505.

Wolak, F. A. (2009). *An assessment of the performance of the New Zealand wholesale electricity market*. Commerce Commission. Retrieved from http://www.comcom.govt.nz/investigation-reports/

Yang, C.-C., & Yang, C.-C. (2007). Separating latent classes by information criteria. *Journal of Classification, 24*(2), 183-203. doi:10.1007/s00357-007-0010-1

Yao, R. (2012). *The non-market value of biodiversity enhancement in New Zealand's planted forests*. The University of Waikato. Retrieved from http://researchcommons.waikato.ac.nz/bitstream/handle/10289/6399/thesis.pdf?sequence=3

Yao, R., & Kaval, P. (2007). *Non-market valuations in New Zealand: 1974 through 2005*. Department of Economics Working Paper in Economics 07/17. University of Waikato. Hamilton, New Zealand. Retrieved from http://researchcommons.waikato.ac.nz/bitstream/handle/10289/1608/Economics_wp_0717.pdf?sequence=1

Zarnikau, J. (2003). Consumer demand for 'green power' and energy efficiency. *Energy Policy, 31*(15), 1661-1672. doi:10.1016/s0301-4215(02)00232-x

Zhang, L., & Wu, Y. (2012). Market segmentation and willingness to pay for green electricity among urban residents in China: The case of Jiangsu Province. *Energy Policy, 51*, 514-523. doi:10.1016/j.enpol.2012.08.053

Zoric, J., & Hrovatin, N. (2012). Household willingness to pay for green electricity in Slovenia. *Energy Policy, 47*, 180-187. doi:10.1016/j.enpol.2012.04.055

Appendix 1. Final survey questionnaire

Q1. What do you consider when choosing your electricity supplier?

Purpose

The purpose of this survey is to collect information on what people consider when choosing their electricity supplier. This kind of information is important and your participation will assist in developing policies that reflect electricity consumers' preferences, and also help electricity suppliers in providing services that meet consumers' needs.

The Waikato Management School Ethics Committee has approved this study.

What are we asking you to do?

We ask that you agree to answer some questions about electricity retailers and the services they provide. There are also a few general questions about you - this will help us in relating your answers to questions on electricity retailers to your characteristics. We expect that the survey will take 15-20 minutes.

Who is the researcher?

Tom Ndebele, a PhD student in the Department of Economics at the University of Waikato. My chief supervisor is Dr. Dan Marsh.

Researcher's contact details

Phone 07 8431132
Cell 0211810693
Email tn73@waikato.ac.nz

Chief supervisor's contact details

Dr. Dan Marsh
Phone 07 8384950
Email dmarsh@waikato.ac.nz

What will happen to the data?

The information that you provide will be combined with that provided by others for the purposes of analysis. The information you provide will be treated confidentially and will only be accessible to the researcher and supervisors. Your name will not appear with the information that we are collecting ensuring anonymity. What are your rights as participants? Your participation in this study is voluntary. If you decide to take part, you have the right to refuse to answer any particular question; to stop filling in this survey at any time; to ask any further questions about the study that occur to you during your participation and be given access to a summary of the findings of this study when it is complete.

Your Consent

	Yes	No
Do you agree to participate in this study under the conditions set out above?	❍	❍
Are you at least 18 years old?	❍	❍

Q2. Are you responsible for paying the electricity bill or do you have a say in choosing which supplier your household buys electricity from?

❍ YES
❍ NO

Q3. What is your gender?

❍ Male
❍ Female

Q4. Which age group do you belong to?

❍ 19 and Under
❍ 20-24
❍ 25-29
❍ 30-34
❍ 35-39
❍ 40-44
❍ 45-49
❍ 50-54
❍ 55-59
❍ 60-64
❍ 65+

Q5. Which of the following categories best describes your personal annual income before tax?

❍ Zero - $15 000
❍ $15 001 - $30 000
❍ $30 001 - $40 000
❍ $40 001 - $50 000
❍ $50 001 - $70 000
❍ $70 001 - $100 000
❍ $100 000 and above
❍ I prefer not to answer this question

Q6. Which ethnic group do you most closely identify with?

❍ NZ European
❍ Maori
❍ Asian
❍ Pacific Island
❍ Other

Q7. Where do you live?

- ❍ Auckland
- ❍ Bay of Plenty
- ❍ Canterbury
- ❍ Gisborne/Poverty Bay
- ❍ Hawke's Bay
- ❍ Manawatu-Wanganui
- ❍ Marlborough
- ❍ Nelson
- ❍ Northland
- ❍ Otago
- ❍ Southland
- ❍ Taranaki
- ❍ Waikato
- ❍ Wellington
- ❍ West Coast

Q8. Approximately how long have you lived at your current address?

- ❍ Less than 6 months
- ❍ 1 year
- ❍ 2 year
- ❍ 3 years
- ❍ 4 years and over

Q9. What best describes your living situation?

- ❍ Own
- ❍ Rent

Q10. How many people usually live with you?

	0	1	2	3	4	5	6	7	8	9	10 or more
Children under the age of 18	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍
Adults 18 years and over	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍	❍

Q11. Apart from secondary school qualifications, do you have another completed qualification?

- ❍ Yes
- ❍ No

Answered if Yes is selected in Q11

Q12. What is your highest qualification? (Don't include qualifications that take less than 3 months of full-time study to get)

- ❍ Vocational/Trades
- ❍ Diploma or Certificate
- ❍ Bachelors
- ❍ Honours Degree/PG Certificate
- ❍ Masters or PhD

Q13. What is the name of the company (electricity supplier) that you pay your monthly electricity bills to?

- ❍ Auckland Gas Company
- ❍ Bay of Plenty Energy
- ❍ Bosco Connect
- ❍ Contact Energy
- ❍ Empower
- ❍ Energy Direct NZ
- ❍ Energy Online
- ❍ Genesis Energy
- ❍ Just Energy
- ❍ King Country Energy
- ❍ Mercury Energy
- ❍ Meridian Energy
- ❍ Nova Energy
- ❍ Opunake Hydro
- ❍ Payless Energy
- ❍ Powershop
- ❍ Pulse Energy
- ❍ Tiny Mighty Power
- ❍ TrustPower
- ❍ Not sure/Other

Q14. What were your reasons for choosing this company? Please select all relevant reasons from the list below.

- ❑ Approached by supplier
- ❑ Recommended by friends or family
- ❑ Well-known power company
- ❑ Offered a better package of price and service
- ❑ Responded to an advertisement or visited a price comparison website
- ❑ Power company was already supplying power to the premises
- ❑ Other (please specify) ____________________

Q15. Have you switched electricity supplier in the past 24 months?

- ❍ Yes
- ❍ No

Answered if Yes is selected in Q15

Q16. How many times have you switched supplier in the past 24 months?

- ❍ 1 (once)
- ❍ 2 (Twice)
- ❍ 3 (Thrice)
- ❍ 4 or more times
- ❍ Not sure

Answered if No is selected in Q16

Q17. Please indicate which of the following reasons for not switching in the past 24 months apply to you.

	Applies	Does not Apply
1. Happy with price of current retail supplier plus current supplier will match any deals	❍	❍
2. Happy with service from current retail supplier	❍	❍
3. Did not trust there would be real gains from switching	❍	❍
4. Too busy to investigate the best deals available	❍	❍
5. Switching seemed too much hassle	❍	❍
6. Was already locked into a contract	❍	❍

Q18. Would you have switched supplier in the past 24 months if it could have saved you $100 per year on your power bills?

- ❍ Yes
- ❍ No

If Yes is selected, then skipped to Q22

Q19. Now suppose you could have saved $200 per year, would you have switched supplier in the past 24 months?

- ❍ Yes (1)
- ❍ No (0)

If Yes is selected, then skipped Q22

Q20. How about a saving of $300 per year, would you have switched supplier in the past 24 months?

- ❍ Yes
- ❍ No

If Yes is selected, then skipped to Q22

Q21. What about saving $400 per year, could this have been enough to make you switched supplier in the past 24 months? If not please state the minimum amount of savings per year that would have been enough to persuade you to switch.

- ❍ Yes
- ❍ No ____________________

Q22. How often do you look for opportunities to switch supplier?

- ❍ Never
- ❍ Once a month
- ❍ Once every six months
- ❍ Once a year
- ❍ Once every two years or more

Q23. Below is a list of reasons often given for switching electricity supplier. Please rate how important each reason would be for you if you were to consider switching supplier.

Reasons for switching supplier	Not at all important	Not really important	Somewhat important	Quite important	Very important
A financial incentive from other electricity suppliers	❍	❍	❍	❍	❍
High electricity bills	❍	❍	❍	❍	❍
Poor customer service	❍	❍	❍	❍	❍
To have a gas and electricity account with the same company	❍	❍	❍	❍	❍
Fixed power rates offered by other electricity suppliers	❍	❍	❍	❍	❍
To have other services e.g. broadband services with the same electricity supplier	❍	❍	❍	❍	❍
Prompt payment and/or on-line payment discounts offered by other electricity suppliers	❍	❍	❍	❍	❍
Prefer to buy from a retailer producing electricity from sustainable sources	❍	❍	❍	❍	❍
Electricity supplier is 100% NZ owned	❍	❍	❍	❍	❍

Q24. Please indicate how satisfied you are with your current electricity supplier in terms of the following:

	Very Satisfied	Quite Satisfied	Somewhat Satisfied	Neither Satisfied nor Dissatisfied	Somewhat Dissatisfied	Quite Dissatisfied	Very Dissatisfied
General overall service	❍	❍	❍	❍	❍	❍	❍
Value for money	❍	❍	❍	❍	❍	❍	❍

Q25. Now we are interested in your beliefs and attitude towards switching electricity supplier. The questions that follow make use of rating scales and you are to click on the option that best describes your opinion. Some of the questions or statements may appear to be similar, but they address somewhat different issues or test for consistency in your responses. Please read each question carefully.

Q26. How likely or unlikely is it that you will switch to a supplier offering a better package of price and services in the next 12 months?

- ❍ Extremely Likely
- ❍ Quite Likely
- ❍ Slightly Likely
- ❍ Neither Likely nor Unlikely
- ❍ Slightly Unlikely
- ❍ Quite Unlikely
- ❍ Extremely Unlikely

Q27. For me switching to a supplier offering a better package of price and services would be

- ❍ Extremely Good
- ❍ Quite Good
- ❍ Slightly Good
- ❍ Neither Good nor Bad
- ❍ Slightly Bad
- ❍ Quite Bad
- ❍ Extremely Bad

Q28. How likely is it that most people who are important to you think that you should switch to a supplier offering a better package of price and services?

- ❍ Extremely Likely
- ❍ Quite Likely
- ❍ Slightly Likely
- ❍ Neither Likely nor Unlikely
- ❍ Slightly Unlikely
- ❍ Quite Unlikely
- ❍ Extremely Unlikely

Q29. For me switching to a supplier offering a better package of price and services would be

- ❍ Extremely Rewarding
- ❍ Quite Rewarding
- ❍ Slightly Rewarding
- ❍ Neither Rewarding nor Punishing
- ❍ Slightly Punishing
- ❍ Quite Punishing
- ❍ Extremely Punishing

Q30. How likely or unlikely is it that most people who are important to you would approve if you switch to a supplier offering a better package of price and services?

- Extremely Likely
- Quite Likely
- Somewhat Likely
- Neither Likely nor Unlikely
- Somewhat Unlikely
- Quite Unlikely
- Extremely Unlikely

Q31. I intend to switch to a supplier offering a better package of price and services in the next 12 months.

