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

Consumer choice of electricity supplier: Investigating preferences for attributes of electricity services.

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Paper presented at the 2013 NZARES Conference

Lincoln University – Canterbury, New Zealand. August 28-30, 2013

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Abstract

The retail electricity market in New Zealand is evolving as the government continues to promote the development of a competitive and efficient market. Encouraging consumer switching through the "What's My Number" campaign is expected to put pressure on electricity retailers to reduce prices. Recent reports indicate that relatively few customers have switched supplier in the past two years despite potential average savings of NZ$165 per year per household. This suggests that non-price factors are also important determinants of switching behavior. We use choice experiments to investigate residential consumers' preferences for the attributes of electricity suppliers and the possible role of attitudes in explaining preference heterogeneity among the sampled respondents. Data required for the study was collected through a web survey administered to an online panel of bill payers in New Zealand. Willingness to pay (WTP) is estimated for attributes of electricity suppliers such as renewable portfolio, local ownership, discount rates, fixed rate plan, loyalty rewards and supplier type. WTP estimates indicate the importance of the attributes and hence provide guidance to suppliers in designing their price and service offers. Knowledge of how attitudes influence switching behavior may inform future policy directed at stimulating competition in the retail market.

Key words electricity suppliers; environmental attitude; choice experiments; latent class model; willingness to pay

[1] This conference paper was prepared by PhD student Tom Ndebele under the supervision of Dr. Dan Marsh and Professor Riccardo Scarpa.

1. Introduction

Promoting competition in the electricity market for the long-term benefit of consumers is part of the Electricity Authority's statutory objective. Success in achieving a competitive and efficient market depends critically on consumers' switching behavior. Increased switching activity puts pressure on retailers to lower prices and improve service offers. On the other hand a high level of consumer stickiness – that is, when too many consumers fail to make affirmative choices and switch to other providers, prevents the full impact of competitive forces from being realized and allows incumbent retailers to charge a premium. About 1.683 million residential electricity customers account for 33% of electricity consumption in New Zealand (MED 2012). Under the current deregulated electricity market consumers are free to choose among 5 to 17 retail brands available depending on the region (Electricity Authority, 2013).

In 2009 a Ministerial Review of the electricity market found evidence that the full benefits of retail competition introduced in 1998 had not been realized because residential consumers could benefit by an average of $165 per year by switching supplier (Castalia Strategic Advisors, 2010). A "Switching Fund" to promote the benefits of price comparisons and switching electricity supplier was set up and the "What's My Number" campaign became the central program of activity for this fund by encouraging consumers to shop around and also providing information about consumers' ability to switch, potential savings and prices. This campaign is based on the belief that consumers are price sensitive and that small changes in prices will cause consumer to switch suppliers (Cai, Deilami, & Train, 1998).

Despite reports indicating that switching rates have been trending upwards since 2008, from an annual rate of 10.5% in 2008 to 19.5% in 2011 (Electricity Authority, 2013) and that NZ switching rates are the second highest in the world after Victoria, Australia (VaasaETT, 2012), the switching rates are still relatively low given high potential savings that are still obtainable in the market. For example, only 30% of residential customers have switched supplier in the past two years and of these 86% have only switched once (EA 2013) yet average savings as high as $150 per year still prevail.

Market research in NZ has identified important attributes of electricity services and barriers to switching (UMR Research, 2011, 2012, 2013). These studies find that although price is the major driving force behind switching activity, there are other non-price attributes that are important to consumers. However, some key questions remain about how consumers value various attributes of electricity services. This information will help retailers in designing their service offering in order to increase profits and maintain market share. This will also help the EA in identifying additional information that may be provided to consumers to encourage them to switch.

