NZARES New Zealand Agricultural & Resource Economics Society (Inc.)

Environmental attitude and the demand for green electricity in the context of supplier choice: A case study of the New Zealand retail electricity market

Tom Ndebele & Dan Marsh

Department of Economics, Waikato Management School, University of Waikato, N.Z.

Paper presented at the 2014 NZARES Conference

Tahuna Conference Centre, Nelson, New Zealand. August 28-29, 2014

Environmental attitude and the demand for green electricity in the context of supplier choice: A case study of the New Zealand retail electricity market

Tom Ndebele and Dan Marsh

Department of Economics, Waikato Management School, University of Waikato, New Zealand

E-mail: tn73@students.waikato.ac.nz

Abstract

There is growing interest in non-market valuation research to explore the importance of attitudes and perceptions in explaining heterogeneity of preferences among consumers. Previous research on environmental attitude (EA) and its influence on preferences has been criticised for the non-systematic way in which researchers have measured EA. This paper investigates the effect of environmental attitude on the demand for green electricity in New Zealand, identifies groups (latent classes) with homogenous preferences, and estimates willingness (WTP) for "green" electricity in the context of supplier choice or switching. The New Ecological Paradigm (NEP) Scale is used to measure EA, and we examine the effect of using sub-scales of the NEP Scale on posterior class membership probabilities. To generate the data required for this research, an online choice experiments survey targeting residential electricity bill payers in New Zealand was conducted in February 2014. A usable sample of 224 respondents was achieved. Data was analysed using a latent class framework in which the integration of EA with stated choice is either direct via the utility function as interactions with the attribute levels of alternatives or as a variable in the class membership probability model. We identify three latent classes with different preferences for the attributes of electricity suppliers. A typical respondent with a high NEP Scale score is willing to pay on average $12.80 more per month on their power bill to secure a 10% increase in electricity generated from renewable energy sources compared to respondents with low NEP scores. Furthermore, the results suggest that the sub-scales of the NEP Scale are less accurate in assigning respondents to environmental classes and that the sub-scale with 5 items is less accurate than the sub-scale with 10 items.

Key words: electricity suppliers; choice experiments; "green" electricity; willingness to pay; latent class model; New Ecological Paradigm Scale; environmental attitude; New Zealand

1. Introduction

Since the mid 1980's New Zealand (NZ) has embarked on a series of electricity market reforms aimed at promoting a competitive and efficient electricity market for the long term benefit of consumers. Under the current deregulated electricity market consumers are free to choose their preferred supplier from the 5 to 17 retail brands available, depending on the region (Electricity Authority, 2013). However, the NZ electricity market is characterised by a high degree of vertical integration between generation and retail. Five major generators (often referred to as 'gentailers') which account for 92% of all generation also dominate the retail electricity markets accounting for 95% of the market (Ministry of Economic Development, 2012). Wholesale electricity is traded via a "pool", where generators offer electricity to the market and retailers bid to buy electricity at prices set half-hourly. Despite the "pool" system most customers should be able to associate their retailers with the main energy sources used to generate electricity due to the high degree of vertical integration between generation and retail. In 2011 electricity generation from renewable sources, hydro (57.6%), geothermal (13.4%), wind (4.5%), and bioenergy (1.3%), accounted for 77% of total generation and is set to grow (Ministry of Economic Development, 2012). 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 New Zealand is indirect via the emissions trading scheme. 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 New Zealand. "Green" marketing has been used in countries like the USA, UK, and Australia to support the development of electricity generation from renewables.

According to a New Zealand 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 New Zealand. Livengood and Bisset (2009) assess the potential of various mechanisms that could be used to facilitate consumer-driven renewable power development in New Zealand and identify renewable energy certificates (RECs) as the most appropriate mechanism for the NZ market. The study also notes the scantity of research on consumer preferences in the NZ electricity markets. This paper aims to address this issue by providing the first in-depth study of consumer preferences for "green" electricity in the context of supplier choice in NZ using choice experiments. 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, Duke, & Parsons, 2007; 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 use socio-demographic characteristics (SDCs) and attitudes to explain differences in WTP. Income has been found to be a significant determinant of WTP (Batley et al., 2001; Batley et al., 2000; Bollino, 2009; Kotchen & Moore, 2007; Zoric & Hrovatin, 2012). 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 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; Kotchen & Moore, 2007; Zoric & Hrovatin, 2012). This paper focuses on the influence of environmental attitude (EA), measured using the NEP Scale, on WTP for “green” electricity.

It has been noted that in much previous research on environmental attitude (EA) and its influence on consumer preferences for products or services whose production or consumption is associated with environmental outcomes researchers have, in general, constructed measures of EA in a rather arbitrary manner (Hawcroft & Milfont, 2010). In such cases each study has produced a new measure of EA. Some of these arbitrary measures are constructed from few or even single questions (e.g., Amador, Gonzalez, & Ramos-Real, 2013). These questions may not be based on any attitude-behavior theories and it is questionable whether they actually measure what they are intended to measure. For example, it is debateable whether recycling is a consistent measure of environmental attitude or a measure of environmental attitude at all especially in urban areas where local authorities provide recycling bins to every dwelling. In such cases utilization of the recycling bins, hence recycling, may also be motivated by potential savings from reduced use of rubbish bags.

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. Results show considerable variation in the way the NEP Scale is used, particularly with regards to the number of items used and the number of points on the Likert scale employed. Weighted regression analyses 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 versions of the scale containing 5, 7, 8 or 10 items. The study strongly recommends that researchers use all 15 items of the revised NEP Scale whenever possible.

A number of established attitude-behavior theories are available which can be used to measure environmental attitude and other psychological constructs. Although the New Ecological Paradigm Scale developed by Dunlap, Van Liere, Mertig, and Jones (2000) is one of the instruments most frequently used by social scientists to measure environmental attitude (Dunlap, 2008; Hawcroft & Milfont, 2010), only a few studies in environmental economics have used it. 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 researchers of the existence of the scale, for some reason the uptake is very low. One possibility is the length of the scale which consists of 15 items or statements. In developing survey questionnaires researchers try to reduce the length of the survey to lower costs and obtain quality responses by keeping respondents engaged, reducing fatigue and incomplete responses. For example, Stern, Dietz, and Guagnano (1995) used 7 items from the original 12-item scale based on item-total correlation whilst Clark, Kotchen, and Moore (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) use only 5 items but the motivation behind a shorter sub-scale of NEP and the criteria for selection is not provided although a closer look at the items reveals that one item was selected from each of the five so called ‘facets’ of ecological worldview in such a way that anti- and pro-NEP statements were nearly balanced. Both Stern et al. (1995) and Clark et al. (2003) use 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, Preisendoerfer, and Meyerhoff (2011) combine 3 items from the NEP Scale with 2 other questions to measure environmental concern. A question can be raised as to whether the various versions of the NEP Scale classify respondents into the same groups of environmental preferences. This is another issue which this paper investigates.