- Strongly Agree
- Quite Agree
- Slightly Agree
- Neither Agree nor Disagree
- Slightly Disagree
- Quite Disagree
- Strongly Disagree

Q32. I believe that I can switch to a supplier offering a better package of price and services if I want

- Strongly Agree
- Quite Agree
- Slightly Agree
- Neither Agree nor Disagree
- Slightly Disagree
- Quite Disagree
- Strongly Disagree

Q33. For me switching to a supplier offering a better package of price and services would be

- Extremely Easy
- Quite Easy
- Somewhat Easy
- Neither Easy nor Difficult
- Somewhat Difficult
- Quite Difficult
- Extremely Difficult

Q34. How far do you agree or disagree with the following statements

Statement	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
I feel morally obliged to switch to a supplier that generates most of its power from renewable sources.	❍	❍	❍	❍	❍
I believe that switching to a supplier that produces electricity from renewable sources would be good for the environment.	❍	❍	❍	❍	❍
I feel personally responsible for helping to reduce carbon dioxide emissions by switching to a supplier that generates electricity from clean energy sources.	❍	❍	❍	❍	❍
My switching to a supplier that generates electricity from renewable sources will not make a difference to the environment.	❍	❍	❍	❍	❍

Q35. Listed below are statements about the relationship between humans and the environment. For each statement please indicate how far you agree or disagree with it

	Strongly agree	Mildly Agree	Neither Agree nor Disagree	Mildly Disagree	Strongly Disagree
1. We are approaching the limit of the number of people the earth can support.	❍	❍	❍	❍	❍
2. Humans have the right to modify the natural environment to suit their needs.	❍	❍	❍	❍	❍
3. When humans interfere with nature it often produces disastrous consequences.	❍	❍	❍	❍	❍
4. Human ingenuity will ensure that we do not make the earth unlivable.	❍	❍	❍	❍	❍
5. Humans are severely abusing the environment	❍	❍	❍	❍	❍
6. The earth has plenty of natural resources if we just learn how to develop them.	❍	❍	❍	❍	❍
7. Plants and animals have as much right as humans to exist.	❍	❍	❍	❍	❍
8. The balance of nature is strong enough to cope with the impacts of modern industrial nations.	❍	❍	❍	❍	❍
9. Despite our special abilities, humans are still subject to the laws of nature.	❍	❍	❍	❍	❍
10. The so-called ‘ecological crisis’ facing human kind has been greatly exaggerated.	❍	❍	❍	❍	❍
11. The earth is like a spaceship with very limited room and resources.	❍	❍	❍	❍	❍
12. Humans were meant to rule over the rest of nature.	❍	❍	❍	❍	❍
13. The balance of nature is very delicate and easily upset.	❍	❍	❍	❍	❍
14. Humans will eventually learn enough about how nature works to be able to control it.	❍	❍	❍	❍	❍
15. If things continue on their present course, we will soon experience a major ecological catastrophe.	❍	❍	❍	❍	❍

Q36. What do you consider in choosing your electricity supplier?

In this section of the survey you will be presented with 12 scenarios in which three hypothetical electricity suppliers are described in terms of a number of ASPECTS which include their characteristics and what they offer. These ASPECTS are described in detail in the table below. We are using these scenarios to understand how people would choose their electricity supplier under different conditions where information on competing suppliers is available.

You are probably aware that the government is promoting competition among electricity suppliers by encouraging consumers to shop around for better deals. Electricity suppliers compete for customers in a number of ways. For example, by offering discounts on bills paid on time or on-line, fixed price guarantees, improved customer service, loyalty rewards, and promoting themselves as New Zealand owned or supplying electricity generated from renewable sources.

In each scenario we would like you to compare ‘Supplier A’ and ‘Supplier B’ with the supplier indicated as ‘Your Current Supplier’. We would like you to imagine that the supplier indicated as ‘Your Current Supplier’ is your current supplier. In all the scenarios the characteristics and services offered by ‘Your Current Supplier’ remain the same whilst those of ‘Supplier A’ and ‘Supplier B’ change. What we want to know is: If the conditions described in each scenario were to occur would you switch from ‘Your Current Supplier’ to either ‘Supplier A’ or ‘Supplier B’.

Please read the following information carefully. You will need it to understand the scenarios that will be presented to you.

ASPECT	DESCRIPTION
Call waiting time	This is the average time it takes for telephone calls to be answered by a customer service representative.
Fixed rate guarantee	This is the length of time over which fixed electricity prices are guaranteed. The customer is locked in a contract over this period and breaking it incurs termination fees.
Prompt payment discount	This refers to the discount that customers get for paying their electricity bills on time including on-line prompt payments. The discount does NOT apply if the bills are paid after the due date.
Loyalty rewards	Refers to Fly Buys, Brownie points, annual prize draws, and annual account credits (excludes annual network dividends)
Electricity supplied from renewable sources	This is the proportion of electricity generated from wind, hydro, geothermal, bioenergy and solar.
Supplier type	Indicates the type of supplier in terms of whether they are well-know or new and whether they are an electricity company or not.
NZ Ownership	Indicates the percentage local (NZ) ownership of supplier
Monthly electricity bill	This is the average monthly electricity bill you would pay under each supplier before any discounts. The net amount after discount is indicated in brackets

Before we present you with the scenarios, we would like to find out how you rate your ACTUAL current electricity supplier in terms of the above aspects. The next few questions will take you through this process.

Q36. This is a timing question not visible to participants. This is used to monitor how much time respondents spend reading the instructions

First Click
Last Click
Page Submit
Click Count

Q37. Approximately how much was your most recent monthly power bill (before discount if any)? Select an amount that closely matches your power bill or select the last option and state the amount.

- ❍ $100
- ❍ $200
- ❍ $300
- ❍ $400
- ❍ Other (specify) ____________________

Q38 For your current supplier please approximate

	25%	50%	75%	100%	Not sure
How much of the electricity it supplies is generated from renewable sources	❍	❍	❍	❍	❍
Its local ownership (what percentage is owned by Kiwis)	❍	❍	❍	❍	❍

Answered if in the previous question respondent indicated that they were not sure about how much electricity their supplier generates from renewable sources.

Q39. In the previous question you indicated that you are not sure about how much electricity your supplier generates from renewable sources. We are now interested in your best guess

	25%	50%	75%	100%
How much of the electricity it supplies is generated from renewable sources	❍	❍	❍	❍

Answered if in the previous question respondent indicated that they were not sure about the ownership of their supplier

Q40. In the previous question you indicated that you are not sure about your supplier's local ownership. We are now interested in your best guess

	25%	50%	75%	100%
Its local ownership (what percentage is owned by Kiwis) (1)	❍	❍	❍	❍

Q41. Does your supplier offer loyalty rewards such as Fly Buys, Brownie points, annual prize draws, annual account credits, etc?

❍ Yes
❍ No

Q42. From the list below select the discount rate that closely matches the one offered by your supplier

❍ No discount
❍ 10%
❍ 15%
❍ 20%
❍ Other (specify) ____________________

Q43. You would describe your supplier as a:

❍ New electricity company
❍ New non-electricity company
❍ Well-known non-electricity company
❍ Well-known electricity company

Q44. Which fixed rate plan are you on?

❍ Not on fixed rate plan
❍ 12 months fixed rate plan
❍ 24 months fixed rate plan
❍ 36 months fixed rate plan
❍ Other (specify) ____________________

Q45. Thinking of occasions when you called your supplier, on average how long would you say you were made to wait in a phone queue before you were attended to by a customer service representative?

❍ 5 minutes
❍ 10 minutes
❍ 15 minutes
❍ 20 minutes
❍ Other (specify) ____________________

Q46. AN EXAMPLE OF A COMPLETED QUESTION

We provide an example of how to answer the questions under the scenarios that will be presented to you.

ASPECT	***Your Current Supplier***	***Supplier A***	***Supplier B***
Call waiting time	15 minutes	15 minutes	0 minutes
Fixed rate guarantee	0 months	24 months	0 months
Prompt payment discount	10%	20%	20%
Loyalty rewards	no	yes	no
Electricity supplied from renewable sources	50%	50%	100%
NZ ownership	50%	100%	75%
Supplier type	Well-known electricity company	New electricity company	Well-known non-electricity company
Monthly electricity bill	$250 ($225 after discount)	$300 ($240 after discount)	$300 ($240 after discount)
Which supplier would you prefer?	○	○	●

In this example the consumer switches from his/her current supplier to Supplier B even if it is more expensive. Possible reasons could be that they put more value on local ownership, electricity generation from renewable sources, higher discount, and less call waiting time which Supplier B offers. Although the monthly bill is the same under Supplier A and Supplier B, the customer prefers Supplier B because they think it's too risky to deal with a new company and they are prepared to forgo the fixed price guarantee, loyalty rewards, and higher local ownership offered by Supplier A.

Q46.This is a timing question to show how much time respondents spent on the example of a completed choice task

First Click
Last Click
Page Submit
Click Count

Q47. In the scenarios that follow please only consider the information provided in deciding whether to switch supplier or not. Assume that any information not provided is the same for the three suppliers.

SCENARIO 1 of 12

Please indicate below which supplier you would prefer?

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	0 minutes	15 minutes
Fixed rate guarantee	0 months	0 months	36 months
Prompt payment discount	10%	10%	30%
Loyalty rewards	Yes	Yes	No
Electricity supplied from RENEWABLE sources	50%	50%	75%
NZ ownership	50%	25%	100%
Supplier type	Well-known electricity company	New electricity company	Well-known non-electricity company
Average monthly electricity bill	$250 ($225 after discount)	$150 ($135 after discount)	$200 ($160 after discount)
Which supplier would you choose?	❍	❍	❍

Q48. SCENARIO 2 of 12

Indicate below which supplier you would prefer

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	0 minutes	15minutes
Fixed rate guarantee	0 months	12 months	24 months
Prompt payment discount	10%	30%	0%
Loyalty rewards	Yes	No	Yes
Electricity supplied from RENEWABLE sources	50%	25%	100%
NZ ownership	50%	100%	25%
Supplier type	Well-known electricity company	New electricity company	Well-known electricity company
Average monthly electricity bill	$250 ($225 after discount)	$250 ($175 after discount)	$150 ($150 after discount)
Which supplier would you choose?	❍	❍	❍

Q49. SCENARIO 3 of 12

Indicate below which supplier you would prefer

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	0 minutes	15 minutes
Fixed rate guarantee	0 months	36 months	0 months
Prompt payment discount	10%	20%	0%
Loyalty rewards	Yes	No	Yes
Electricity supplied from RENEWABLE sources	50%	75%	75%
NZ ownership	50%	25%	100%
Supplier type	Well-known electricity company	Well-known electricity company	New electricity company
Average monthly electricity bill	$250 ($225 after discount)	$200 ($160 after discount)	$200 ($200 after discount)
Which supplier would you prefer?	❍	❍	❍

Q50. SCENARIO 4 of 12

Indicate below which supplier you would prefer

	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	5 minutes	10 minutes
Fixed rate guarantee	0 months	24 months	12 months
Prompt payment discount	10%	0%	20%
Loyalty rewards	Yes	Yes	No
Electricity supplied from RENEWABLE sources	50%	75%	25%
NZ ownership	50%	50%	25%
Supplier type	Well-known electricity company	Well-known non-electricity company	New non-electricity company
Average monthly electricity bill	$250 ($225 after discount)	$250 ($250 after discount)	$250 ($200 after discount)
Which supplier would you prefer?	❍	❍	❍

Q51. SCENARIO 5 of 12

Indicate below which supplier you would prefer

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	5 minutes	5 minutes
Fixed rate guarantee	0 months	36 months	0 months
Prompt payment discount	10%	30%	20%
Loyalty rewards	Yes	Yes	No
Electricity supplied from RENEWABLE sources	50%	100%	25%
NZ ownership	50%	100%	50%
Supplier type	Well-known electricity company	New non-electricity company	Well-known non-electricity company
Average monthly electricity bill	$250 ($225 after discount)	$300 ($210 after discount)	$150 ($120 after discount)
Which supplier would you prefer?	❍	❍	❍