Outside the context of willingness to pay (WTP) for green electricity there is limited international literature that has estimated values of the attributes of electricity services presumably because market data required for such analysis is not readily available. Previous studies that have estimated values of the attributes of electricity services have relied primarily on stated preference data collected using conjoint experiments (Cai et al., 1998; Goett, Hudson, & Train, 2000; Revelt & Train, 2000). In these studies respondents were presented with a series of choice tasks in which at least two options of hypothetical offers by electricity retailers were described in terms of a number of attributes and were asked to indicate their preferred option in each case. For example Revelt and Train (2000) examine the type of pricing (fixed, time-of-day, and seasonal), type of supplier (whether it's well-known or not), and length of contract whilst Cai et al. (1998) examines price, power outages, whether supplier used renewable sources, and conservation programs. Goett et al. (2000) extend on previous studies by estimating the distribution of values of more than 40 attributes of electricity services using a mixed logit model.

Results of these studies indicate that consumers prefer a supplier producing a larger proportion of electricity from renewables, fixed rates to variable rates, shorter contracts, well-known electricity supplier to other types of supplier, shorter power outages, and to deal with a real person. Although these studies find considerable heterogeneity of preferences across respondents they do not offer much insight into the causes of this heterogeneity.

In this paper we extend conjoint-type research of previous studies by estimating values for seven attributes of electricity services, and identifying groups of consumers with homogenous preferences for the attributes of electricity services. A latent class model is used to analyze responses to the choice questions and to estimate WTP for the service attributes.

The remainder of this paper is arranged as follows. Section 2 describes the methodology. Section 3 presents and discusses the results. Section 4 provides a conclusion and suggested further research.

2. Methods

2.1 Survey questionnaire and choice experiment design

A survey questionnaire was developed to collect the data required for this research. The first part of the survey questionnaire elicits socio-demographic and attitudinal information using psychological constructs based on the New Ecological Paradigm (NEP) Scale (Dunlap, Van Liere, Mertig, & Jones, 2000), the theory of planned behavior (TPB) (Ajzen, 1988, 1991, 2011), and the norm activation theory (NAT) (Schwartz, 1977). The NEP Scale measures the respondents' general environmental attitude whilst the TPB constructs measure respondents' attitude towards a behavior (switching), subjective norm, and perceived behavioral control, and NAT measures respondents' altruism. The second part of the survey questionnaire elicits information on respondents' choices among experimentally designed alternatives followed by a debriefing to identify respondents' information processing strategies. Following Cummings and Taylor (1999), a cheap talk script presented prior to the choice questions was used to mitigate hypothetical bias.

Identification and selection of attributes and attribute levels that are important in this research context was based on previous New Zealand studies, international literature review and focus groups. Table 1 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. 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 1 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
		10%	DISC10D = 1, 0
		20%	DISC20D = 1, 0
		30%	DISC30D = 1, 0
Rewards	Loyalty rewards such as Fly Buys, Brownie points, prize draws, and annual account credits (excludes annual network dividends)	No	0
		Yes	1
Renewable	Proportion of electricity generated from wind, hydro, geothermal, bioenergy and solar.	(25%, 50%, 75%, 100%)	25, 50, 75, 100
		25%	REN25D = 1, 0
		50%	REN50D = 1, 0
		75%	REN75D = 1, 0
Ownership	%NZ ownership of supplier	25%, 50%, 75%, 100%	25, 50, 75, 100
Supplier type	Type of supplier	New electricity company	NEWELCD = 1
		New non-electricity company	NEWNOND = 1
		Well-known electricity supplier	W_KELCD = 1
		Well-known non-electricity company	W_KNOND = 1
Bill	Average monthly electricity bill before GST, levy and discounts.	$100, $200, $300, $400	100, 200, 300, 400

The parameter estimates from the first stage were used in a D-efficient homogenous pivot design for a MNL model. 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 adjusted slightly to suit the purposes of the study.

Before respondents were presented with choice tasks, they were asked to describe their actual current suppliers in terms of the attribute levels used in the experimental design to provide information on revealed preferences. Each respondent was asked to make a series of choices under ten scenarios in which three hypothetical electricity suppliers were described in terms of the attributes and attribute levels used in the experimental design (see Figure1).

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.

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.