It is interesting to note that although the 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, most researchers in environmental economics have failed to look to social psychology for guidance in constructing attitudinal questions that are based on valid attitude-behaviour theory.

The remainder of this paper is organised as follows. Section 2 provides a review of valuation studies that use environmental attitude to explain preferences for green electricity followed by an overview of the New Ecological Paradigm (NEP) Scale. Section 3 describes the methodology and section 4 presents and discusses the results. Section 5 provides a conclusion and suggestions for further research.

2. Consumer preferences for "green" electricity and environmental attitudes

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 homogenous 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 natural 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 the "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 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, Barreiro-Hurle, & Perez y Perez, 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. 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 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, Deilami, & Train, 1998; Goett, Hudson, & Train, 2000; Kaenzig, Heinzle, & Wuestenhagen, 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.

This paper 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 environmental attitude on WTP for "green" electricity and examining a different set of attributes of electricity suppliers. Unlike other studies that use arbitrary constructs to measure environmental concern, we use the New Ecological Paradigm (NEP) Scale which is grounded in social psychology theory (Dunlap, 2008; Stern et al., 1995) to measure environmental attitude. We test the following hypothesis.

Hypothesis: Environmental attitude plays a systematic role in explaining preference heterogeneity for electricity generated from renewable sources

Furthermore, we use the latent class model which allows us to identify market segments with homogenous 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 choice experiments in the context of supplier choice. We are not aware of any previous studies that have used the latent class model to estimate WTP for “green” electricity in the context of supplier choice. Studies that employ the multinomial logit (NML) model focus on the average taste intensity for each attribute which assumes that respondents have homogenous preferences with respect to each attribute (e.g., Zhang & Wu, 2012), whilst those 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 latent class model 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 homogenous preferences or taste intensities. This places the latent class model between the two extremes represented by the MNL and the mixed logit.

Cai et al. (1998) use double bounded questions on price discounts on a sample of 400 residential customers and 400 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, 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 provide 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 is 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.

Goett et al. (2000) use a sample of USA 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 has no renewables, they would only pay an extra $1.80 per month for a supplier that has 50% hydro compared to a supplier 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, 20000, and 200000 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 supply reliability, share of renewables, availability of a complementary energy audit service, and supplier type. 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 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. The attributes included in the study are: fuel mix, type of supplier, location of generation plant, green certification, cancellation period, and monthly power bill. Results indicate at apart from the price electricity mix is the most important product attribute. WTP for green electricity was estimated at €12 per month which is equivalent to about 16% of the average household power bill.

2.2 The New Ecological Paradigm Scale and the measurement of environmental attitude

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 statement 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 primitive beliefs about the relationship between humans and the environment. 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).

Each facet of ecological worldview is measured using three items which are interspaced with items measuring other facets. Table 1 presents the 15 items comprising the NEP Scale. Responses are recoded on a 5-point scale as "strongly agree", "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 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 world-view is the sum of the scores on the 15 items and has a range of 15 to 75 with higher scores indicating pro-NEP. Before the item scores are combined into a single summated scale, they are checked for internal consistency.

Table 1 The New Ecological Paradigm Scale items

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

3. Methods

An online survey questionnaire was developed to collect the data required for this research. The first part of the survey questionnaire elicited socio-demographic and environmental attitude (EA). EA was measured using the 15 items of the New Ecological Paradigm (NEP) Scale (Dunlap et al., 2000) discussed in the previous section. The second part of the survey questionnaire elicited information on respondents' choices among experimentally designed alternatives followed by a debriefing to identify respondents' information processing strategies and respondents' certainty about their choices.Champ, Bishop, Brown, and McCollum (1997) and Champ and Bishop (2001) identify respondents with low certainty scores as the source of hypothetical bias.

3.1 The choice experiment

Non-market valuation techniques have evolved over time and choice experiments (CEs) represents cutting edge technique in non-market valuation. Choice experiments 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 realistic markets and allow researchers to estimate the values of multiple attributes of a good or service at once. In choice experiments, 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. In this study we design CEs in which residential electricity customers are asked to choose their preferred supplier amongst three alternatives. This approach has been used in previous studies investigating WTP for the attributes of electricity services in a number of countries (Abdullah & Mariel, 2010; Amador et al., 2013; Cai et al., 1998; Goett, 1998; Goett et al., 2000; Kaenzig et al., 2013). Although CEs avoid some of the major problems associated with earlier techniques such as the CVM there are still some issues of concern with the technique such as hypothetical bias and attribute non-attendance.

A major challenge with CEs involves the design of the choice experiments. Experimental design (ED) is the way in which the attribute levels of alternatives are set and structured into the choice sets (Bennett & Adamowicz, 2001). The ED is complex, time consuming, and can heavily influence the outcomes (validity and reliability) and conclusions of the research (Hensher, Rose, & Greene, 2005a; Johnson et al., 2013; Louviere, Hensher, & Swait, 2000; Louviere, Islam, Wasi, Street, & Burgess, 2008; Lusk & Norwood, 2005). Important decisions are made at the design stage such as, 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 experimental design used. 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 objective of any ED is to maximize the statistical efficiency for a given model. Burgess and Street (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.

In this study the identification and selection of attributes and attribute levels that are important in this research context was based on previous New Zealand studies (Electricity Authority, 2010, 2011, 2012; Electricity Commission, 2008), international literature review and focus groups. Table 2 presents the attributes and attribute levels used in the experimental design. 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 the design was the first stage of experimental design.

Table 2 Attributes, attribute levels and design codes used to develop the experimental design

Attributes	Description	Levels	Design codes
Time	Average time for telephone calls to be answered by a customer service representative	0, 5,10, 15 (minutes)	0, 5, 10, 15
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%)	0, 10, 20, 30
Rewards	Loyalty rewards such as Fly Buys, Brownie points, prize draws, and annual account credits (excludes annual network dividends)	No Yes	0 1
Renewable	Proportion of electricity generated from wind, hydro, geothermal, bioenergy and solar.	(25%, 50%, 75%, 100%)	25, 50, 75, 100
Ownership	%NZ ownership of supplier	25%, 50%, 75%, 100%	25, 50, 75, 100
Supplier type	Type of supplier	New electricity company New non-electricity company Well-known electricity supplier Well-known non-electricity company	0 1 2 3
Bill	Average monthly electricity bill before GST, levy and discounts.	\$150, \$200, \$250, \$300	150, 200, 250, 300

The parameter estimates from the first stage were used as priors in a D-efficient homogenous pivot design for a MNL model. The design was tested on a pilot sample of 70 respondents. A MNL model was estimated and the parameter estimates were used as priors in a Bayesian D-efficient design for the final survey. In a homogenous pivot design each respondents faces the same reference alternative (status quo). Although a supplier's customers on the same electricity plan face similar attribute levels except for the monthly bill which depends on the unit price and power consumption, 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.