Q52. SCENARIO 6 of 12

Indicate below which supplier you would prefer

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	15 minutes	0 minutes
Fixed rate guarantee	0 months	24 months	12 months
Prompt payment discount	10%	0%	30%
Loyalty rewards	Yes	No	Yes
Electricity supplied from RENEWABLE sources	50%	50%	100%
NZ ownership	50%	75%	50%
Supplier type	Well-known electricity company	Well-known electricity company	Well-known non-electricity company
Average monthly electricity bill	$250 ($225 after discount)	$200 ($200 after discount)	$200 ($140 after discount)
Which supplier would you prefer?	❍	❍	❍

Q53. SCENARIO 7 of 12

Indicate below which supplier you would prefer

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	10 minutes	10 minutes
Fixed rate guarantee	0 months	12 months	24 months
Prompt payment discount	10%	10%	10%
Loyalty rewards	Yes	Yes	No
Electricity supplied from RENEWABLE sources	50%	75%	50%
NZ ownership	50%	50%	50%
Supplier type	Well-known electricity company	Well-known non-electricity company	New non-electricity company
Average monthly electricity bill	$250 ($225 after discount)	$300 ($270 after discount)	$300 ($270 after discount)
Which supplier would you prefer?	❍	❍	❍

Q54. SCENARIO 8 of 12

Indicate below which supplier you would prefer

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	10 minutes	5 minutes
Fixed rate guarantee	0 months	24 months	12 months
Prompt payment discount	10%	10%	10%
Loyalty rewards	Yes	No	Yes
Electricity supplied from RENEWABLE sources	50%	50%	50%
NZ ownership	50%	50%	25%
Supplier type	Well-known electricity company	Well-known non-electricity company	New non-electricity company
Average monthly electricity bill	$250 ($225 after discount)	$300 ($270 after discount)	$300 ($270 after discount)
Which supplier would you prefer?	❍	❍	❍

Q55. SCENARIO 9 of 12

Indicate below which supplier you would prefer

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	5 minute	10 minutes
Fixed rate guarantee	0 months	0 months	36 months
Prompt payment discount	10%	0%	30%
Loyalty rewards	Yes	No	Yes
Electricity supplied from RENEWABLE sources	50%	100%	50%
NZ ownership	50%	100%	75%
Supplier type	Well-known electricity company	New non-electricity company	New electricity company
Average monthly electricity bill	$250 ($225 after discount)	$200 ($200 after discount)	$250 ($175 after discount)
Which supplier would you prefer?	❍	❍	❍

Q56. SCENARIO 10 of 12

Indicate below which supplier you would prefer

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	10 minutes	5 minutes
Fixed rate guarantee	0 months	36 months	0 months
Prompt payment discount	10%	20%	20%
Loyalty rewards	Yes	Yes	No
Electricity supplied from RENEWABLE sources	50%	25%	100%
NZ ownership	50%	75%	75%
Supplier type	Well-known electricity company	New non-electricity company	Well-known electricity company
Average monthly electricity bill	$250 ($225 after discount)	$150 ($120 after discount)	$300 ($240 after discount)
Which supplier would you prefer?	❍	❍	❍

Q57. SCENARIO 11 of 12

Indicate below which supplier you would prefer

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	15 minutes	0 minutes
Fixed rate guarantee	0 months	12 months	24 months
Prompt payment discount	10%	20%	10%
Loyalty rewards	Yes	No	Yes
Electricity supplied from RENEWABLE sources	50%	100%	25%
NZ ownership	50%	25%	100%
Supplier type	Well-known electricity company	New electricity company	Well-known electricity company
Average monthly electricity bill	$250 ($225 after discount)	$150 ($120 after discount)	$250 (225 after discount)
Which supplier would you prefer?	❍	❍	❍

Q58. SCENARIO 12 of 12

Indicate below which supplier you would prefer

ASPECT	Your Current Supplier	Supplier A	Supplier B
Call waiting time	5 minutes	15 minutes	0 minutes
Fixed rate guarantee	0 months	0 months	36 months
Prompt payment discount	10%	30%	0%
Loyalty rewards	Yes	Yes	No
Electricity supplied from RENEWABLE sources	50%	25%	75%
NZ ownership	50%	75%	75%
Supplier type	Well-known electricity company	Well-known electricity company	New electricity company
Average monthly electricity bill	$250 ($225 after discount)	$250 ($175 after discount)	$150 ($150 after discount)
Which supplier would you prefer?	❍	❍	❍

Q59. Please indicate which of the following you IGNORED, if any, in choosing your preferred electricity supplier in Scenarios 1 to 12.

- ❑ Call waiting time
- ❑ Fixed rate guarantee
- ❑ Prompt payment discount
- ❑ Loyalty rewards
- ❑ Electricity supplied from renewable sources
- ❑ 100% NZ owned
- ❑ Supplier type
- ❑ Monthly electricity bill
- ❑ NONE

Q60. On a scale of 0 to 10 where 0 is very unsure and 10 means very sure, please indicate how sure you are that you would have made the same choices you made in SCENARIOS 1 to 12 if you were faced with the same choice situations in real life.

- ❍ Very Unsure 0
- ❍ 1
- ❍ 2
- ❍ 3
- ❍ 4
- ❍ Neither Sure nor Unsure 5
- ❍ 6
- ❍ 7
- ❍ 8
- ❍ 9
- ❍ Very Sure 10

Q61. Please rate your understanding of the SCENARIOS 1 to 12 and the tasks you were asked to do.

- ❍ Did not understand at all 0
- ❍ 1
- ❍ 2
- ❍ 3
- ❍ 4
- ❍ Fair 5
- ❍ 6
- ❍ 7
- ❍ 8
- ❍ 9
- ❍ Understood completely 10

Q62. How easy was it to make your choices in SCENARIOS 1 to 12?

- ❍ Very Difficult
- ❍ Difficult
- ❍ Somewhat Difficult
- ❍ Neutral
- ❍ Somewhat Easy
- ❍ Easy
- ❍ Very Easy

Q63. Any comments

……………………………………………………………………………………………
……………………………………………………………………………………………
……………………………………………………………………………………………
……………………………………………………………………………………………
……………………………………………………………………………………………

Q64. Thank you very much for participating in this survey. If you would like to get a summary of the results please type your e-mail address in the space provided.

……………………………………………………………………………………………
……………………………………………………………………………………………
……………………………………………………………………………………………

Appendix 2. Pilot survey results

2.1. Analysis of responses to the NEP Scale statements

Table A2-1 summarises the responses to the 15 items of the NEP Scale obtained from the pilot survey. The percentage distribution of responses to the NEP Scale items indicated that respondents tend to have pro-NEP attitude with respect to most items. For example, 73.3% of respondents "mildly or strongly agree" with the statement that "when humans interfere with nature it often produces disastrous consequences", whilst only 14.1% agree with the statement that "the balance of nature is strong enough to cope with the impact of modern industrial nations." The general pattern of the distribution of responses to the NEP Scale items reported in Table A2-1 is similar to that found in other studies using the NEP Scale (e.g., Aldrich et al., 2007; Dunlap et al., 2000; Ek & Soderholm, 2008). The response categories were coded as follows: SD = 1, MD = 2, NAND = 3, MA = 4 and SA = 5, giving a range for a possible score for each item of 1 to 5. An individual's NEP Scale score is the sum of the scores of all NEP Scale items and ranges from 15 to 75. The sample minimum and maximum scores were 26 and 72 respectively. The mean score was 53.72 with a standard deviation of 9.8. Before we combined the responses to the 15 items of the NEP Scale into a single measure of environmental attitude, the existence of a high degree of internal consistency among the items was examined.

Internal consistency of the NEP constructs was tested, based on practice in previous studies, using the corrected item-total correlation ($r_{i\text{-}t}$), Cronbach's coefficient alpha (α), and principal components analysis (PCA) (e.g., Clark et al., 2003; Dunlap et al., 2000; Kotchen & Reiling, 2000). Internal consistency describes the extent to which all the 15 items of the NEP Scale measure the same concept or construct. The corrected item-total correlation is the correlation coefficient between each item's score and the sum of the scores of the other 14 items. A good candidate for inclusion in the final index should correlate well with the item-total score. Although there is no rule on the acceptable level of $r_{i\text{-}t}$ literature suggests that a minimum value of 0.3 is acceptable. Cronbach's alpha is a coefficient of reliability used to test whether items are sufficiently inter-related to justify their combination in an index. Previous literature suggests that $\alpha \geq 0.70$ can be taken to indicate "acceptable" reliability (e.g., Clark et al., 2003).

Reasonably strong corrected item-total correlations ranging from 0.26 to 0.76 and a high Cronbach's coefficient alpha of 0.87 indicated a high degree of internal consistency for the NEP Scale. However, the item-total correlation of 0.26 for NEP6 is insignificant at the 5% level indicating that this item correlated poorly with other items. Removing this item from the scale resulted in a slight improvement in Cronbach's alpha from 0.87 to 0.876 suggesting that its inclusion did not severely reduce the internal consistency of the scale. These results compare favourably with those of Dunlap et al. (2000) with an item-total correlations range of 0.33 to 62 and an alpha of 0.83. Table A2-2 presents a comparison of these results with those of previous studies.

Table A2-1: Summary statistics, percentage distributions, corrected item-total correlations and factor loadings for the NEP Scale items (N = 70)

	Mean	Std.dev.	SA	MA	NAND	MD	SD	r_{i-t}	Factor loading*	
									F1	F2
NEP1	2.5	1.3	23.9	33.8	18.3	15.5	8.5	0.54	**0.62**	-0.13
NEP2	2.7	1.2	4.2	28.2	21.1	23.9	22.5	0.53	**0.59**	0.37
NEP3	1.9	1.0	43.7	29.6	19.7	5.6	1.4	0.45	**0.55**	-0.17
NEP4	2.8	1.2	7.0	22.5	28.2	23.9	18.3	0.41	**0.46**	**0.69**
NEP5	2.2	1.2	36.6	29.6	16.9	9.9	7.0	0.40	**0.51**	-0.47
NEP6	3.6	1.2	23.9	39.4	16.9	14.1	5.6	0.22	0.26	**0.43**
NEP7	1.9	1.1	49.3	23.9	16.9	7.0	2.8	0.58	**0.69**	-0.17
NEP8	2.3	1.1	2.8	11.3	29.6	29.6	26.8	0.75	**0.81**	0.15
NEP9	1.8	0.8	45.1	32.4	22.5	0.0	0.0	0.39	**0.48**	-0.12
NEP10	2.8	1.3	9.9	21.1	28.2	21.1	19.7	0.55	**0.62**	0.12
NEP11	2.5	1.0	14.1	38.0	31.0	14.1	2.8	0.52	**0.61**	-0.36
NEP12	2.3	1.3	7.0	12.7	22.5	23.9	33.8	0.61	**0.68**	0.12
NEP13	2.0	0.9	32.4	42.3	22.5	1.4	1.4	0.76	**0.84**	-0.25
NEP14	2.6	1.1	4.2	15.5	38.0	19.7	22.5	0.48	**0.52**	**0.57**
NEP15	2.4	1.0	16.9	40.8	26.8	11.3	4.2	0.55	**0.65**	-0.31
Eigenvalue									5.559	
Variability (%)									37.06	
Cronbach's alpha		0.87								

*Unrotated factors. SA, MA, NAND, MD, SD and r_{i-t} denote strongly agree, mildly agree, neither agree nor disagree, mildly disagree, strongly disagree, and item-total correlation, respectively

Table A2-2: Comparison of corrected r_{i-t} and Cronbach's alpha from previous studies

Study	r_{i-t} (range)	Cronbach's alpha (α)
Kotchen and Reiling (2000)	0.38 to 0.71	0.83
Dunlap et al. (2000)	0.33 to 0.61	0.83
Ek and Soderholm (2008)	0.12 to 0.55	0.79
Cooper et al. (2004)	0.34 to 0.55	0.72
Clark et al. (2003)	0.32 to 0.59	0.80
Current Study	0.26 to 0.76	0.87

Results of PCA presented in Table A2-3 showed that all but one items of the NEP Scale loaded heavily (from 0.46 to 0.84) on the first unrotated factor with 11 of the items loading heaviest on this factor. The first unrotated factor had an eigenvalue of 5.559 and explained 37.1% of the total variance among the items compared to the second factor extracted which had an eigenvalue of 1.777 and only explained 11.9% of the variance among the items. The pattern of eigenvalues (5.559, 1.777, 1.568, and 1.015), the relatively high item-total correlations for 14 items, and an alpha equal to 0.87 indicated a high degree of internal consistency for the scale.