2.2 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 (K) 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 ($\beta_k' X_{int}$) and a random component ($\varepsilon_{int|k}$) as follows (Boxall & Adamowicz, 2002; Walker & Ben-Akiva, 2002):

$$U_{int|k} = \beta_k' x_{int} + \varepsilon_{int|k} \tag{1}$$

where

- $U_{int|k}$ is the utility of alternative *i* to individual *n* in choice situation *t* conditional on class k membership
- x_{int} is a union of all attributes and characteristics that appear in all utility functions,
- $\varepsilon_{int|k}$ 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 k membership, and β_k 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 probability that an individual *n* chooses alternative *i* conditional on class k membership ($P_{(n,i|k)}$) can be expressed as a product of two probabilities (Kamakura & Russell):

$$P_{(n,i|k)} = \sum_{k=1}^{K} \left[\frac{\exp(\alpha_k S_n)}{\sum_{k=1}^{K} exp(\alpha_k S_n)}\right] \left[\frac{\exp(\beta_k X_i)}{\sum_{j=1}^{J} exp(\beta_k X_i)}\right], \text{ k =1, 2, ….. , K; } \alpha_K = 0 \tag{2}$$

were $\frac{\exp(\alpha_k S_n)}{\sum_{k=1}^{K} exp(\alpha_k S_n)}$ is the k^{th} class membership probability of individual *n* (with socio-demographic characteristics [SDC] S_n) defined parametrically using a multinomial logit as membership equation, α_k is a vector of class-specific parameters (or constants), $\frac{\exp(\beta_k X_i)}{\sum_{j=1}^{J} exp(\beta_k X_i)}$ represents the probability of an individual *n* in class *k* choosing alternative *i*, and β_k 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:

$$\ln L = \sum_{n=1}^{N} ln \left[\sum_{k=1}^{K} \frac{\exp(\alpha_k S_n)}{\sum_{k=1}^{K} \exp(\alpha_k S_n} \prod_{t=1}^{T} \frac{\exp(\beta_k X_i)}{\sum_{j=1}^{J} \exp(\beta_k X_j)} \right] \quad (3)$$

We maximize the likelihood with respect to the K structural parameter vector β_k and the K-1 latent class parameter vector α_k. Since the β_k'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). Morey et al. (2006) and Nocella et al. (2012) discuss the performance of these criteria and also provide formulae for their calculation.

. 2.3 Data collection

An online survey was administered in June 2013 to a stratified sample of 70 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 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)

3. Results

3.1 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. Males are slightly over-represented by 1%, whilst females are under represented by the same percentage. The average personal income of respondents (about $46, 100) 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.

Table 2 Sample statistics versus national population

Characteristic	Sample (N = 70)	National[1]
Gender	(%)	(%)
Male	50	49
Female	50	51
Age Group	(%)	(%)
18 - 24	11	13
25 - 34	18	17
35 - 44	24	21
45 - 54	15	18
55 +	30	31
Ethnicity	(%)	(%)
NZ European	77	70
Maori	8	12
Asian	7	10
Pacific Island	1	5
Other	7	2
Average personal income	$46, 100	$37, 500
Average monthly electricity bill	$162.65	$190*

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

3.2 Model estimation

In addition to the LC model we also estimate the multinomial logit (MNL) and random parameter logit (RPL) error-components for comparison. Table 3 presents a summary of the results for these models estimated with continuous attribute levels for Discount, Renewable, and Ownership. These will be compared with the results for the models estimated with categorical levels for Discount and

Renewable (see Appendix). In estimating the models it was found that entering the BILL both linearly and in log form improves model fit. In a study investigating consumer choice of electricity supplier Goett et al. (2000) find that entering the price both linearly and in log form was needed to accurately represent consumers' choices. Entering BILL only in linear form implies that a given increase in monthly power bill is valued the same, independent of the level of the power bill. On the other hand entering BILL only in log form implies that consumers value a given percentage change in BILL the same independent of the absolute change in the power bill which the percentage represents.