Before respondents were presented with choice tasks, they were asked to describe their current suppliers in terms of the attribute levels used in the experimental design to provide information on their revealed preferences. Each respondent was asked to make a series of choices under twelve scenarios in which three hypothetical electricity suppliers were described in terms of the attributes and attribute levels used in the experimental design (see Figure1). Respondents were advised that the scenarios were used to understand how people would choose their electricity supplier under different conditions. In each scenario, respondents were asked to compare "Supplier A" and "Supplier B" with the supplier indicated as being their current supplier ("Your Current Supplier") and indicate if they would switch if conditions described in each scenario were to occur.

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	$250	$200
Which supplier would you prefer?	○	○	○

Figure 1 Stated choice scenario and example of a choice task.

3.2 Latent class model

We use a latent class (LC) choice model based on random utility maximization (RUM) to identify latent groups with similar preferences and tease out marginal WTP estimates for the attributes of electricity services. In this application of the LC model we assume that the population consists of a finite number of preference classes (*C*) with respect to the attributes of electricity services. Latent class models have been used in previous studies to investigate preference heterogeneity in various contexts (Boxall & Adamowicz, 2002; Breffle, Morey, & Thacher, 2011; Greene & Hensher, 2003; Milon & Scrogin, 2006; Morey, Thacher, & Breffle, 2006; Morey, Thiene, De Salvo, & Signorello, 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 alternative ($\beta_c' X_{int}$) and a random component ($\varepsilon_{int|c}$) as follows (Boxall & Adamowicz, 2002; Walker & Ben-Akiva, 2002):

$$U_{int|c} = \beta_c' X_{int} + \varepsilon_{int|c} \tag{1}$$

where

- $U_{int|c}$ is the utility of alternative *i* to individual *n* in choice situation *t* conditional on class c membership
- X_{int} is a union of all attributes and characteristics that appear in all utility functions,
- $\varepsilon_{int|c}$ is identically and independently distributed (iid) with Extreme Value Type 1 (Gumbel-distributed) error component that captures unobserved heterogeneity (Train, 2009) for individual *n* and alternative *i* in choice situation *t* conditional on class *c* membership, and βc is a class specific parameter vector to be estimated.

The parameters of the LC model are modelled as having a discrete distribution with a small number of support points (Kamakura & Russell, 1989). An individual *n* is viewed as belonging to a latent class which is not revealed to the researcher. The unconditional probability that an individual *n* chooses alternative *i* can be expressed as a product of two probabilities (Kamakura & Russell):

$$P_{in} = \sum_{c=1}^{C} \left[\frac{\exp(\alpha_c S_n)}{\sum_{c=1}^{C} exp(\alpha_c S_n)}\right] \left[\frac{\exp(\beta_c X_i)}{\sum_{j=1}^{J} exp(\beta_c X_i)}\right], \text{ c} = 1, 2, \ldots, \text{C}; \alpha_C = 0 \tag{2}$$

were $\frac{\exp(\alpha_c S_n)}{\sum_{c=1}^{C} exp(\alpha_c S_n)}$ is the c^{th} class membership probability of individual *n* (with socio-demographic characteristics [SDC] S_n) defined parametrically using a multinomial logit as membership equation, α_c is a vector of class-specific parameters (or constants), $\frac{\exp(\beta_c X_i)}{\sum_{j=1}^{J} exp(\beta_c X_i)}$ represents the conditional probability of an individual *n* in class *c* choosing alternative *i*, and βc denotes the class-specific taste intensities. Following Morey et al. (2006), we assume that class membership is a function of SDC. However, the class specific probabilities may be a set of fixed constants if no observable characteristics that help in class separation are observed.

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

$$\ln L = \sum_{n=1}^{N} ln\left[\sum_{c=1}^{C} \frac{\exp(\alpha_c S_n)}{\sum_{c=1}^{C} \exp(\alpha_c S_n} \prod_{t=1}^{T} \frac{\exp(\beta_c X_i)}{\sum_{j=1}^{J} \exp(\beta_c X_j)}\right] \quad (3)$$

We maximize the likelihood with respect to the *C* structural parameter vector βc and the *C-1* latent class parameter vector α_c. Since the βc's which include the coefficient of the cost element vary across classes, the latent class 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 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 (2003), Morey et al. (2006), and Yang and Yang (2007) discuss the performance of these criteria and also provide formulae for their calculation.

3.3 Data collection

An online survey was administered in January 2014 to a stratified sample of 224 NZ residential electricity bill payers drawn from an online panel managed by a market research company. Stratification was based on age group, gender and income group. Quotas for the stratification criteria were set based on NZ 2006 census statistics. Screening criteria ensured that respondents were at least 18 years old and were either directly responsible for paying the electricity bill or had a say in choosing their electricity supplier. The target sample size was achieved over night.

The advantages of using online surveys to collect data 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 (MacKerron, 2011). The use of online panels allows the target sample size to be achieved relatively quickly, in this case 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.

4. Results

4.1 Sample statistics

Table 2 presents a summary of the sample statistic. In terms of gender, age-group, and income-group, the sample characteristics closely correspond to that of the population. Females are slightly over-represented by 2%, whilst males are under represented by the same percentage. The average personal income of respondents (about $45, 000) is higher than the national average of about $37, 500. The difference may be due to the inclusion of the 15 – 17 year age group in the national average which lowers the average income as most people in this age group are likely to be on minimum wages. In terms of ethnicity, Maori are under-represented whilst NZ Europeans are overrepresented. The sample average monthly electricity bill is lower than the national average which is expected as the national average is based on the whole year which includes high winter bills whereas the sample average is based on respondents' most recent power bill for a summer month.

Table 3 Sample statistics versus national population

Characteristic	Sample (N = 224)	National[1]
Gender	(%)	(%)
Male	47	49
Female	53	51
Age Group	(%)	(%)
18 - 24	13	13
25 - 34	17	17
35 - 44	20	21
45 - 54	18	18
55 +	32	31
Ethnicity	(%)	(%)
NZ European	77	70
Maori	5	12
Asian	9	10
Other	9	7
Average personal income	$45,000	37,500
Average monthly electricity bill	$174	$190*

[1]Data source: NZ Statistics – 2006 Census Data and NZ Income Survey: June 2012 quarter. *MED Energy Data File 2012

4.2 Analysis of responses to the NEP Scale items

Table 4 summarises the responses to the 15 items of the NEP Scale. The response categories for each item are provided in section 2.2. The percentage distribution of responses to the NEP Scale items indicates that respondents tend to have pro-NEP attitude with respect to most items. For example, 70.9% of respondents mildly or strongly agree with the statement “When humans interfere with nature it often produces disastrous consequences” (NEP3), 68.3% mildly or strongly agree that “the balance of nature is very delicate and easily upset” (NEP13), and 79.4% mildly or strongly agree with the statement “Despite our special abilities humans are still subject to the laws of nature” (NEP9). Only 20.1% 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 attitude 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 4 is similar to that found in other studies using the NEP Scale such as, Aldrich, Grimsrud, Thacher, and Kotchen (2007), Clark et al. (2003), Cooper et al. (2004), Dunlap et al. (2000), Ek and Soderholm (2008), and Kotchen and Reiling (2000).