The dimensionality of the NEP Scale was investigated by employing Varimax rotation to create orthogonal dimensions. The three limits-to-growth items (1, 6, 11) and item 12 (anti-anthropocentrism) loaded heaviest on the first rotated factor (or dimension D1) with two balance-of-nature items (8, 13) having strong cross-loadings on this dimension. All three ecocrisis items (5, 10, 15) and two balance of nature items (8, 13) loaded heaviest on the fourth rotated factor (D4). Two anti-exemptionalism items (4, 14) and item 2 (anti-anthropocentrism) loaded heaviest on the second factor (D2). Item 3 (balance-of-nature), item 7 (anti-anthropocentrism) and item 9 (anti-exemptionalism) loaded heaviest on the third dimension (D3). D1, D2 and D4 mainly captured limits-to-growth, anti-exemptionalism and ecocrisis/balance-of-nature facets respectively whilst D3 mainly captured a mix of facets. These results suggested the existence of four NEP subscales. Although Dunlap et al. (2000 p.435) find similar evidence they argue that they are not inclined to create four NEP subscales "because all 15 items load heavily on the first unrotated factor, have strong item-total correlations and yield an alpha of 0.83 when combined into a single scale." It seems reasonable to adopt the same approach for this study since our results are similar to theirs.

Table A2-3: Principal components analysis of NEP items with Varimax rotation (N =70)

Item	Facet of ecological worldview	Factor Loadings							
		F1	F2	F3	F4	D1	D2	D3	D4
NEP1	Limits to growth	**0.62**	-0.13	0.39	0.15	**0.65**	0.09	0.07	**0.38**
NEP2:	Anti-anthropocentrism	**0.59**	0.37	-0.19	-0.07	0.11	**0.63**	0.24	0.24
NEP3	Frugality of nature's balance	**0.55**	-0.17	-0.53	-0.04	-0.03	0.21	**0.71**	0.27
NEP4	Anti-exemptionalism	**0.46**	**0.69**	-0.22	-0.13	-0.05	**0.86**	0.07	0.11
NEP5	Possibility of an ecocrisis	**0.51**	-0.47	0.02	-0.16	0.21	-0.18	**0.36**	**0.54**
NEP6	Limits to growth	0.26	0.43	**0.59**	0.29	**0.60**	**0.36**	**-0.43**	-0.03
NEP7	Anti-anthropocentrism	**0.69**	-0.17	-0.25	0.08	0.27	0.21	**0.59**	**0.32**
NEP8	Frugality of nature's balance	**0.81**	0.15	0.15	-0.25	**0.32**	**0.48**	0.13	**0.65**
NEP9	Anti-exemptionalism	**0.48**	-0.12	**-0.56**	0.33	0.15	0.22	**0.77**	-0.07
NEP10	Possibility of an ecocrisis	**0.62**	0.12	0.37	-0.45	0.22	**0.33**	0.17	**0.75**
NEP11	Limits to growth	**0.61**	-0.36	0.32	0.46	**0.82**	-0.12	0.29	0.20
NEP12	Anti-anthropocentrism	**0.68**	0.12	0.14	0.24	**0.56**	**0.37**	0.22	0.23
NEP13	Frugality of nature's balance	**0.84**	-0.25	-0.22	0.06	**0.48**	0.17	**0.50**	**0.52**
NEP14	Anti-exemptionalism	**0.52**	**0.57**	-0.01	0.16	0.19	**0.77**	0.21	-0.03
NEP15	Possibility of an ecocrisis	**0.65**	-0.31	0.05	-0.42	0.12	0.03	0.28	**0.78**
Eigenvalue		5.559	1.777	1.568	1.015	5.559	1.777	1.568	1.015
Variability (%)		37.06	11.85	10.45	6.77	15.74	16.98	15.84	17.56
Cumulative (%)		37.06	48.91	59.36	66.13	15.74	32.72	48.56	66.13

To explore heterogeneity in environmental attitude cluster analysis (Agglomerative Hierarchical Clustering)[22] was applied to the NEP data to determine the number of clusters or classes. Agglomerative Hierarchical Clustering (AHC) is an iterative classification method which involves calculating dissimilarity (Euclidian distance) between N respondents, clustering two respondents if a given agglomeration criterion (Ward's method) is minimised, and repeating the process until all respondents have been clustered. The analysis suggested the existence of three classes of pro-environmental attitude which we described as *weak* (class 2), *moderate* (class 1) and *strong* (class 3). A profile plot showing the mean item scores for the three classes is depicted in Figure A2-1. It's interesting to note that the mean item score for NEP 6 was the lowest across all three classes. Class 1 consists of 52.9% of respondents with a mean total NEP Scale score of 55.7 whilst classes 2 and 3 have 28.6% and 18.5% of respondents respectively with mean total NEP Scale scores of 41.8 and 66.5 respectively.

Previous studies have used responses to the NEP Scale items to identify three classes (*weak, moderate* and *strong*) of pro-environmental attitude (Aldrich et al., 2007; Cooper et al., 2004; Kotchen & Reiling, 2000). Kotchen and Reiling (2000) create the three classes in an arbitrary way by allocating respondents in roughly equal proportions across classes. Our results suggest that respondents are distributed unevenly between classes with 52.9%, 28.6%, and 18.5% of the respondents in classes 1, 2 and 3 respectively. This suggests that it might be unreasonable to assume that respondents' environmental attitudes are evenly distributed between the three classes. In a study assessing the importance and robustness of cluster analysis and latent class analysis as methods to account for unobserved heterogeneity Aldrich et al. (2007) assume, based on Kotchen and Reiling (2000), the existence of three classes.

[22] XLSTAT 2013.4.03 was used for this analysis.

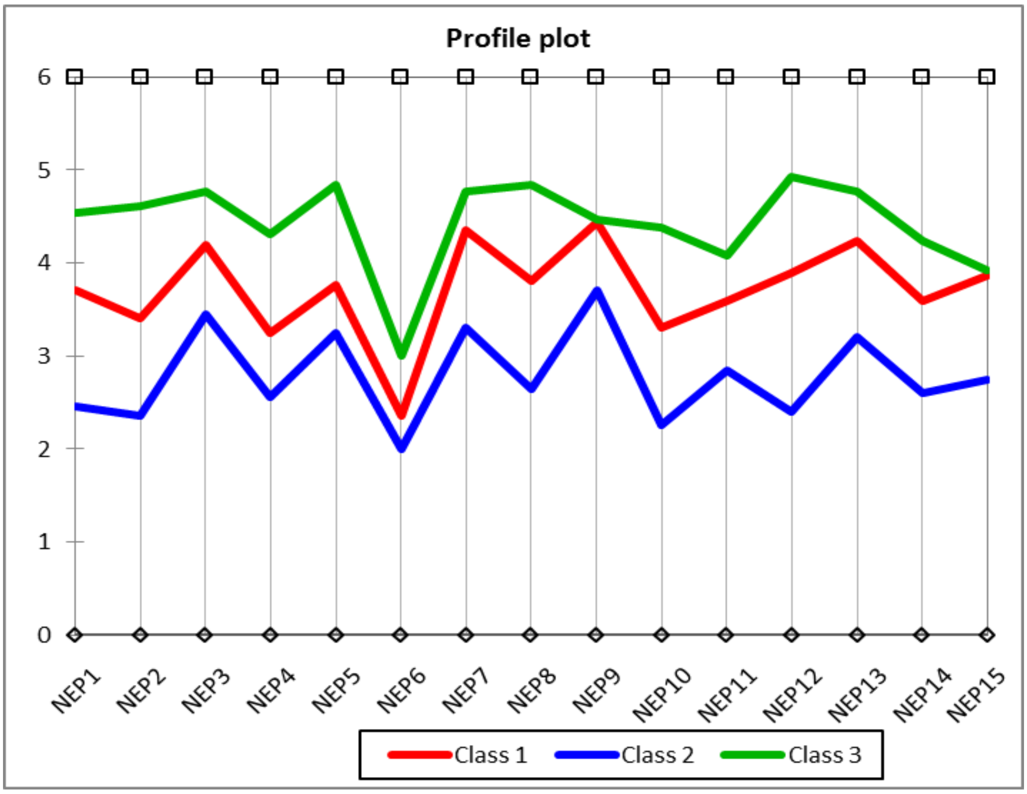


Figure A2-1: Profile plot showing mean item scores for each class

2.2. Analysis of responses to the TPB statements – pilot survey

Table A2-4 shows the distribution of responses to the statements measuring TBP constructs obtained in the pilot survey (N = 70). A correlation analysis was carried out to assess correlation of each pair of statements measuring the same construct (see Table A2-5). The pairs of scores measuring ATT, SN, PBC, and BI were found to have correlations ranging from 0.438 for the SN items to 0.74 for the ATT items and were all significant at the 5% level. The high correlation for ATT and PBC items suggested that each pair could be combined into a single index for each construct. Although the correlation between the SN items was statistically significant, it was rather low. This was addressed by changing the evaluative semantic differential scale in the final survey. To improve the correlation between the scores for the BI items the second statement was refined in the final survey.

Table A2-4: Percentage distribution of responses to the TPB statements (N = 70)

Variable	Response categories coded on a 7-point scale from -3 to 3							Mean Score
	-3	**-2**	**-1**	**0**	**1**	**2**	**3**	
ATT1	0%	0%	3%	6%	10%	38%	44%	2.15
ATT2	0%	0%	1%	11%	13%	48%	27%	1.89
SN1	6%	11%	6%	28%	14%	23%	13%	0.53
SN2	0%	0%	1%	48%	6%	28%	17%	1.12
PBC1	0%	4%	3%	10%	20%	32%	31%	1.66
PBC2	0%	3%	14%	14%	27%	24%	18%	1.09
BI1	10%	24%	6%	23%	28%	10%	0%	-0.36
BI2	1%	3%	3%	10%	30%	27%	27%	1.53

Table A2-5: Correlation matrix (Pearson (n)) for the TPB constructs (N = 70)

Variables	ATT1	ATT2	SN1	SN2	PBC1	PBC2	BI1	BI2
ATT1	1.000	**0.740**	0.228	0.320	0.438	0.505	0.417	0.761
ATT2	**0.740**	1.000	0.404	0.488	0.398	0.416	0.374	0.715
SN1	0.228	0.404	1.000	**0.438**	0.087	0.029	0.331	0.234
SN2	0.320	0.488	**0.438**	1.000	0.313	0.354	0.059	0.364
PBC1	0.438	0.398	0.087	0.313	1.000	**0.595**	**0.384**	**0.459**
PBC2	0.505	0416	0.029	0.354	**0.595**	1.000	0.429	0.455
BI1	0.417	0.374	0.331	0.059	**0.384**	0.429	1.000	**0.492**
BI2	0.761	0.715	0.234	0.364	**0.492**	0.455	**0.492**	1.000

To test the relationship postulated in TPB as applied to this study we examined the correlation of ATT, SN, and PBC with BI, and performed linear regression using responses from the pilot survey. The correlations of ATT, SN and PBC with BI were 0.687, 0.340, and 0.557 respectively and were all significant at the 5% level. Linear regression results of BI on ATT, SN and PBC are presented in Table A2-6. The results indicated that only ATT was a significant determinant of BI, whilst PBC and SN were marginally significant and insignificant respectively. The significance of each construct depends on the context (Ajzen, 2005). The model R^2 of 0.816 indicated an acceptable level of model fit. We interpreted the insignificance of SN and PBC as indicating a weak influence in determining behavioral intentions and hence switching. When SN and PBC were replaced with the individual items (SN1, SN2, PBC1, and PBC2) all were statistically significant at the 5% level except PBC2 although R^2 decreased to 0.556. This suggested that these items could be treated as individual scales in model estimation. The pilot results indicated that respondents may have provided reasonable responses to the statements as all the TPB constructs had the expected signs. However, inspection of individual responses identified some inconsistent responses which we address below.