The estimated models fit the data relatively well with pseudo R^2 ranging from 0.39 for the MNL to 0.49 for the LC model. Hensher, Rose, and Greene (2005) suggest that a pseudo R^2 of 0.3 represents a decent model fit for a discrete choice model. All the parameters have the expected signs. Model fit statistics and likelihood ratio-tests indicate that the LC model performs better than either MNL or RPL model and the RPL performs better than the MNL model. Given the small sample size (N = 70) the estimation of more than two classes is not feasible as the number of estimated parameters increases rapidly. As a result our analysis of heterogeneity of preferences for the attributes of electricity services is based on a model with two classes (class 1 and class 2).

Based on the MNL model, call waiting time, fixed term, and loyalty rewards are not significant determinants of supplier choice. However results of the LC (class 2) and RPL models indicate that loyalty rewards are significant determinants of supplier choice, hence the probability of choice is higher for suppliers offering loyalty rewards than those that do not, *ceteris paribus.* Positive and statistically significant coefficients of Discount, Renewable, and Ownership indicate that these attributes are significant determinants of supplier choice. Suppliers offering higher levels of these attributes have a higher probability of selection than those offering lower levels, *ceteris paribus*. On the other hand negative and significant coefficients of the dummy variables (NEWELCD, NEWNOND, and W_KNON) representing supplier type indicates that these supplier types are less preferred compared to a "Well-known Electricity Supplier" type which was used as the base level in model estimation. This is expected if respondents prefer to deal with current incumbents rather than new entrants who may be viewed as risky. Negative and significant coefficients of BILL and (-)lnBILL indicate the importance of the cost of electricity in choosing a supplier and that cheaper suppliers are preferred.

Table 3 Estimation results

	MNL model	LC model		RPL model	
		Class 1	Class 2	Coefficients	Std. Devs
Variables					
ASCSQ	0.1816	-0.10703	1.1052	0.2005	
	(0.80)	(-0.27)	(2.74)***	(0.54)	
TIME (minutes)	-0.0204	-0.0125	-0.031	-0.0317	0.0015
	(-1.63)	(-0.53)	(-1.54)	(-1.94)*	(0.05)
FIXED TERM (months)	-0.0039	0.0022	-0.0012	-0.0004	0.0007
	(-0.71)	(0.22)	(-0.14)	(-0.06)	(0.06)
DISCOUNT	0.0476	0.0192	0.0694	0.0714	0.0419
	(5.81)***	(1.1)	(4.90)***	(5.66)***	(2.83)***
REWARDS	0.2923	0.5418	0.7119	0.5417	0.2452
	(1.59)	(1.6)	2.48)**	(2.26)**	(0.53)
RENEWABLE	0.0111	0.0073	0.02112	0.0179	0.0236
	(3.64)***	(1.23)	(4.29)***	(3.42)***	(4.42)***
NZ OWNERSHIP	0.0129	0.0145	0.0135	0.0186	0.0208
	(4.41)***	(2.87)***	(2.66)***	(3.86)***	(3.92)***
New electricity supplier	-0.6329	0.1649	-1.1406	-0.5600	
(NEWELECD)	(-2.56)**	(0.31)	(-3.07)***	(-1.55)	
New non-electricity company	-0.8359	-0.3785	-1.1117	-1.0096	
(NEWNOND)	(-3.12)***	(-0.91)	(-2.42)**	(2.96)**	
Well-known non-electricity	-1.2128	-2.6141	-1.0091	-1.5539	
company (W_KNOND)	(-2.61)***	(-2.23)***	(-1.75)*	(2.71)***	
Monthly electricity BILL	-0.0279	-0.0559	-0.0219	-0.0425	
	(-5.75)***	(3.87)***	(-2.78)**	(-6.11)***	
(-)LNBILL	-2.9049	-4.9727	-3.0686	-4.6325	
	(-3.00)***	(-1.87)*	(-1.88)*	(-3.47)***	
Error component				0.0	1.5492
					(7.00)***
Estimated Latent class probabilities		0.6513	0.3487		
		(10.92)***	(5.85)***		
Model Fit					
Pseudo R^2	0.39	0.49		0.46	
χ^2	592.35 (11 d.f.)	758.17 (25 d.f.)		714.27 (19 d.f.)	
	p-value = .0000	p-value = .00000		p-value = .00000	
LL(β)	-466.23799	-389.94482		-411.89356	
AIC	956.5	829.9		861.8	