An individual’s NEP Scale score is the sum of the scores of all 15 NEP Scale items within a range of 15 to 75. The sample minimum and maximum scores are 23 and 72 respectively. The mean score and standard deviation are 52.2 and 8.3 respectively. Before combining the responses to the 15 items of the NEP Scale into a single measure of environmental attitude, we adopted the approach in previous studies by testing the internal consistency of the NEP constructs using the corrected item-total correlation ($r_{i\text{-}t}$), Cronbach’s coefficient alpha (α), and principal components analysis (PCA) (e.g., Aldrich et al., 2007; Clark et al., 2003; Dunlap et al., 2000; Ek & Soderholm, 2008). 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 $r_{i\text{-}t}$, it is suggested in the literature that a value of 0.3 is acceptable (Aldrich et al., 2007; Clark et al., 2003; Dunlap et al., 2000). 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 (Clark et al., 2003; Dunlap et al., 2000).

Corrected item-total correlation ranges from a low 0.10 for NEP6 to a high of 0.60 for NEP15. All but one corrected item-total correlations are higher than 0.30 and statistically significant at the 5% level. 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 reduce the reliability of the scale. Our results compare favourably with those of Dunlap et al. (2000) and other previous studies despite a relatively smaller sample size (see Table 5).

Table 4 Percentage distributions, corrected item-total correlations and factor loadings for NEP Scale items

	SA*	MA	NAND	MD	SD	r_{i-t}	F1**	F2	F3	F4	F5
NEP 1	14.7%	36.6%	28.1%	15.6%	4.9%	0.35	**0.46**	-0.21	**0.60**	-0.08	-0.22
NEP 2	4.0	23.7	23.7	30.4	18.3	0.51	**0.59**	**0.35**	-0.27	0.01	-0.01
NEP 3	26.3	44.6	15.6	8.9	4.5	0.48	**0.62**	**-0.32**	0.01	0.25	0.19
NEP 4	6.7	33.0	29.5	21.0	9.8	0.41	**0.46**	**0.46**	0.25	**0.50**	-0.04
NEP 5	31.7	40.2	16.5	7.6	4.0	0.49	**0.62**	-0.27	0.05	-0.23	**0.35**
NEP 6	22.8	39.7	25.4	8.9	3.1	0.10	0.11	**0.58**	**0.48**	-0.13	-0.22
NEP 7	49.1	27.2	14.7	6.3	2.7	0.31	**0.44**	**-0.30**	**-0.45**	-0.09	**-0.46**
NEP 8	1.8	18.3	22.8	37.9	19.2	0.57	**0.66**	0.27	-0.09	-0.07	-0.18
NEP 9	33.9	45.5	16.5	3.6	0.4	0.39	**0.49**	-0.20	-0.24	**0.57**	-0.24
NEP 10	4.9	24.6	34.4	22.3	13.8	0.56	**0.65**	0.26	-0.07	**-0.37**	0.00
NEP 11	11.6	40.2	30.8	12.9	4.5	0.46	**0.57**	-0.19	**0.44**	0.14	-0.07
NEP 12	6.3	14.3	25.0	28.1	26.3	0.39	**0.46**	**0.43**	**-0.35**	-0.17	-0.15
NEP 13	25.9	42.4	24.1	5.8	1.8	0.42	**0.56**	**-0.37**	-0.06	-0.01	0.13
NEP 14	5.4	22.8	35.3	19.6	17.0	0.34	**0.42**	**0.39**	-0.13	0.17	0.58
NEP 15	18.8	35.7	32.1	8.9	4.5	0.60	**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) measure of sampling adequacy							0.82				

*SA, strongly agree; MA, mildly agree; NAND, neither agree nor disagree; MD, mildly disagree; SD, strongly disagree; *r*i–t, item–total correlation. Percentages may not sum to 100 due to rounding. **Unrotated factors

Results of the PCA presented in Table 4 show that all 15 items of the NEP Scale (except item 6) 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. 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 measuring instrument of environmental attitude.

Table 5 Comparison of corrected $r_{i\text{-}t}$ and Cronbach's alpha from previous studies

Study and country	N	Target population	$r_{i\text{-}t}$ (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
Current Study. New Zealand	224	Power bill payers	0.10 to 0.60	0.81

To identify heterogeneity in environmental attitude, latent class linear regression analysis was applied to the NEP responses to determine the number of classes or and identify the factors influencing environmental attitude. Two sub-scales of the NEP Scale were constructed and used in the latent class analysis and the results compared with those of the full scale. A 5-item sub-scale of the NEP Scale was constructed using the first five items of the full scale. The remaining 10 items from the full scale were used to construct a 10-item sub-scale of NEP. In the 5-item sub-scale each facet of ecological worldview is measured using one item whilst in the 10-item sub-scale two items are used to measure each facet. Both sub-scales are well balanced in terms of *anti*- and *pro*-NEP items which meets the condition of the full scale. Cronbach's alpha measuring the internal consistency of the sub-scales was 0.61 and 0.72 for the 5-item and 10-item sub-scales respectively. Internal consistency of the 5-item sub-scale is below the recommended $\alpha = 0.70$. Kotchen and Moore (2007) obtained $\alpha = 0.68$ for one of their samples using a different set of 5 items from the NEP Scale. The For the latent class analysis we used a base model suggested by Heckman and Singer (1984) in which class verification is based on a constant term α_c which varies across classes. Class probabilities are parameterized using a multinomial logit formulation to impose the adding up and positivity restriction on class probability (probabilities must be positive and sum to one across all classes). Thus,

$$Prob(class = c) = \frac{\exp(\propto_c)}{\sum_k \exp(\propto_c)}, \quad c = 1, \ldots, C; \quad \propto_C = 0 \tag{4}$$

The model is estimated using NLOGIT 5. Latent class analysis results are presented in Table 6. The models estimated using the three NEP scales all suggest the presence of two classes of environmental attitude which we refer to as s*trong* (class1) and *weak* (class 2). The model parameters which are all significant at the 1% level include the mean, standard deviation and probability for each class. Results show that the 5-item sub-scale assigns a small mass on class 1 and a larger mass on class 2 compared to the other scales. The 10-item subscale and the full NEP Scale assign similar probabilities to the two classes. With an appropriate command NLOGIT 5 estimates individual specific posterior 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 sub-scale as the number of respondents a sub-scale assigns to the same class as the full NEP Scale divided by sample size times 100. The 10-item scale has an 'accuracy' of 92.4% whilst the 5-item sub-scale has an 'accuracy' of 64.7% suggesting that the accuracy of the sub-scales declines as they become shorter.