Table A2-6: Linear regression results for BI on ATT, SN, and PBC (N = 70)

	Coefficients	*Std. Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
ATT	0.7027	0.0956	7.3***	0.0001	0.5119	0.8936
SN	0.0308	0.0932	0.33	0.7420	-0.1553	0.2169
PBC	0.14864	0.1037	1.43	0.1566	-0.0584	0.3557
$R^2 = 0.816$ Adj.$R^2 = 0.796$						
Regressing BI on individual items except ATT						
Intercept	-1.1720	0.2649	-4.42***	0.0001	-1.7012	-0.6428
SN1	0.1693	0.0684	2.47**	0.0159	0.0326	0.3060
SN2	-0.2333	0.1014	-2.30**	0.0246	-0.4358	-0.0308
PBC1	0.1581	0.0988	1.59	0.1147	-0.0394	0.3555
PBC2	0.2054	0.0981	2.09**	0.0403	0.0093	0.4015
ATT	0.7160	0.1436	4.98***	0.0001	0.4291	1.0029
$R^2 = 0.579$ Adj.$R^2 = 0.546$						

***significant at .0001, **significant at .05

The low correlations in some of the item scores may have been a result of inconsistent responses due to some respondents not understanding the statements well or did not take the survey seriously and provided random responses. For example, some respondents provided opposite answers on the two evaluative semantic differential scales for to the same statement. This issue was raised with Research Now NZ, the marketing company providing the online panel, who promised that the panel would be advised against this practice as they are paid to take surveys. This produced improved results on the second survey (energy sources sample) where all correlations between pairs of statements measuring the same constructs were high and statistically significant at the 5% level and a linear regression of BI on ATT, SN, and PBC had an R^2 of 0.854 (correlation and regression results for the energy source sample are provided in the appendix).

Factor analysis of the scores measuring ATT, SN, and PBC showed that all three measures loaded heaviest on F1 (the first unrotated factor) (see Table A2-7).

However, SN loaded equally (0.688) on the first and second unrotated factors which was not surprising given that the two item scores used to construct SN were not highly correlated. F1 had an eigenvalue of 1.81; accounted for 60.32% of the variance among the constructs; and appeared to represent BI which is postulated under TPB to be a function of ATT, SN and PBC. However, a Cronbach's alpha of 0.665, which was lower than the minimum level of 0.70 recommended in previous literature (e.g., Clark et al., 2003), indicated that the constructs could not be combined into a single index. However, when the factors are subjected to Varimax rotation, the TPB constructs loaded heavily onto different dimensions. ATT loaded heaviest onto D3 and SN and PBC loaded heaviest on D2 and D1 respectively. This justified the use of these constructs as subscales in the TPB.

Table A2-7: Principal components analysis of TPB constructs with Varimax rotation

Variables	F1	F2	F3	D1	D2	D3
ATT	**0.871**	-0.063	0.487	0.279	0.232	**0.932**
SN	**0.688**	**0.688**	-0.233	0.088	**0.975**	0.206
PBC	**0.760**	-0.550	-0.347	**0.962**	0.090	0.256
Eigenvalue	1.810	0.779	0.411			
Variability %	60.323	25.962	13.715	33.725	33.714	32.562
Cumulative%	60.323	86.285	100.000	33.725	67.438	100.000

2.3 Analysis of responses to the NAT statements – pilot survey

Responses to the AC and AR statements were spread over all possible response categories indicating considerable individual heterogeneity in terms of "awareness of consequences" and "ascription of responsibility". However, the percentage distribution of responses showed that respondents tended to have a more positive evaluation of "awareness of consequences" compared to "ascription of responsibility". For example, about 72% of the respondents "strongly or somewhat agree" that switching to a supplier that produces electricity from renewable sources would be good for the environment whilst only 7% disagreed. Respondents seemed to exhibit low levels of self-efficacy as 27% "somewhat agree or strongly agree" with AC2 to the effect that their behaviour won't make any difference to the environment whilst only 46% "somewhat disagree or strongly disagree with it.The majority of respondents provided neutral responses to the two AR questions. For example only 34% of respondents at least agreed with AR2 and 42% provided neutral responses.

The internal consistency of the AC and AR statements (or items) was tested using the correlations among the items. To obtain an index for each construct, the two scores for the relevant statements are averaged to obtain a score. Principal components analysis was not performed as only two statements were used for each construct. Summary statistics and correlations for the AC and AR constructs are provided in Table 2-4. Correlation between the AC statements is 0.285 whilst that of the AR statements is 0.704. Both correlations are significant at the 5% level. However a higher level of correlation between the AC statements is required and this was considered in refining the statements for inclusion in the final survey. Some previous studies have combined AC and AR into a single scale measuring altruism (e.g., Clark et al., 2003; Cooper et al., 2004). Examining the correlations between AC2 and the two AR statements showed that an attempt to combine the items into a single scale would be problematic as some of the correlations are small and statistically insignificant.

Table A2-8: Summary statistics and Correlation matrix (Pearson (n) for AC and AR items* (N = 70)

Variables	Min	Max	Mean	Std. dev	AC1	AC2	AR1	AR2
AC1	1	5	3.843	0.927	1	**0.285**	**0.476**	**0.501**
AC2	1	5	3.214	1.006	**0.285**	1	0.099	0.161
AR1	1	5	3.071	1.012	**0.476**	0.099	1	**0.704**
AR2	1	5	3.043	1.013	**0.501**	0.161	**0.704**	**1**

*All correlations in bold are significant at the 5% level

Appendix 3. Chronology of market reforms

3.1 NZ electricity market reforms

Table A3-1: Key dates in the development of the New Zealand electricity industry

Date	Event
1886	The first high-voltage electricity transmission line is built, running between Skippers Canyon in Central Otago and a mining company 6 kilometers away
1888	Reefton is the first town in the southern hemisphere to have a public electricity supply
1903	The Water Act empowers the Crown to use water for generating electricity
1911	The Hydro-Electric Branch of the Public Works Department is established
1914	The first major state hydro scheme at Coleridge begins generating power
1923	Government calls tenders for Arapuni, which is commissioned 6 years later, initiating hydro development on the Waikato River.
1949	Commencement of Roxburgh dam construction starts the development of the Clutha River hydro system
1958	The State Hydro-Electric Department becomes the New Zealand Electricity Department (NZED).
1965	The North and South Islands are linked by seafloor electricity cables across Cook Strait
1987	NZED is corporatised as the Electricity Corporation of New Zealand (ECNZ), which trades for a time as Electricorp
1994	ECNZ’s transmission business is split off as Transpower. The electricity industry establishes the Metering and Reconciliation Information Agreement (MARIA) to facilitate the bilateral trading of electricity between buyers and sellers
1996	ECNZ is split again, with a new generation business, Contact Energy, being formed. A wholesale spot electricity market, the New Zealand Electricity Market (NZEM), is established. Like MARIA, the NZEM is industry self-governed
1998	Industry Reform Act 1998 provides for the setting up of a profiling system that would enable consumers to switch electricity retailers easily
1999	Contact Energy is privatised. The remainder of ECNZ is split, with the major assets divided between Mighty River Power, Genesis and Meridian Energy, and the minor assets sold off
2003	The Electricity Commission is established to manage the NZ electricity market
2009	A Ministerial Review into the performance of the electricity market determines that the full benefits of retail competition have not been realised and recommends the setting up a of switching fund to promote the benefits of comparing and switching electricity retailer
2010	The Electricity Commission is replaced by the Electricity Authority, tasked with governing the electricity market under the new Electricity Industry Act 2010.
2011	The Authority reports completion of priority matters specified in the Act: compensation to consumers and a floor on spot prices during electricity shortages; a mechanism to help manage price risk caused by transmission constraints; facilitating active responses by large users to wholesale market conditions; more standardisation of distribution tariff structures and terms; and improving electricity hedge market liquidity
2011	Electricity Authority launches “Whats My Number” campaign in terms of the 2009 Ministerial Review
2013	Mighty River Power and Meridian Energy are partially privatized: government sells off 49% of the stake
2014	Genesis Energy is partially privatized: government sells off 49% of the stake

Source: Adapted from Electricity Authority (2011)

3.2 How the wholesale spot market price is determined

In this section we describe how the wholesale spot price is determined. Any increases in wholesale spot prices are directly passed onto consumers as a component of the retail price.

The wholesale spot price of electricity is determined by the forces of supply and demand. An equilibrium price is determined at a level that clears the market. Generators connected to the national grid, retailers and some large industrial consumers participate in the wholesale market through a platform called the wholesale and information trading system (WITS). Each generator competes for the supply of electricity by submitting offer schedules for each trading period (half-hour period) through the WITS. An offer schedule indicates a generator's intention to sell a specific quantity of electricity at a particular location called a node or grid injection point, at a particular price and time. Each offer schedule consists of a series of tranches each specifying the volume (in megawatts - MW) and price (in $/MWh).

The tranches are based on generators' specific plants, that is, plant capacity and marginal cost, and indicate the minimum price at which a generator is willing to supply a given quantity of electricity. Generation capacity from plants that are expensive to shut down and take long to restart (referred to as 'must-run plant') is usually offered first at prices close to zero or even negative prices (NZX Ltd, 2014) and usually provide the base load. This is followed by tranches that are offered at progressively higher prices reflecting increasing cost of supply, with the smallest and usually most expensive gas-coal thermal plants offered last or as peaking plant. This is consistent with the standard upward sloping supply curve which reflects increasing marginal cost of progressive plants offered for dispatch. Each generator's offer schedule is therefore its supply curve. To obtain the supply curve for the market, the individual generators' offer schedules are aggregated (see Figure A3-1).

Retailers and large industrial consumers submit bid schedules that indicate intention to buy specific quantities of electricity at particular locations (nodes), at particular prices and times. The bid schedules consist of a series of tranches whose prices progressively decrease and each price represents the maximum amount a retailer is willing to pay to secure a particular quantity of electricity. The aggregate of all bid schedules at each node during a given trading period form the market demand curve for that node. The offers and bids are then used by NZX Energy, as pricing manager, to determine the market clearing price for each trading period at each node. A scheduling, pricing, and dispatch (SPD) model is used to calculate optimal dispatch and clearing price at each node. The model minimizes the cost of generation plus the cost of reserves for any given level of demand subject to system constraints. Dispatch involves ranking generators' offers from the least to the most expensive to form an offer stack for each node. Usually the least expensive offers are dispatched first except where there are constraints in transmission. The offer stack determines the short run marginal cost curve for the market. In a competitive wholesale market where each generator assumes that they are not the marginal plant, the optimal offer for each generator is the true marginal cost of generation (NZX Ltd, 2014).

For each half-hour trading period, demand is not responsive to the wholesale spot price and is vertical. One reason for the non-responsiveness of demand to half-hourly spot market prices is that most consumers cannot see the fluctuations in half-hourly prices. However, demand varies during the course of the day peaking during the morning, early afternoon and early evening. This induces volatility in the wholesale spot price as supply and demand is matched in each half-hour trading period. In a hypothetical example presented in Figure 3-2, the market clearing price is $60 per MWh. All generators dispatched at this node are paid the same price ($60) for all the units supplied irrespective of the lower prices offered on non-marginal plants. This is commonly referred to as "uniform pricing" or marginal cost pricing where all units supplied are priced at the marginal cost of the last unit supplied.