*Significant at 0.1level, **Significant at 0.05level, **Significant at 0.01 level

Results of the RPL model indicate significant variance in the distribution of the mean taste intensities in the sampled population for Discount, Renewable, and Ownership. The error component is statistically significant indicating increased variance in the utility functions of the non-status quo alternatives. This is expected as the attribute levels of the non-status quo alternatives change over choice tasks and respondents find them harder to evaluate compared to the status quo which is fixed

In the LC model class 1 is larger than class 2 and represents approximately 65% of the sample. In class 1 most of the utility parameters are not statistically significant with the exception of Ownership, W_KNOND, and BILL. Respondents in this class appear to represent a group of consumers who do not care about most attributes of electricity services (or perceive suppliers to be the same with respect to these attributes) and would only choose their preferred supplier on the basis of the levels of three attributes whose coefficients are statistically significant. For example, a well-known electricity supplier that offers a lower price and higher percentage of NZ ownership would attract this class of customer. Offering higher loyalty rewards and higher discount would not attract these customers probably because (1) they don't participate in collecting Fly Buys, (2) they think that other loyalty rewards such as cash credits are temporary, and (3) they have a problem making prompt payments since the discount is only applied when payments are made on or before due date. The alternative specific constant for the status quo (ASCSQ) represents the average utility of this alternative. For class 1 the ASCSQ is not significantly different from zero suggesting little or no "inertia" for these customers. The market segment represented by class 1 is less sticky and if they are offered favourable levels of Ownership, W_KNOND and BILL they would switch supplier. However, the ASCSQ for class 2 is positive and significant suggesting that respondents in this class prefer to stay with their current supplier, all else equal, and represent a stickier segment of the market. For respondents in class 2 only two attributes, TIME and FIXED TERM are not important determinants in supplier choice.

3.3 Marginal WTP estimates for the attributes of electricity services

Marginal WTP for an attribute is calculated as $\delta U/\delta x$ divided by $-\delta U/\delta p$. The derivative of the utility function with respect to BILL is equal to $\beta_B + (\beta_{lnB}/BILL)$, where β_B and β_{lnB} are the coefficients of BILL and (-)lnBILL respectively. Marginal WTP for an attribute is therefore estimated by dividing its coefficient by minus $(\beta_B + (\beta_{lnB}/BILL))$. The minimum, mean, mode, and maximum of the most recent power bill paid by respondents are \$78, \$163, \$100, and \$400 respectively. Since \$100 is the amount paid by most respondents and \$250 represents the level for the status quo, marginal WTP for the attributes will be calculated at these levels of the bill amount. Table 4 reports the marginal WTP estimates for the attributes.

The values highlighted in grey are based on coefficients that are statistically insignificant and cannot be relied on although their signs make intuitive sense. Statistically insignificant parameter estimates imply zero marginal WTP for the attributes which are not significant determinants of choice. Respondents in class1 are not willing to pay anything for nearly all attributes except for NZ OWNERSHIP and W_KNOND. Based on a monthly power bill of \$100, respondents in class 1 are willing to pay an additional \$0.14 for a 1% increase in local ownership compared to \$0.26 for respondents in class 2. For class 1 respondents, a well-known non-electricity company (W_KNOD) would have to charge at least \$24.75 less per month than a well-known electricity supplier if it were to enter the market, *ceteris paribus*. However, a new electricity supplier and new non-electricity company are not preferred differently from a well-known electricity supplier by class 1 respondents. This implies that these two types of supplier can attract customers just like a well-known electricity supplier if they offered a similar package. Respondents in class 2 prefer a well-known electricity supply and a well-known non-electricity company to the new companies which have to charge at least \$21.16 less per month to attract customers *ceteris paribus*.