Table 6 Latent class model results for environmental attitude

	15-item NEP Scale	10-item NEP Scale	5-item NEP Scale
Score	Coefficient	Coefficient	Coefficient
	Model parameters for latent class 1		
Constant	3.91668***	3.91657***	4.51301***
Sigma	1.10525***	1.12550***	0.55646***
	Model parameters for latent class 2		
Constant	3.05977***	3.09597***	3.31547***
Sigma	1.02722***	1.03575***	1.12178***
	Estimated prior probabilities for class membership		
Class1Pr	0.48734***	0.46625***	0.13321***
Class2Pr	0.51266***	0.53375***	0.86679***
'Accuracy'		92.4%	64.7%

***Significant at 1%

For the full NEP Scale the estimated prior probabilities for the *strong* and *weak* classes are 0.49 and 0.51 respectively. The mean NEP Scale cores for these classes are 59.04 and 45.75 respectively. The characteristics of respondents in the *weak* and *strong* environmental attitude classes based on the full scale are presented in Table 7. The *weak* class has a higher proportion of men, higher average income, less graduates and a lower proportion of respondents with dependent children than the *strong* class. This is consistent with previous studies supporting the notion that on average men are less pro-environmental than women, educated people are more pro-environmental, and that respondents with dependent children tend to be more pro-environmental.

Table 7 Characteristics of respondents in the weak and strong environmental attitude classes

Variable		Weak	Strong
Number of respondents		116 (51.8%)	108 (48.21%)
Mean NEP Scale score		45.75	59.04
Gender (male %)		50%	43%
Average Income ($)		47,000	42,800
Average Age (years)		44	45
Ethnicity	NZ Euro	76%	78.7%
	Maori	4%	4.6%
	Other	20%	16.7%
Education (at least Bachelors)		29%	31%
Proportion with dependent children		39%	43%

4.3 Determinants of pro-NEP attitude

To investigate the factors that influence environmental attitude, we extend the model in equation 4 to include socio-demographic characteristics (SDCs) of respondents (z_i) to allow class probabilities and environmental attitude to vary with these variables. The extended model is:

$$Prob(class = c: z_i) = \frac{exp(\propto_c' z_i)}{\sum_c exp(\propto_c' z_i)}, \quad c = 1, \ldots\ldots C; \quad \propto_C = 0 \qquad 5$$

First we present the results of ordinary least squares (OLS) regression in which the dependent variable is the NEP Scale item score and the independent variables are respondents' SDCs. The OLS regression results are summarised in Table 8. The overall fit of the model is poor with a small R-squared indicating that SDCs are poor predictors of internal variables such as environmental attitude. This finding is consistent with previous studies that have found SDCs to be poor predictors of attitudes (e.g., Walker, 2001). The model has a highly significant and large positive intercept indicating the average influence of unobserved factors on respondents' environmental attitude. However, based on the F test we reject the null hypothesis that all the parameter estimates are equal to zero and conclude that the data are inconsistent with the null hypothesis. The results suggest that older respondents tend to report higher scores on the five-point Likert scale for environmental attitude. Consistent with previous studies, the negative and significant coefficient on gender suggests that males have on average lower environmental scores compared to females whilst income has a negative influence on environmental attitude. There are significant differences in environmental attitude between ethnic groups. Compared to 'Other' ethnic group Maori have on average higher environmental attitude scores whilst NZ-Europeans have lower scores albeit at the 10% level. The results also suggest that there is no significant difference even at the 10% level in environmental attitude scores between respondents with dependent children and those without. Respondents with at least a bachelor's degree on average tend to have higher scores than respondents with lower educational qualifications

Table 8 OLS regression results (N = 224)

Variable	Coefficient	Std. Error	z	Prob. |z|>Z	95% confidence interval	
					LB	UB
Constant	4.22084***	0.28070	15.04	.0000	3.67069	4.77100
Age (years)	0.00406***	0.00145	2.79	.0052	0.00121	0.00691
Gender (male = 1)	-0.05406***	0.02090	-2.59	.0097	-0.09503	-0.01308
Log(income)	-0.08123***	0.02692	-3.02	.0026	-0.13399	-0.02846
NZ-Euro	-0.06761*	0.03888	-1.74	.0820	-0.14381	0.00858
Maori	0.14690**	0.06548	2.24	.0249	0.01856	0.27524
Child	-0.01170	0.02168	-0.54	.5893	-0.05419	0.03078
Bachelor's Plus	0.04775*	0.02441	1.96	.0505	-0.00010	0.09560
Adjusted R^2	0.00619					
F[7, 3352] (Prob.)	4.0 (.0002)					

***Significant at 1%, **Significant at 5%, *Significant at 10%

The results of the linear regression latent class analysis are presented in Table 9. The LCM includes a class assignment model with dummy variables indicating ethnicity. Class1 accounting for about 55% of the respondents is the *strong* environmental attitude group in which factors such as age, gender, income, higher educational qualification and having dependent children are significant determinants of environmental attitude. In the *weak* environmental attitude class the main factors influencing environmental attitude are gender, ethnicity and having dependent children. The characteristics of respondents in the two classes of environmental attitude are presented in Table 10.

In order to obtain unbiased estimates of WTP for "green" electricity it is important to take into account the information processing strategies adopted by respondents. There is accumulating empirical evidence in previous research that suggest that 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 (Campbell, Hensher, & Scarpa, 2011; Campbell, Hutchinson, & Scarpa, 2008; Carlsson, Kataria, & Lampi, 2009; Hensher, 2008; Hensher, Rose, & Greene, 2005b; Lockwood, 1996; Scarpa, Gilbride, Campbell, & Hensher, 2009). As part of debriefing, respondents were asked to: state the attributes they ignored in choosing their preferred supplier; indicate on a Likert scale how easy the choice tasks were; and how sure they were that they would have made the same choices if the choice were real. Attitudinal questions also included questions measuring 'awareness of the consequences' (AC) of switching to a supplier that generates most of its electricity from renewables and how far they felt personally responsible ('ascription of responsibility' (AR)) for reducing CO_2 emissions by switching to a supplier that generates electricity from renewable energy sources.