The marginal plant that clears the market determines the wholesale spot price. Assuming that the wholesale market is competitive, the difference between the wholesale spot market price and the offers for non-marginal plant at each node would reflect "scarcity rents" which allow firms to recover capital costs and act as signals for the location and type of new capacity generation investments. The scarcity rents also provide incentives for generators to increase efficiency hence no need for regulations on efficiency and investments in new capacity. However, if the market is less competitive as argued by the critics of the current market structure, the Big 5 collude and exercise market power to push wholesale spot prices up resulting in excess profits which is not in the long term benefit of consumers. Based on current market shares, the Herfindahl-Hirschman index for the NZ wholesale market is around 0.2036 which indicates a highly concentrated market, hence a potential for the exercise of market power. However, whether the Big 5 have been able to exercise market power is debatable and is difficult to measure.

The wholesale electricity market in New Zealand is an energy-only market in which "the distribution of electricity prices over time, including peak, off-peak, and fuel-shortage periods must not only fund the operational costs involved in producing electricity, but also provide capital cost recovery to cover the cost of maintaining and expanding capacity" (Evans, Hogan, & Jackson, 2012, p. 3). There are no side payments made to generators to compensate them for any losses or incentives to invest in new capacity to meet future demand. However, the emissions trading scheme increases the competitiveness of plants which use renewable energy for generation.

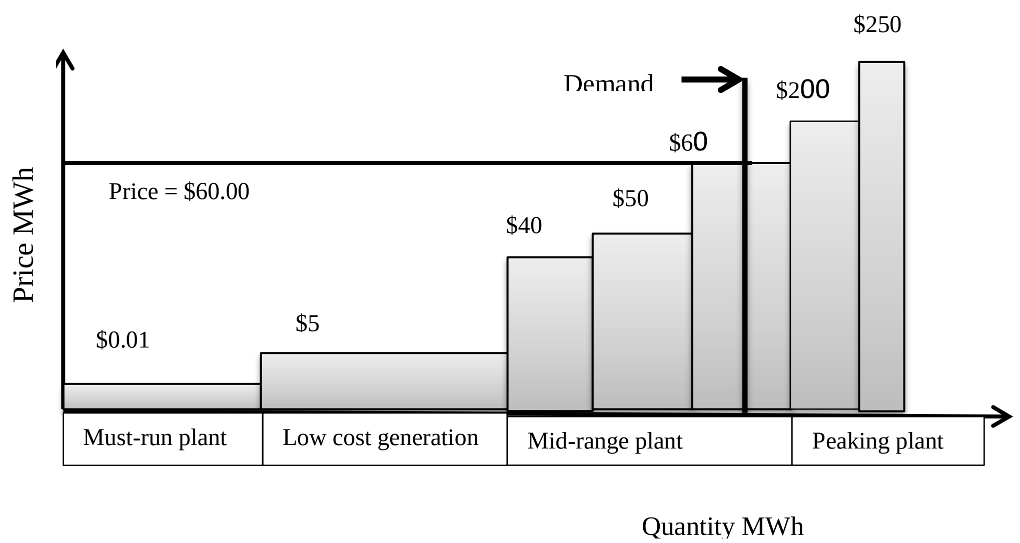


Figure A3-1: Offer stack and demand (Source: NZX Ltd, 2014)

Appendix 4. Supplementary tables for Chapter 4

Table A4-1: MNL results and WTP estimates

Variable	Coef	Std err	p-value	WTP	Std err	p-value
ASCALT1	.6124^{c}	.0756	.0000			
Time	-.0404^{c}	.0072	.0000	1.49^{c}	0.27	.0000
Fixed	.0055^{b}	.0021	.0106	-0.20^{b}	0.08	.0111
Rewards	.3839^{c}	.0703	.0000	-14.14^{c}	2.57	.0000
Renewable	.0089^{c}	.0012	.0000	-0.33^{c}	0.05	.0000
Ownership	.0092^{c}	.0014	.0000	-0.34^{c}	0.05	.0000
New electricity company	-.3557^{c}	.0947	.0002	13.10^{c}	3.42	.0001
New non-electricity company	-.6744^{c}	.1228	.0000	24.84^{c}	4.56	.0000
Well-known non-electricity company	-.3891^{c}	.1139	.0006	14.33^{c}	4.18	.0006
Savings	.0272^{c}	.0008	.0000			
K		10				
LL		-2136.9601				
AIC		4293.9				
BIC		4352.9				
McFadden Pseudo-R^2		0.2731				

^{a} Significant at 0.1, ^{b} Significant at 0.05, ^{c} Significant at 0.01

Table A4-2: RPL-EC regression results

Variable	Coefficient	S.E.	p-value	SD	S.E.	p-value
ASCALT1	.4489	.1887	.0174			
Time	-.0313	.0056	.0000	.0117	.0158	.4577
Fixed	.00644**	.0026	.0121	.0184***	.0039	.0000
Rewards	.1691***	.0641	.0083	.0340	.1213	.7790
Renewable	.0105***	.0014	.0000	.0101***	.0019	.0000
Ownership	.0114***	.0021	.0000	.0165***	.0021	.0000
New electricity company	-.4496***	.1070	.0000	.0385	.2203	.8613
New non-electricity company	-.9336***	.1413	.0000	.0493	.1585	.7559
Well-known non-electricity company	-.7079***	.14127	.0000	.0341	.1387	.8056
$Switch_{100}$-Savings	.0428***	.00168	.0000			
$Switch_{200}$-Savings	.0329***	.00209	.0000			
$Switch_{300}$-Savings	.0274***	.00305	.0000			
$Switch_{400}$-Savings	.0282***	.00309	.0000			
Error Component (EC)	0.0 ...(Fixed Parameter)….			2.0391***	.1435	.0000
K	22					
LL	-1848.6881					
AIC	3741.4					
BIC	3871.1					
McFadden Pseudo-R^2	.374					

* Significant at 0.1, ** Significant at 0.05, *** Significant at 0.01. S.E and SD are the standard error and standard deviation, respectively

Table A4-3: Predicted probabilities of switching to different supplier types

Savings per month (NZ$)	Well-known electricity company	New electricity company	Well- known non-electricity company	New non-electricity company
-55	0.0818	0.0583	0.0571	0.0437
-50	0.0818	0.0583	0.0571	0.0437
-45	0.0951	0.0681	0.0666	0.0511
-40	0.1102	0.0793	0.0776	0.0597
-35	0.1274	0.0921	0.0902	0.0697
-30	0.1468	0.1069	0.1047	0.0811
-25	0.1687	0.1236	0.1211	0.0943
-20	0.1930	0.1426	0.1398	0.1093
-15	0.2199	0.1639	0.1607	0.1264
-10	0.2494	0.1877	0.1842	0.1457
-5	0.2815	0.2140	0.2102	0.1674
0	0.3159	0.2430	0.2388	0.1915
5	0.3525	0.2745	0.2700	0.2183
10	0.3909	0.3085	0.3036	0.2477
15	0.4306	0.3446	0.3395	0.2796
20	0.4714	0.3827	0.3773	0.3139
25	0.5124	0.4222	0.4166	0.3504
30	0.5534	0.4628	0.4571	0.3886
35	0.5936	0.5038	0.4981	0.4284
40	0.6326	0.5448	0.5391	0.4690
45	0.6699	0.5852	0.5796	0.5101
50	0.7052	0.6245	0.6191	0.5511
55	0.7382	0.6622	0.6571	0.5913

Appendix 5. Supplementary results for Chapter 5

Table A5-1: Regression results for MNL models estimated with different cut-off points on certainty scale

	M0	M1(4)	M2(5)	M3(6)	M4(7)	M5(8)
ASCALT1	0.515	0.505	0.378	0.382	0.385	0.397
	(7.01)	(6.71)	(4.47)	(4.09)	(3.38)	(2.40)
Time	-0.048	-0.051	-0.049	-0.058	-0.075	-0.098
	(-6.61)	(-6.79)	(-5.69)	(-5.72)	(-5.00)	(-4.05)
Fixed	0.003	0.003	0 .004	0.006	0.005	-0.002
	(1.41)	(1.49)	(1.59)	(2.02)	(1.32)	(-0.33)
Discount	0.008	0.008	0.009	0.014	0.015	0.021
	(3.09)	(2.85)	(3.11)	(4.06)	(3.32)	(3.00)
Loyalty Rewards	0.417	0.424	0.398	0.422	0.468	0.715
	(6.00)	(5.96)	(5.00)	(4.73)	(4.09)	(3.83)
Renewable	0.009	0.009	0.009	0.009	0.010	0.011
	(7.29)	(6.93)	(6.75)	(5.97)	(4.71)	(3.11)
Local Ownership	0.007	0.006	0.008	0.007	0.007	0.006
	(5.05)	(4.67)	(5.15)	(3.82)	(3.12)	(1.65)
New electricity company	-0.276	-0.301	-0.367	-0.401	-0.293	-0.039
	(-2.91)	(-3.13)	(-3.32)	(-3.18)	(-1.75)	(-0.15)
New non-electricity company	-0.724	-0.736	-0.915	-0.966	-0.891	-0.710
	(-5.98)	(-6.01)	(-6.47)	(-5.97)	(-4.07)	(-1.95)
Well-known non-electricity company	-0.498	-0.529	-0.651	-0.696	-0.564	-0.549
	(-4.35)	(-4.55)	(-4.89)	(-4.56)	(-2.76)	(-1.56)
Monthly Power Bill	-0.025	-0.025	-0.027	-0.027	-0.028	-0.028
	(-31.13)	(-30.58)	(-28.68)	(-25.91)	(-21.20)	(-14.36)
LL	-216.6	-2083.5	-1620.5	-1300.8	-820.5	-361.2
AIC [AIC/N]	4353.1	4188.9	3263.1	2623.6	1663.1	744.4
	[1.62]	[1.62]	[1.55]	[1.52]	[1.49]	[1.48]
BIC [BIC/N]	4418.0	4253.4	3325.3	2683.6	1718.3	790.9
	[1.64]	[1.64]	[1.57]	[1.55]	[1.54]	[1.57]
Pseudo-R^2	0.2633	0.2653	0.2945	0.3066	0.3199	0.3385
Sample size	224	216	176	144	93	42

z-scores are in round brackets. M0, M1(4), M2(5), M3(6), M4(7), M5(8) are MNL models – number in brackets indicates the cut-off point on the certainty scale.

Table A5-2: WTP estimates based on different cut-off points on the certainty scale[1]

	M0	M1(4)	M2(5)	M3(6)	M4(7)	M5(8)
Time	-1.92[c]	-2.02[c]	-1.85[c]	-2.13[c]	-2.69[c]	-3.46[c]
	(0.29)	(0.30)	(0.33)	(0.37)	(0.54)	(0.86)
Fixed	NS	NS	NS	0.21[b]	NS	NS
				(0.10)		
Discount	0.33[c]	0.30[c]	0.35[c]	0.51[c]	0.52[c]	0.76[c]
	(0.11)	(0.11)	(0.12)	(0.13)	(0.16)	(0.26)
Loyalty Rewards	16.60[c]	16.80[c]	14.83[c]	15.56[c]	16.80[c]	25.36[c]
	(2.74)	(2.79)	(2.93)	(3.25)	(4.06)	(6.54)
Renewable	0.36[c]	0.35[c]	0.36[c]	0.35[c]	0.36[c]	0.39[c]
	(0.05)	(0.05)	(0.05)	(0.06)	(0.08)	(0.13)
Local Ownership	0.27[c]	0.25[c]	0.30[c]	0.24[c]	0.25[c]	0.22[a]
	(0.05)	(0.05)	(0.05)	(0.06)	(0.08)	(0.13)
New electricity company	-10.97[c]	-11.91[c]	-13.67[c]	-14.77[c]	-10.54[a]	NS
	(3.71)	(3.74)	(4.03)	(4.56)	(5.95)	
New non-electricity company	-28.80[c]	-29.16[c]	-34.08[c]	-35.64[c]	-32.00[c]	-25.17[a]
	(4.86)	(4.90)	(5.31)	(6.03)	(7.93)	(12.85)
Well-known non-electricity company	-19.81[c]	-20.96[c]	-24.26[c]	-25.66[c]	-20.26[c]	NS
	(4.53)	(4.58)	(4.92)	(5.58)	(7.24)	