Table 4 Marginal WTP estimates for electricity services

	LCM			
	Class 1		Class 2	
	WTP @		WTP @	
	\$100	\$250	\$100	\$250
VARIABLES				
ASCSQ	-1.01	-1.41	21.03	32.38
TIME (minutes)	-0.12	-0.16	-0.59	-0.91
FIXED TERM (months)	0.02	0.03	-0.02	-0.04
DISCOUNT	0.18	0.25	1.32	2.03
LOYALTY REWARDS	5.13	7.15	13.55	20.86
RENEWABLE	0.07	0.10	0.40	0.62
NZ OWNERSHIP	0.14	0.19	0.26	0.39
New electricity supplier (NEWELECD)	1.56	2.18	-21.71	-33.41
New non-electricity company (NEWNOND)	-3.58	-5.00	-21.16	-32.57
Well-known non-electricity company (W_KNOND)	-24.75	-34.50	-19.2	-29.56

Respondents in class 2 tend to stick to their current supplier and would rather pay \$21.03 more per month and remain with their current supplier rather than move to another supplier all else being equal. A 1% discount is valued at \$1.32 when the power bill is \$100 and \$2.03 when the power bill is \$250. Whilst respondents in class 1 do not value loyalty rewards offered by electricity suppliers, respondents in class 2 value these at \$13.55 and \$20.86 when estimated at the power bills of \$100 and \$250 respectively. This indicates that respondents in class 2 value participating in draws, collecting Fly Buy points that can be redeemed for other goods and value the annual cash credits offered as loyalty rewards. Respondents in class 2 representing 35% of the sample are willing to pay \$0.40 for a 1% increase in the proportion of electricity generated from renewable sources. This indicates a potential for green marketing in the retail electricity market although this would be targeted to a smaller segment of the market as respondents in class 1 (65%) are not willing to pay extra for electricity generated from renewable sources.

Marginal WTP estimates for the LCM estimated with contrast coded levels for Discount and Renewable are presented in Table 5. To test whether the model with categorical values for Renewable and Discount attributes is better than a model with continuous levels for these attributes, a likelihood ratio-test suggested by Hensher et al. (2005) was applied as:

χ^2 $(_{\text{d.f. = 33-25}})$ = -2*(-389.94482- (-383.19104) = 13.51

This Chi-square test statistic is less than the critical chi-square value of 15.51 with 8 degrees of freedom at the 95% level. The null hypothesis that the model with categorical levels for Renewable and Discount attributes does not statistically improve the LL over the model with continuous levels for the attributes cannot be rejected. Respondents in class 1 have no preferences for most attributes as in the model with continuous variables. However, a positive and statistically significant alternative specific constant for the status quo indicates that respondents in this class would rather pay more ($20.01) per month with their current supplier than switch to another supplier offering the same attribute levels. Respondents in this class do not value discount even at 30%. Furthermore, they are indifferent to a reduction of renewables from 100% to 50% or 75% but would pay an extra $26.25 per month to avoid a 25% renewable level. A 1% change in ownership is valued at $0.48. Respondents in class 1 are indifferent between a "Well–known non-electricity company" and a "Well-known electricity supplier" or a "New non-electricity company". However, they would pay $50.39 more to a "New electricity supplier" compared to a "Well–known non-electricity company" offering the same attribute levels. This might be an indication that respondents in this class are not happy with current electricity suppliers probably due to bad service and would welcome new entrants in the market. This might explain the current success enjoyed by small new electricity suppliers particularly Pulse Energy whose market share has been growing fast over the past few years (NZ Energy Data File 2012).

Respondents in class 2 prefer shorter fixed rate contracts and would be willing to pay $0.25 more per month to reduce the fixed rate contract by one month. In an environment where electricity suppliers are approaching consumers with lower prices, customers would not want to be locked into long term fixed rate contracts as they would not be able to benefit from immediate price reductions. Respondents in class 2 value a 10% discount the same as a zero discount. However, 20% and 30% discounts are valued at $13.18 and $15.57 respectively. A supplier offering a 20% or 30% discount could potentially charge $13.18 or $15.57 respectively per month more than a supplier offering no discount and still retain the customers. Electricity suppliers offering a 10% discount would not be able to attract respondents in this class. Respondents are indifferent between 100% and 75% renewable but prefer 100% to either 50% or 25% and would be willing to pay $11.17 and $15.48 per month respectively to avoid these levels. While these respondents do not care about ownership, they would pay $19.85 more to a well-known electricity company than move to a well-known non-electricity company offering the same attribute levels.