Table 9 Latent class linear regression results (N= 224)

Variable	Coefficient	Std. Error	z	Prob. |z|>Z
		Model parameters for latent class 1		
Constant	4.38441***	0.73402	5.97	.0000
Age	0.00567***	0.00211	2.69	.0072
Gender	-0.05414**	0.02604	-2.08	.0376
Log(income)	-0.06339*	0.03519	-1.80	.0716
NZ-Euro	-0.07127	0.62766	-0.11	.9096
Maori	0.35867	1.25282	0.29	.7747
Child	-0.11392***	0.02985	-3.82	.0001
Bachelors plus	0.09682***	0.03228	3.00	.0027
Sigma	1.11115***	0.01432	77.60	.0000
		Model parameters for latent class 2		
Constant	3.51674***	0.45768	7.68	.0000
Age	-0.00077	0.00202	-0.38	.7030
Gender	-0.06626**	0.03094	-2.14	.0322
Log(income)	-0.03279	0.04302	-0.76	.4459
NZ-Euro	-0.20937***	0.07817	-2.68	.0074
Maori	0.29543**	0.13753	2.15	.0317
Child	-0.06606**	0.02670	-2.47	.0134
Bachelors plus	-0.03864	0.03021	-1.28	.2009
Sigma	0.99655***	0.01255	79.39	.0000
		Estimated prior probabilities for class membership		
One_1	-0.18881	0.65394	-0.29	.7728
NZ-European_1	0.40623	0.66396	0.61	.5407
Maori_1	-1.07655	1.26218	-0.85	.3937
One_2	0.0	..... (Fixed Parameter).....		
Gender_2	0.0	..... (Fixed Parameter).....		
Maori_2	0.0	..... (Fixed Parameter).....		
ProbCls1	0.54972			
ProbCls2	0.45028			
LL	-5070.47			
AIC	10182.9			
BIC	10311.5			

***Significant at 1%, **Significant at 5%, *Significant at 10%

Table 10 Characteristics of respondents in the weak and strong attitude classes (N = 224)

Variable		Weak	Strong
Number of respondents		101 (45.1%)	123 (54.9%)
Mean NEP Scale score		45.3%	57.8
Gender (male %)		45%	48%
Average Income ($)		45,900	44,200
Average Age (years)		44.5	44.8
Ethnicity	NZ Euro	76%	78%
	Maori	8%	2%
	Other	16%	20%
Education (at least Bachelors)		27%	33%
Proportion with dependent children		31%	49%

To account for attribute non-attendance in model estimation we coded our data to reflect stated serial non-attendance to specific attributes. Table 11 presents a comparison of SDCs of respondents who stated that they ignore renewables in making their choices to those who did not. There are no statistical differences in the means of the two groups in terms of age, gender, education, ethnicity, income, and most resent power bill. However, there are significant differences in the means between the two groups in terms of environmental attitude (NEP Scale score), awareness of the consequences (AC), ascription of responsibility (AR), how sure they were of their choices (certainty) and how easy the tasks were (easy). Those who did not ignore renewables reported higher NEP Scale, AC, and AR scores than those who ignored renewables. Respondents who ignored renewables reported higher scores on certainty and easy and this makes sense as they only considered a sub-set of the attributes in making their which simplified their choice tasks.

Table 11 Comparison of characteristics of respondents who ignored the Renewable attribute with those who attended to it

Variable		Ignored Renewable	Attended to Renewable
Number of respondents		77 (34.4%)	147 (65.6%)
Average NEP Scale score		49	54***
Average AC		3.31	3.63***
Average AR		2.42	3.30***
Gender (male %)		48%	46%
Average Income ($)		41,000	47,000
Average Age (years)		43	45
Ethnicity	NZ Euro	81%	76%
	Maori	3%	5%
	Other	10%	9%
Education (at least Bachelors)		27%	32%
Certainty		7.38	6.90**
Easy		5.60	4.88***

*Statistically different at 0.1, **Statistically different at 0.05, ***Statistically different at 0.01

4.4 Model estimation

In addition to the LCM we estimate a multinomial logit (MNL) model as our base model and a random parameter logit model with an error component for comparison. Environmental attitude enters the model as an interaction with renewables. We divide our sample into three approximately equal groups of environmental attitude – *weak*, *moderate* and *strong* such that NEP Scale scores of individuals in different groups did not overlap. Aldrich et al. (2007), Cooper et al. (2004), and Kotchen and Reiling (2000) adopt a similar approach. The *week* group consists of 70 respondents with NEP Scale scores equal to or less than 47 and an average score of 42.96. The *moderate* group consists of 77 respondents with NEP Scale scores ranging from 48 to 55 and an average score of 51.48. The *strong* group has 77 respondents with NEP Scale scores greater than 55 and an average of 61.21. We create two dummy variables for the moderate and strong environmental groups and interact these dummy variables with renewable to create new variables MNEP_RENEWABLE and SNEP_RENEWABLE.

4.4.1 Regression results and marginal WTP

In this section we present the results for the estimated MNL, LCM and RPL-EC models. Regression results are presented in Table 13. The estimated models fit the data relatively well with pseudo R^2 ranging from 0.37 for the RPL model to 0.41 for the LCM. Hensher et al. (2005a) suggest that a pseudo R^2 of 0.3 represents a decent model fit for a discrete choice model. Model fit statistics and likelihood ratio tests indicate that the LCM performs better than either MNL or RPL-EC model and that the RPL-EC model performs better than the MNL. For the base MNL model, all the parameters except for Renewable are significant at the 5% level and have the expected signs. Although Renewable is not significant, the two interaction terms MNEP_RENEWABLE and SNEP_RENEWABLE capturing the combined effect of environmental attitude and renewable on probability of selection have positive signs and are significant at the 5% level indicating that environmental attitude as measured by the NEP Scale has a positive influence on the probability of choosing a supplier that offers more renewables. The significance of the interaction effects between Renewable and environmental attitude supports the underlying hypothesis that environmental attitude affects preferences for “green” electricity. Based on the MNL respondents have positive preferences for fixed term contracts, discount, loyalty rewards, renewables and ownership. The negative sign on the three supplier type dummy variables indicates that respondents have a negative preference for these types of suppliers compared to a well-known electricity supplier. The positive and significant alternative specific constant for current supplier represents inertia or positive preference for the status quo.

The pattern of signs and significance of the parameters is similar in both the MNL and the RPL-EC model except that for the latter MNEP_RENEWABLE is only significant at the 10% level. Results of the RPL-EC indicate significant variance in the distributions of the mean taste intensities for Time, Fixed term, Discount, interaction of a dummy variable indicating strong environmental attitude with Renewable, and Ownership in the sampled population. Loyalty rewards, Renewable and all three supplier types were treated as non-random variables based on insignificant standard deviation estimates from previous model estimation. The coefficient of the power bill was treated as non-random for the purposes of estimating willingness to pay which is a ration of each attribute's coefficient to that of the monthly power bill. Significant standard deviations of the other variables indicate considerable preference heterogeneity in preferences for the respective attributes of electricity suppliers. The standard deviation for the error component is significant indicating increased variance in the utility functions of the non-status quo alternatives. This is expected as the attribute levels of these alternatives vary over choice tasks and respondents find it harder to evaluate the alternatives compared to the status quo whose attribute levels remain the same across all choice tasks.