[1] Cut-off points are 4, 5, 6, 7, and 8; [c], [b], [a] denote significance at the .01, 00.5, and .1 level respectively

Table A5-3: Test for equality of WTP estimates

	M0 vs. M1 (4)		M0 vs. M2 (5)		M0 vs. M3 (6)		M0 vs. M4 (7)		M0 vs. M5 (8)	
	Ratio	ANTS	Ratio	ANTS	Ratio	ANTS	Ratio	ANTS	Ratio	ANTS
Time	1.05	1.51	0.96	-0.53	1.11	0.90	1.40	**1.69**	1.80	**1.89**
Fixed	-	NS	-	NS	-	**2.00**	-	NS	-	1.41
Discount	0.91	0.98	1.06	-0.59	1.55	**-2.54**	1.58	-1.61	2.30	**-1.80**
Loyalty Rewards	1.01	-0.37	0.89	**1.69**	0.94	0.59	1.01	-0.07	1.53	-1.47
Renewable	0.97	1.45	1.00	-0.01	0.97	0.16	1.00	0.02	1.08	-0.28
Local Ownership	0.93	**1.72**	1.11	-1.32	0.89	0.82	0.93	0.37	0.81	0.40
New electricity company	1.09	**1.97**	1.25	**1.71**	1.35	1.44	0.96	-0.09	-	-1.08
New non-electricity company	1.01	0.58	1.18	**2.46**	1.24	**1.92**	1.11	0.51	0.87	-0.30
Well-known non-electricity company	1.06	**1.75**	1.22	**2.33**	1.30	**1.80**	1.02	0.08	-	-0.03

Appendix 6. EA and WTP for green electricity: supplementary results

6.1 Analysis of responses to the NEP Scale statements: Supplementary analysis

6.1.1 Facets of ecological worldview

The mean scores for the individual facets of ecological worldview presented in Table 6A-1 show that respondents have the lowest average score (9.12) for "Limits" (NEP1, NEP6, NEP11). This is due to the weakest pro-environmental attitudes associated NEP6. On the other hand, respondents have the highest average score (11.19) for "Balance" (NEP3, NEP8, NEP13). The scores for the individual facets are bounded between 3 and 15 and our results show that overall, respondents have a positive attitude with respect to all the facets of ecological worldview. ANOVA suggests that at least one of the mean scores for the facets is statistically different from the other scores. Tests for pairwise differences in means using the t-test indicate that the mean scores for all the facets are statistically different from each other except for 'A*nti-anthropocentrism'* and 'B*alance'*. This suggests that an attempt to reduce the length of the survey questionnaire by using a single facet of ecological worldview to measure environmental attitudes may not be appropriate. Each facet is measured using only three items (see Table 6-2).

Table A6-1: Average total scores for individual facets of ecological worldview*

Facet of ecological worldview	Items	Average score	Variance
Limits to growth (Limits)	1, 6, 11	9.12	4.55
Human domination of nature (Anti-anthropocentrism)	2, 7, 12	11.03	6.09
Frugality of nature's balance (Balance)	3, 8, 13	11.19	4.96
Human exemption from the constraints of nature (Anti-exemptionalism)	4, 9, 14	10.23	4.63
Possibility of an ecological crisis (Eco-crisis)	5, 10, 15	10.59	6.29

*Possible score range is 3 to 15

6.1.2 The dimensionality of the NEP Scale

The dimensionality of the NEP Scale is investigated by employing Varimax rotation to create orthogonal dimensions or uncorrelated factors. The results are presented in Table A6-2. When the four factors with eigenvalues greater than 1 are subjected to Varimax rotation, five items load heaviest on the first rotated factor D1 with two other items cross-loading heavily on this factor. The items that load heaviest or cross-load heavily on D1 tap three facets of ecological worldview: 'reality of limits to growth' (items 1 and 11), 'fragility of nature's balance' (items 3 and 13), and 'possibility of an eco-crisis' (items 10 and 15). All three anti-anthropocentrism items (2, 7 and 12); all eco-crisis items (5, 10 and 15); one balance of nature item (8) and one 'rejection of exemptionalism' item (14) load heaviest or cross-load heavily on the second rotated factor D2.

The items that tap the 'rejection of exemptionalism' facet (items 4, 9, and 14) load heaviest or cross-load heavily on the third rotated factor D3 whilst two items (6 and 11) that tap 'limits to growth' facet also cross-load heavily on this factor. Only one item (4) loads heaviest on the third factor D3 but four other items (6, 9, 11, and 14) cross-load heavily on it. None of anti-anthropocentrism items (2, 7 and 12) and exemptionalism items (4, 9 and 14) either load heaviest or cross-load heavily on D1. Five items (3, 6, 7, 9, 13), one from each facet, load heaviest or cross-loads heavily on the forth rotated factor D4.

Most items have substantial cross loadings (more than 0.30) on one or two other factors. These results suggest that the first major factor D1 taps limits to growth, eco-crisis and balance of nature facets heavily but weakly taps the remaining two facets, anti-anthropocentricism and anti-exemptionalism which are mainly captured in D2 and D3. These results also suggest the existence of four NEP subscales.

Although Dunlap et al. (2000 p.435) find similar evidence they argue that they are not inclined to create four NEP subscales "because all 15 items load heavily on the first unrotated factor, have strong item-total correlations and yield an alpha of 0.83 when combined into a single scale." It seems reasonable to adopt the same approach for this study since our results are similar to theirs.

Table A6-2: Principal components analysis of NEP items with Varimax rotation

Item	Facet of ecological worldview	Factors (or Dimensions)			
		D1	**D2**	**D3**	**D4**
NEP 1	Limits to growth	**0.75**	-0.07	0.19	-0.10
NEP 2	Anti-anthropocentrism	0.06	**0.66**	0.27	0.18
NEP 3	Frugality of nature’s balance	**0.48**	0.12	0.20	**0.51**
NEP 4	Anti-exemptionalism	0.11	0.19	**0.83**	0.05
NEP 5	Possibility of an ecocrisis	**0.60**	**0.32**	-0.09	0.20
NEP 6	Limits to growth	0.12	0.18	**0.43**	**-0.60**
NEP 7	Anti-anthropocentrism	0.17	**0.37**	-0.25	**0.52**
NEP 8	Frugality of nature’s balance	0.27	**0.60**	0.26	0.10
NEP 9	Anti-exemptionalism	0.12	0.08	**0.36**	**0.72**
NEP 10	Possibility of an ecocrisis	**0.35**	**0.71**	0.06	-0.07
NEP 11	Limits to growth	**0.67**	-0.01	**0.33**	0.13
NEP 12	Anti-anthropocentrism	-0.06	**0.73**	0.12	0.04
NEP 13	Frugality of nature’s balance	**0.49**	0.19	-0.05	**0.42**
NEP 14	Anti-exemptionalism	-0.03	**0.44**	0.41	0.11
NEP 15	Possibility of an ecocrisis	**0.72**	**0.37**	-0.09	0.14
Eigenvalue		5.149	1.548	1.318	1.129
Variability (%)		18.40	14.74	10.23	10.94
Cumulative (%)		18.40	33.15	43.37	54.31

6.2 Panel ordered probit model

Table A6-3: Regression results for the panel ordered probit model (N=224)

Variable	Coefficient	S.E	z	Prob.|z|>Z	95% CI	
					LB	UB
	Index function for probability					
Constant	2.289[c]	0.255	8.99	.0000	1.791	2.789
Gender (male = 1)	-0.099[c]	0.038	-2.60	.0093	-0.175	-0.026
Age (years)	0.004[c]	0.001	3.10	.0020	0.002	0.007
Child (1 if respondent has dependent children, otherwise 0)	-0.025	0.039	-0.63	.5271	-0.103	0.053
*ln*Icome	-0.078[c]	0.025	-3.17	.0015	-0.127	-0.03
NZ European	-0.003	0.053	-0.06	.9507	-0.106	0.099
Maori	0.191[a]	0.099	1.92	.0545	-0.004	0.385
Education (at least bachelors)	0.084[a]	0.045	1.87	.0616	-0.004	0.171
	Threshold parameters for index					
μ_1	0.838[c]	0.022	37.78	.0000	0.794	0.881
μ_2	1.539[c]	0.021	73.24	.0000	1.498	1.581
μ_3	2.425[c]	0.026	93.87	.0000	2.374	2.476
LL	-4998.7					
AIC	10019.3					
BIC	10086.6					
Chi-squared (7 d.f.)	29.96631 [p-value = .0001]					

[c] Significant at 0.01 level, [b] Significant at 0.05 level, [a] Significant at 0.10 level. CI denotes confidence interval

Table A6-4: Marginal effects of respondents' SDCs on NEP Scale responses

Variable	Partial effect	Elasticity	| z |	Prob.|z|>Z	95% confidence interval LB	UB
		Partial effects on Prob[Response category = 1]				
GENDER (male = 1)	0.0107[c]	0.2119	2.58	.0099	0.0025	0.0188
AGE (years)	-0.0004[c]	-1.3892	3.09	.0020	-0.0007	-0.0001
CHILD	0.0026	0.0532	0.63	.5287	-0.0056	0.0110
*ln*INCOME	0.0084[c]	1.7365	3.15	.0016	0.0031	0.0135
NZ_EURO	0.0003	0.0068	0.06	.9506	-0.0105	0.0112
MAORI	-0.0176[b]	-0.3490	2.24	.0254	-0.0330	-0.0021
BACHELORS'	-0.0087[a]	-0.1719	1.92	.0554	-0.0175	0.0002
		Partial effects on Prob[Response category = 2]				
GENDER (male = 1)	0.0186[c]	0.1159	2.60	.0093	0.0045	0.0325
AGE (years)	-0.0008[c]	-0.2140	3.10	.0019	-0.0012	-0.0002
CHILD	0.0046	0.0291	0.63	.5273	-0.0098	0.0191
*ln*INCOME	0.0146[c]	0.9547	3.17	.0015	0.0055	0.0236
NZ_EURO	0.00060	0.0037	0.06	.9507	-0.0185	0.0197
MAORI	-0.0343[b]	-0.2136	2.01	.0446	-0.0676	-0.0008
BACHELORS'	-0.0155[a]	-0.0965	1.88	.0600	-0.0316	0.0006
		Partial effects on Prob[Response category = 3]				
GENDER (male = 1)	0.0104[c]	0.0419	2.61	.0092	0.0025	0.0182
AGE (years)	-0.0004[c]	-0.0779	3.07	.0022	-0.0007	-0.0001
CHILD	0.0026	0.0105	0.64	.5253	-0.0054	0.0107
*ln*INCOME	0.0082[c]	0.3477	3.14	.0017	0.0030	0.0133
NZ_EURO	0.0003	0.0013	0.06	.9508	-0.0105	0.0111
MAORI	-0.0229[a]	-0.0924	1.72	.0849	-0.0490	0.0031
BACHELORS'	-0.0090[a]	-0.0364	1.81	.0697	-0.0188	0.0007
		Partial effects on Prob[Response category = 4]				
GENDER (male = 1)	-0.0108[b]	-0.0334	2.56	.0105	-0.0191	-0.0025
AGE (years)	0.0004[c]	0.0613	3.06	.0022	0.0001	0.0007
CHILD	-0.0027	-0.0084	0.63	.5296	-0.0112	0.0057
*ln*INCOME	-0.0084[c]	-0.2736	3.12	.0018	-0.0137	-0.0031
NZ_EURO	-0.0003	-0.0010	0.06	.9506	-0.0113	0.0107
MAORI	0.0159[c]	0.0490	2.71	.0067	0.0043	0.0273
BACHELORS'	0.0086[a]	0.0266	1.94	.0522	-0.0000	0.0173
		Partial effects on Prob[Response category = 5]				
GENDER (male = 1)	-0.0289[c]	-0.1330	2.60	.0093	-0.0506	-0.0071
AGE (years)	0.0012[c]	0.2464	3.08	.0021	0.0004	0.0019
CHILD	-0.0072	-0.0334	0.63	.5263	-0.0297	0.0152
*ln*INCOME	-0.0227[c]	-1.0991	3.16	.0016	-0.036	-0.0086
NZ_EURO	-0.0009	-0.0043	0.06	.9507	-0.0308	0.0289
MAORI	0.0589[a]	0.2717	1.81	.0699	-0.0047	0.1226
BACHELORS'	0.2457*	0.11322	1.84	0.0652	-0.0015	0.0506