Table 5 Marginal WTP estimates with contrast coded levels for Discount and Renewable

Variables	Class 1		Class 2	
	WTP @ $100	WTP @ $250	WTP @ $100	WTP @ $250
ASCSQ	20.01	26.19	-8.70	-13.85
TIME	-0.30	-0.40	0.02	0.03
FIXED	0.23	0.30	-0.25	-0.40
DISC10D	0.60	0.79	10.35	16.47
DISC20D	10.57	13.84	13.18	20.97
DISC30D	22.03	28.83	15.57	24.79
REWARDS	5.03	6.58	5.94	9.45
REN25D	-26.25	-34.36	-15.48	-24.63
REN50D	-21.78	-28.51	-11.17	-17.78
REN75D	-23.35	-30.57	-2.28	-3.63
NZ OWNERSHIP	0.48	0.63	0.00	0.00
New electricity supplier (NEWELECD)	50.39	65.95	6.98	11.11
New non-electricity company (NEWNOND)	26.00	34.03	-2.10	-3.34
Well-known Electricity Supplier (W_KELECD)	17.76	23.24	19.85	31.58

4. Conclusion

Previous research identifies the price as the major driving force behind switching in New Zealand (UMR 2011). This is expected due to the homogenous nature of the product and the structure of the electricity market, hence the argument that electricity suppliers can only differ in terms of price. However, our results indicate that suppliers may be perceived to differ in terms of three or eight attributes depending on the market segment. Most respondents (77%) in our sample have not switched supplier in the past two years which compares favourably with 70% in the UMR study. Results of the latent class analysis shades light into the observed low rates of switching. For example, respondents in class 1, constituting 65% of the sample, only consider three attributes in choosing their preferred supplier whilst those in class 2 (35%) exhibit significant 'inertia' which would require larger price reductions by other suppliers or significant price increase and/or reduction in the levels of preferred attributes by their current supplier to induce them to switch.

The results from this study should be treated with caution as they are based on a pilot study with a small sample size which limited our ability to estimate models with more than two classes. For example, a larger sample size may reveal the existence of more than two latent classes. The results of this study will be used in the next stage of the experimental design which will allow for the incorporation of interactions of psychological constructs with the attributes of electricity services.

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Appendix

Table A1 Regression results for LCM with contrast coded levels

	Class1	Class 2
Variables	coefficients	
ASCSQ	1.80107 (3.47)***	-0.66006 (-1.69)*
TIME	-0.0271 (-0.72)	0.00162 (0.08)
FIXED	0.02036 (1.29)	-0.01912 (-2.31)**
DISC10D	0.05417 (0.05)	0.78478 (1.79)*
DISC20D	0.95189 (0.88)	0.99912 (2.06)**
DISC30D	1.98321 (1.85)*	1.18098 (2.90)***
REWARDS	0.45287 (0.85)	0.45022 (1.74)*
REN25D	-2.36295 (-2.16)**	-1.17368 (-3.25)***
REN50D	-1.96077 (-1.89)*	-0.84736 (-2.08)**
REN75D	-2.10223 (-1.81)*	-0.17301 (-0.40)
NZ OWNERSHIP	0.04339 (4.53)***	-0.000098 (-0.02)
New electricity supplier (NEWELECD)	4.53563 (2.17)**	0.52954 (1.16)
New non-electricity company (NEWNOND)	2.34038 (1.59)	-0.15905 (-0.31)
Well-known Electricity Supplier (W_KELECD)	1.59862 (1.15)	1.50487 (3.29)***
BILL|1|	-0.05462 (-2.41)**	-0.02886 (-4.18)***
LNBILL|1|	-3.53950 (-0.83)	-4.69675 (-3.28)***
PrbCls	0.60878 (10.24)***	0.39122 (6.58)***
Model fit		
Pseudo R^2	0.501	
χ^2	771.67513 (33 d.f.) p-value = .00000	
LL(β)	-383.19104	
AIC	832.4	