To determine the number of classes to retain for our analysis we relied on information criteria, and other factors such as the pattern of significant parameters and relative signs, ease of interpreting the results, and the need to avoid over-fitting the model. 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 12 present the criteria used to determine the number of classes. Information criteria indicate the presence of three or five classes with different preferences for the attributes of electricity suppliers. Based on CAIC and BIC only three classes should be retained compared to five indicated by AIC, crAIC, AIC3, and HQC. However a closer look at the improvements in AIC3 and HQC as the number of classes increases from three to four reveals very small improvements of 0.67% and 0.23% respectively. When a model with four classes is estimated, the probability of one of the classes is small and insignificant and a large number of coefficients become insignificant suggesting that three classes may be a better option. Simulation studies investigating the performance of information criteria find that CAIC and BIC have a tendency of lower over-fitting rate and AIC3 as the best criteria (Andrews & Currim, 2003), HQC and AIC3 have the best average accuracy rate (Yang & Yang, 2007), and CAIC and BIC are more accurate than AIC (Lin & Dayton, 1997). In view of the above and the need to avoid over-fitting, and retain ease of interpretation of the results, the model with three classes was retained as the one supported by our data. Results for the LCM are also presented in Table 13.

Table 12 Criteria for selecting the number of support points for the finite mixture model

No. of classes	No. of Parameters	*lnL*	AIC	crAIC	AIC3	CAIC	BIC	HQ
1	13	-2153.4	4332.8	4332.9	4345.8	4422.4	4409.4	4360.5
2	27	-1884.7	3823.5	3824.0	3850.5	4009.7	3982.7	3881.1
3	41	-1748.4	3578.8	3580.1	3619.8	3861.6	3820.6	3666.3
4	55	-1715.3	3540.6	3543.0	3595.6	3919.9	3865.0	3657.9
5	69	-1682.4	3502.8	3506.5	3571.8	3978.7	3909.7	3650.0
6	83	-1674.5	3514.9	3520.3	3597.9	4087.3	4004.3	3691.9

The latent class analysis suggests the presence of three segments of homogenous preferences for the attributes of electricity suppliers. Class 1 consists of 54% of respondents who prefer their current supplier, have negative preferences for time and power bills, and don't care about the other attributes. This seems to be a group of people who are opposed to the partial privatisation of electricity companies. It's interesting to note that survey was conducted at the time when government was about to proceed with the partial sale of Genesis Energy. Class 2 accounts for 35% of respondents, who have no preference for their current supplier, do not perceive a new electricity company any worse than their current supplier, but care about the rest of the attributes of electricity suppliers. In this class there are no significant differences in taste intensities for renewable between respondents with *weak* and *moderate* environmental attitude (EA). However, respondents with *strong* EA show a more positive preference for renewables compared to those with weak EA. For this class, EA influences respondent's choice of electricity supplier. Class 3 represents 11% of respondents who only care about how much they pay for electricity as they don't care about any other attributes of electricity suppliers. These respondents show a very strong preference for their current supplier but also show a very high sensitivity to discount suggesting that they may have high power bills.

Table 13 MNL, LCM, and RPL-EC regression results[a]

Variables	MNL	LCM			RPL-EC	
		Class 1	Class 2	Class 3	Parameter	Std.Dev
ASC_{SQ}	0.5766***	0.5213***	0.0953	3.2544***	0.684***	
	(7.75)	(2.75)	(0.75)	(6.68)	(4.09)	
Time (minutes)	-0.043***	-0.0378**	-0.034***	-0.0420	-0.0485***	0.04485***
	(-5.87)	(-2.16)	(-2.92)	(-1.20)	(-4.74)	(3.03)
Fixed Term (months)	0.0046**	0.0057	0.0103**	-0.0033	0.0076**	0.02611***
	(2.16)	(0.86)	(2.30)	(-0.26)	(2.21)	(5.90)
Discount	0.0096***	0.0054	0.0157***	0.0516***	0.0128***	0.01588***
	(3.60)	(0.94)	(3.56)	(2.74)	(3.84)	(2.41)
Loyalty Rewards	0.3691***	0.2698*	0.3607***	0.4891	0.2921***	
	(5.31)	(1.76)	(2.96)	(1.28)	(3.47)	
%Renewable	0.0031	0.0019	0.0079**	-0.0042	0.0061**	
	(1.31)	(0.32)	(2.21)	(-0.40)	(2.03)	
MNEP_Renewable	0.0066**	0.0075	0.0056	0.0230*	0.0067*	0.00768
	(2.18)	(1.12)	(1.10)	(1.69)	(1.70)	(1.62)
SNEP_Renewable	0.0105***	0.0145*	0.0099**	-0.0003	0.0122***	0.02072***
	(3.50)	(1.78)	(2.21)	(-0.02)	(2.61)	(5.69)
%NZ Ownership	0.0082***	0.0135***	0.0122***	0.0057	0.0115***	0.01639***
	(6.01)	(4.53)	(5.47)	(0.59)	(5.14)	(6.56)
New Electricity	-0.3339***	-0.0906	-0.1844	-0.4442	-0.2742**	
Supplier	(-3.50)	(-0.43)	(-1.14)	(-0.84)	(-2.17)	
New Non-Electricity	-0.7406***	-0.3044	-0.8096***	-1.5427*	-0.8855***	
Company	(-6.06)	(-1.09)	(-4.14)	(-1.84)	(-5.37)	
Well-Known Non-	-0.4246***	-0.0474	-0.3977**	-0.2895	-0.5018***	
Elect Company	(-3.70)	(-0.16)	(-2.22)	(-0.57)	(-3.20)	
Monthly Power Bill	-0.0255***	-0.0572***	-0.0139***	-0.0147**	-0.0337***	
	(-31.28)	(-14.31)	(-8.06)	(-2.40)	(-29.50)	
Probability of Class		0.5374***	0.3479***	0.1147***		
		(12.39)	(8.13)	(5.23)		
Error component					0.00	1.5834***
						(12.17)
Model Fit						
Pseudo R-square	0.39	0.41			0.37	
LL	-2153.4	-1748.41			-1895.91	
AIC	4332.8	3578.8			3841.8	
BIC	4409.4	3820.6			3989.2	
% Prediction					67%	

[a] Numbers in parenthesis are the z-values, *, **, *** Significant at 0.1, 0.05, and 0.01

Table 14 presents WTP estimates based on the three models estimated. WTP estimates based on the MNL model are based on the assumption that respondents are willing to pay the same amount for any given attribute. As a result, differences in WTP between individuals are not revealed and the estimated values represent averages. Based on this model, consumers with moderate NEP Scale scores are willing to pay \$2.60 more per month to secure a 10% increase in electricity generated from renewable sources compared to consumers with a low NEP Scale score or low EA. Consumers with strong EA (high NEP Scale score) are willing to pay \$4.10 more per month to secure a 10% increase in electricity generated from renewables compared with customers with low EA. A supplier that is offering a 10% higher prompt payment discount may charge \$3.80 more per month than other suppliers *ceteris paribus* and still retain its customers. Offering loyalty rewards allows a supplier to charge \$14.46 per month more than suppliers who do not offer loyalty rewards. Compared to well-known electricity suppliers, new electricity suppliers, new non-electricity companies, and well-known non-electricity companies intending to enter the retail market have to charge at least \$13.08, \$29.10 and \$16.63 less per month to attract customers, other things being equal.