[c], [b], [a] Significant at .01, .05, and .1 level respectively

6.3 WTP for green electricity

Table A6-5: Marginal WTP estimates (NZ$$_{(2014)}$/month)

Attribute		MNL_15	RPL_15	LC_15		
				Class 1	Class 2	Class 3
Time		-1.69[c]	-1.42[c]	-0.68[b]	-2.47[c]	*NS*
		(0.29)	(0.30)	(0.31)	(0.90)	
Fixed		0.18[b]	0.23[b]	*NS*	0.75[b]	*NS*
		(0.08)	(0.10)		(0.35)	
Discount		0.38[c]	0.38[c]	*NS*	1.14[c]	*NS*
		(0.11)	(0.10)		(0.38)	
Loyalty Rewards		14.49[c]	8.64[c]	4.78[a]	26.05[c]	*NS*
		(2.71)	(2.48)	(2.68)	(9.23)	
	Weak NEP	0.18[b]	*NS*	*NS*	0.57[b]	*NS*
		(0.09)			(0.27)	
Renewable	*Moderate NEP*	0.18[b]	0.25[a]	*NS*	0.57[b]	*NS*
		(0.09)	(0.14)		(0.27)	
	Strong NEP	0.55[c]	0.24[c]	0.25[a]	1.29[c]	*NS*
		(0.11)	(0.05)	(0.14)	(0.26)	
Local ownership		0.32[c]	0.33[c]	0.24[c]	0.89[c]	*NS*
		(0.05)	(0.06)	(0.05)	(0.17)	
New electricity company		-13.06[c]	-8.15[b]	*NS*	*NS*	*NS*
		(3.66)	(3.69)			
New non-electricity company		-29.01[c]	-26.18[c]	*NS*	-58.53[c]	*NS*
		(4.83)	(4.89)		(15.27)	
Well-known non-electricity company		-16.66[c]	-14.84[c]	*NS*	-28.71[b]	*NS*
		(4.48)	(4.64)		(13.39)	

[c], [b], [a] Significant at .001, .05, and .1 level, respectively. Standard errors are in parentheses. NS = not statistically significant at .1 level

6.4 The influence of shorter versions of the NEP Scale on WTP estimates

6.4.1 Regression results for MNL and RPL-EC

When the dummy codding structure with three levels for the NEP score, *weak*, *moderate* and *strong*, is used we are able to estimate and compare WTP for *Renewable* for three groups of environmental attitude. The regression results are presented in Table A6-6. The Wald test for linear restrictions in all the MNL models has a probability value greater than .05 and the null hypothesis that the slopes of the interaction terms are equal is rejected at the 95% level of confidence. This suggests that the NEP score has a non-linear effect on the utility of *Renewable*.

The coefficient of *Renewable* is insignificant at the .05 level in the MNL models and RPL_10 suggesting indifference towards *Renewable* by respondents with low NEP scores based on these models. The coefficients of the interaction terms *MNEP_Renewable*, and *SNEP_Renewable* capturing the effect of moderate and high NEP scores on the utility of *Renewable* are significant at the .05 level except in RPL_15 where *MNEP_Renewable* is only significant at the .10 level.

Marginal WTP estimates are presented in Table A6-7. The results show that respondents with low NEP scores are not willing to pay any significant amount for power generated from renewables except under model RPL_15 where the estimated WTP is $1.80 per month for a 10% increase in *Renewable.* Based on RPL_15, respondents with low and moderate NEP scores have the same WTP for *Renewable*. Estimates based on the other models indicate that respondents with moderate NEP scores are willing to pay amounts ranging from $2.60 to $4.10 for a 10% increase in *Renewable* depending on the model, whilst respondents with high NEP scores have even higher WTP ranging from $4.10 to $5.50 to secure the same increase in *Renewable*.

Table A6-6 MNL and RPL models of supplier choice (NEP scores coded as weak. moderate and strong)

Variable	MNL_15	MNL_10	MNL_5	RPL	RPL_15	RPL_10	RPL_5
ASCALT1	0.576^{c}	0.577^{c}	0.579^{c}	0.590^{c}	0.617^{c}	0.625^{c}	0.633^{c}
	(.074)	(.074)	(.074)	(.147)	(.150)	(.146)	(.148)
Time	-0.043^{c}	-0.043^{c}	-0.043^{c}	-0.050^{c}	-0.048^{c}	-0.049^{c}	-0.049^{c}
	(.007)	(.007)	(.007)	(.010)	(.010)	(.010)	(.010)
Fixed	0.005^{b}	0.005^{b}	0.005^{b}	0.009^{b}	0.008^{b}	0.007^{b}	0.008^{b}
	(.002)	(.002)	(.002)	(.004)	(.003)	(.004)	(.003)
Disc	0.009^{c}	0.009^{c}	0.009^{c}	0.015^{c}	0.013^{c}	0.013^{c}	0.013^{c}
	(.003)	(.003)	(.003)	(.004)	(.003)	(.003)	(.003)
Loyalty Rewards	0.369^{c}	0.369^{c}	0.369^{c}	0.291^{c}	0.291^{c}	0.290^{c}	0.295^{c}
	(.069)	(.069)	(.069)	(.085)	(.084)	(.085)	(.085)
Renewable	0.003	0.002	0.001	0.012^{c}	0.006^{b}	0.005	0.005^{c}
	(.002)	(.002)	(.002)	(.002)	(.003)	(.003)	(.003)
MNEP_Renewable	0.006^{b}	0.008^{b}	0.010^{c}	-	0.007^{a}	0.009^{b}	0.009^{b}
	(.003)	(.003)	(.003)		(.004)	(.004)	(.004)
SNEP_Renewable	0.010^{c}	0.011^{c}	0.011^{c}	-	0.012^{c}	0.015^{c}	0.014^{c}
	(.003)	(.002)	(.003)		(.005)	(.005)	(.004)
Local ownership	0.008^{c}	0.008^{c}	0.008^{c}	0.010^{c}	0.011^{c}	0.010^{c}	0.010^{c}
	(.001)	(.001)	(.001)	(.002)	(.002)	(.002)	(.002)
New electricity company	-0.333^{c} (.095)	-0.332^{c} (.095)	-0.332^{c} (.095)	-0.298^{b} (.128)	-0.274^{b} (.126)	-0.265^{b} (.127)	-0.271^{b} (.126)
New non-electricity company	-0.740^{c} (.122)	-0.738^{c} (.122)	-0.739^{c} (.121)	-0.954^{c} (.168)	-0.881^{c} (.165)	-0.879^{c} (.165)	-0.895^{c} (.1654)
Well-known non-electricity company	-0.425^{c} (.115)	-0.422^{c} (.115)	-0.424^{c} (.115)	-0.532^{c} (.158)	-0.499^{c} (.157)	-0.479^{c} (.157)	-0.499^{c} (.157)
Power Bill	-0.025^{c}	-0.025^{c}	-0.025^{c}	-0.034c	-0.034^{c}	-0.034^{c}	-0.034^{c}
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Standard Deviations of Random Parameters							
Time				0.041^{c}	0.042^{c}	0.047^{c}	0.048^{c}
				(.015)	(.015)	(.015)	(.014)
Fixed				0.027^{c}	0.027^{c}	0.028^{c}	0.027^{c}
				(.004)	(.004)	(.004)	(.004)
Discount				0.022^{c}	0.015^{b}	0.019^{c}	0.017^{c}
				(.005)	(.007)	(.005)	(.006)
Renewable				0.016^{c}			
				(.004)			
MNEP_Renewable				-	0.007^{a}	0.011^{c}	0.013^{c}
					(.004)	(.004)	(.003)
SNEP_Renewable				-	0.020^{c}	0.020^{c}	0.018^{c}
					(.003)	(.003)	(.004)
Ownership				0.020^{c}	0.016^{c}	0.018^{c}	0.017^{c}
				(.005)	(.003)	(.003)	(.002)
Error component				1.482^{c}	1.598^{c}	1.561^{c}	1.622^{c}
				(.263)	(.133)	(.127)	(.130)
LL	-2153.6	-2153.1	-2151.4	-1872.3	-1887.9	-1883.8	-1886.5
AIC	4333.2	4332.1	4328.8	3808.7	3818.0	3807.9	3813.0
BIC	4409.8	4408.8	4405.5	3997.4	3933.9	3925.5	3930.9
Pseudo R^2	0.2669	0.2671	0.2677	0.3659	0.3607	0.3621	0.3612
Wald [p-value]	2.19	1.42	0.16				
	[.139]	[.234]	[.688]				

^{c}, ^{b}, ^{a} Significant at the .01, 0.5 and .1 level, respectively. Standard errors are in parentheses

Table A6-7 WTP for the attributes of electricity services

Attribute	MNL_15	MNL_10	MNL_5	RPL	RPL_15	RPL_10	RPL_5
Time	-1.69[c]	-1.69[c]	-1.69[c]	-1.49[c]	-1.42[c]	-1.46[c]	-1.45[c]
	(0.29)	(0.29)	(0.29)	(0.30)	(0.30)	(0.31)	(0.31)
Fixed	0.18[b]	0.18[b]	0.18[b]	0.27[b]	0.23[b]	0.22[b]	0.23[b]
	(0.08)	(0.08)	(0.08)	(0.11)	(0.10)	(0.10)	(0.10)
Discount	0.38[c]	0.38[c]	0.38[c]	0.43[c]	0.38[c]	0.38[c]	0.38[c]
	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)	(0.10)
Loyalty Rewards	14.49[c] (2.71)	14.44[c] (2.71)	14.45[c] (2.71)	8.60[c] (2.51)	8.64[c] (2.48)	8.54[c] (2.48)	8.68[c] (2.48)
Renewable	-	-	-	0.36[c]	-	-	-
				(0.06)			
Weak NEP	NS	NS	NS	-	0.18[b]	NS	NS
					(0.09)		
Moderate NEP	0.26[b]	0.31[b]	0.41[c]	-	0.18[b]	0.27[b]	0.28[b]
	(0.12)	(0.12)	(0.12)		(0.09)	(0.12)	(0.12)
Strong NEP	0.41[c]	0.43[c]	0.45[c]	-	0.55[c]	0.45[c]	0.41[c]
	(0.12)	(0.12)	(0.12)		(0.11)	(0.14)	(0.13)
Local ownership	0.32[c] (0.05)	0.32[c] (0.05)	0.32[c] (0.05)	0.31[c] (0.07)	0.33[c] (0.06)	0.30[c] (0.07)	0.31[c] (0.07)
New electricity company	-13.06[c] (3.66)	-13.00[c] (3.66)	-13.01[c] (3.66)	-8.80[c] (3.76)	-8.15[b] (3.69)	-7.80[b] (3.71)	-7.98[b] (3.69)
New non-electricity company	-29.01[c] (4.83)	-28.90[c] (4.83)	-28.95[c] (4.82)	-28.18[c] (4.97)	-26.18[c] (4.89)	-25.87[c] (4.86)	-26.32[c] (4.84)
Well-known non-electricity company	-16.66[c] (4.48)	-16.53[c] (4.48)	-16.61[c] (4.48)	-15.71[c] (4.66)	-14.84[c] (4.64)	-14.09[c] (4.62)	-14.68[c] (4.59)

[c], [b], [a] Significant at the .01, .05 and .1 level, respectively. Standard errors are in parentheses