Table 14 WTP estimates based on MNL, LCM, and RPL-EC models ($NZ\$_{2014}$)[a]

Variables	MNL	LCM			RPL-EC
		Class 1	Class 2	Class 3	
TIME (minutes)	**-1.69**	**-0.66**	**-2.47**	*-2.86*	**-0.56**
Fixed Term (months)	**0.18**	**0.10**	**0.75**	*-0.23*	**0.16**
Discount	**0.38**	*0.10*	**1.14**	**3.51**	**0.33**
Loyalty Rewards	**14.46**	*4.72*	**26.04**	*33.27*	**8.66**
%Renewable	*0.12*	*0.03*	**0.57**	*-0.29*	**0.18**
MNEP_Renewable	**0.26**	*0.13*	*0.40*	*1.56*	0.18
SNEP_Renewable	**0.41**	*0.25*	**0.71**	*-0.02*	**0.36**
%NZ Ownership	**0.32**	**0.24**	**0.88**	*0.38*	***0.19***
New Electricity Supplier	**-13.08**	*-1.59*	*-13.32*	*-30.22*	**-8.13**
New Non-Electricity Company	**-29.01**	*-5.33*	**-58.45**	*-104.95*	**-16.25**
Well-Known Non-Elect Company	**-16.63**	*-0.83*	**-28.72**	*-19.69*	**-14.86**

[a]WTP estimates highlighted in bold are significant at the 5% level

WTP estimates based on the RPL-EC model are all lower than those based on the MNL model except renewable indicating that the model provides more conservative estimates compared to the MNL model. WTP estimates based on the LC model are distinctly different between classes also differ from those obtained using the MNL and the RPL-EC models. Respondents in class 1 are willing to pay on average an extra \$3.60 per month on their power bills to secure a 36 months fixed term contract, \$3.30 to avoid a 5 minutes increase in call waiting time, and \$12 to secure a 50% increase in local ownership. Environmental attitude does not influence WTP for green electricity as respondents in this class do not care about renewables. Compared to class 1, respondents in class 2 are willing to pay more for any attribute. Respondents with high NEP Scale scores in class 2 are willing to pay on average $12.80 more per month on their power bills to secure an increase of 10% in "green" electricity whilst those with moderate NEP Scale scores are willing to pay $5.7 per month for the same increase. This shows that respondents with strong environmental attitude are willing to pay more than twice what respondents with moderate environmental attitudes are willing to pay to secure an increase in "green" electricity. Respondents in class 2 have a strong dislike for non-electricity companies. A new non-electricity company has to charge at least $58.45 less per month whilst a well-known non-electricity company has to charge at least $28.72 less per month to attract customers in this class, other things being equal. Respondents in this class are also willing to pay $26.04 to secure loyalty rewards. This implies that a supplier offering loyalty rewards may charge up to $26.04 more per month compared to similar suppliers which do not offer these rewards and still retain its customers. Respondents in Class 3 are not willing to pay anything other than to secure prompt payment discounts. For these customers a company offering 10% higher discount than its competitors is able to charge $35.10 more per month *ceteris paribus*.

5. Summary and Conclusions

Results from this study suggest that researcher using sub-scales of the NEP Scale run the risk that shorter subscales may fail to properly classify respondents into correct environmental groups. However, more research is required to establish that our findings are not specific to our data set. Another area that needs exploring is whether the use of shorter sub-scales has any significant impact on WTP estimates.

The latent class analysis carried out in this paper reveals the existence of three market segments with clearly distinct preferences for the attributes of electricity suppliers. The largest segment accounting for 54% of the market consists of customers who only consider their monthly power bills, call waiting time and local ownership of the power company. Respondents who show a strong negative preference for call waiting time represent customers who prefer dealing directly with customer service personnel rather than computers. This group of customers may be targeted by new entrants who provide good customer service and are majority owned by New Zealanders. The second largest segment accounting for 35% of the market consists of customers who value most of the attributes of electricity suppliers. Knowledge of the trade-offs these customers make among the attributes will allow retailers to structure their offerings to attract or maintain customers. The smallest segment which accounts for 11% of the market consist of customers who are only concerned about how much their monthly power bill are and how much discount they can get. These customers appear to be bargain hunters but would only move if the discount is high enough to offset the positive preference for their current supplier.

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

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

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. (2003). A comparison of segment retention criteria for finite mixture logit models. *Journal of Marketing Research, 40*(2), 235-243. doi:10.2307/30038851

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

Bennett, J., & Adamowicz, W. (2001). Some fundamentals of environmental choice modelling. In J. Bennett & R. Blamey (Eds.), *The choice modelling approach to environmental valuation*. Chelenham, Uk. Northampton, MA, USA: Edward Elgar.

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. C., & Adamowicz, W. L. (2002). Understanding heterogeneous preferences in random utility models: A latent class A

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 and Resource Economics, 50*(1), 83-110. doi:http://dx.doi.org/10.1007/s10640-006-9054-7

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

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., 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

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

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:http://dx.doi.org/10.1016/j.ecolecon.2004.02.009

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? *The 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.

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 http://www.ea.govt.nz/about-us/media-and-publications/electricity-nz/

Electricity Authority. (2011). *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. (2012). *Consumer switching : A quantitative study supplemented by qualitative research*. Wellington, New Zealand: UMR Research

Retrieved from http://www.ea.govt.nz/search/?q=2011+baseline+national+survey
Electricity Authority. (2013). *Consumer switching fund*. Wellington, New Zealand. Retrieved from http://www.ea.govt.nz/consumer/csf/#survey
Electricity Commission. (2008). *Retail competition: A qualitative and quantitative study*. Wellington, New Zealand: UMR Research
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.
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., & 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
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
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
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. (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.
Hensher, D. A., Rose, J. M., & Greene, W. H. (2005a). *Applied choice analysis: A primer*. Cambridge: 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
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
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*, 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
Kamakura, W. A., & Russell, G. J. (1989). A probabilistic choice model for market segmentation and elasticity structure. *JMR, Journal of Marketing Research, 26*(4), 379.

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.

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

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.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: Analysis and application*. Cambridge: 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., & 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

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.

McLachlan, G., & Peel, D. (2000). *Finite mixture models*. New York: John Wiley & Sons, Inc.

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 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. (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 and Resource Economics, 34*(1), 91-115. doi:http://dx.doi.org/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

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.

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

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

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.

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

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 University Press.

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 http://scholar.google.co.nz/scholar?cites=6149018643301583492&as_sdt=2005&sciodt=0,5&hl=en

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

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