Consumer switching in retail electricity markets: Is price all that matters?

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ABSTRACT

We model consumer switching in retail electricity markets in New Zealand to identify important determinants of switching and estimate willingness to pay (WTP) for six non-price attributes of electricity services, namely, call waiting time, length of fixed rate contract, renewable energy, loyalty rewards, supplier ownership, and supplier type. The results provide important insights into residential consumer switching, which inform policy and enable suppliers to differentiate their products. The analysis is based on 2,688 choice responses generated using an online choice experiment administered to a sample of 224 residential bill-payers. A latent class model is used to distinguish important determinants of switching and preference heterogeneity. We find that non-price attributes of electricity services are significant determinants of consumer switching. Three latent classes with distinct preferences for the attributes are identified. The first class (40%) is mainly concerned about power bills and would switch supplier to save at least NZ$125 per year in power bills, *ceteris paribus*. This value mainly captures the status quo effect or preference for incumbent traditional suppliers. The second class (46%) exhibits no status quo preference, values all attributes, and particularly dislikes entrants from other sectors. These suppliers must charge NZ$135 per year less than traditional suppliers for a 50% chance of attracting customers. The third class (14%) consists of captive and loyal customers who are unlikely to switch supplier for any realistic power bill savings.

KEYWORDS: Consumer switching; choice experiment; preference heterogeneity; willingness to pay; retail electricity markets; latent class model

JEL codes: C93, D01, D12, L94, Q48

HIGHLIGHTS

- Determinants of consumer switching in retail electricity markets are analysed.
- Non-price attributes of electricity services influence consumer switching.
- Three groups with clearly distinct preferences for the attributes are identified.
- Status quo effect and dislike for non-traditional suppliers affect consumer switching.
- Preferences for non-price attributes and the status quo effect explain price dispersion.

1. Introduction

New Zealand, USA, UK, Norway, Sweden, and Australia have all implemented electricity market reforms since the 1980s. These reforms aimed at replacing monopolies with an efficient and competitive electricity sector but had limited success, particularly in the retail electricity sector, where most consumers seem reluctant to switch suppliers (see, Brennan, 2007; Daglish, 2016; Defeuilley, 2009; Deller et al., 2014; Electricity Authority, 2011, 2012a, 2013a, 2015; Giulietti et al., 2014; Hortaçsu et al., 2017; Joskow, 2003). The willingness of consumers to switch suppliers is an important factor in determining the extent to which deregulated retail electricity markets become competitive (Electricity Authority, 2010), so consumers' reluctance to switch suppliers creates a dilemma for policy makers. A better understanding of the factors that influence consumer switching can improve the design, implementation and effectiveness of policies aimed at promoting switching and ultimately achieve a more competitive electricity market. This paper identifies the determinants of consumer switching in New Zealand retail electricity markets.

The model of competition underpinning the deregulation of retail electricity markets is premised on the idea that more competition will attract innovative and efficient entrants. These entrants will compete with incumbents, leading to lower prices and improved product quality (Defeuilley, 2009). At the same time, consumers will learn to find and compare offers and switch to the better supplier[1]. The implicit assumption of this model is that consumers are sensitive to price and other service attributes, and that they will switch to a supplier offering a better package of price and service attributes. However, the influence of service attributes on switching has generally been ignored in previous promotions of consumer switching. For example, switching promotions have mainly focused on the creation of switching websites, which act as one-stop-shops by offering price comparisons and allowing consumers to switch to the cheapest available supplier. Rarely, has any emphasis been placed on the level of provision of non-price attributes.

Promoting switching on the basis of price differences alone appears to be based on the belief that: (1) consumers are price-sensitive, and small changes in price will induce switching, given the homogeneous nature of the product (Cai et al., 1998; Price, 2004); (2) brand value and service factors are likely to be very small for electricity retailing (Electricity Authority, 2010;

[1] Supplier and retailer will be used interchangeably throughout this paper.

Wilson & Price, 2010); and (3) consumers are more likely to view suppliers to be the same except for the price (Gärling et al., 2008). Goett et al. (2000, p. 1) assert that "[t]he power of competitive pressures to lower prices depends on the degree to which customers are willing to switch suppliers in response to offers of lower prices." This suggests that "price is all that matters".

Evidence from previous studies (e.g., Brennan, 2007; Defeuilley, 2009; Deller et al., 2014; Electricity Authority, 2011, 2013a, 2015; Giulietti et al., 2014; Hortaçsu et al., 2017) suggests that the creation of switching websites and their extensive publicity has proved ineffective at increasing switching rates in most jurisdictions, even during periods of rapidly increasing retail prices when substantial potential savings were available. So the level of retail competition in deregulated markets has failed to meet expectations. The relatively low switching rates have placed insufficient discipline on incumbent retailer behaviour leading to higher prices (Electricity Authority, 2010; Gamble et al., 2009; Gärling et al., 2008). For example, residential consumers in New Zealand faced rapidly increasing prices during the period 1985–2010, yet most consumers did not switch despite large price differences and entry of new suppliers into the retail markets. This suggests that switching behaviour may be influenced by other factors worth investigating further.

Indeed, previous stated preference literature on consumer switching in retail electricity markets has shown that non-price attributes of electricity services are important determinants of supplier choice. However, this body of literature is relatively limited and has, for some time, been dominated by a few, somewhat dated, American and British studies conducted around the late 1990s and 2000 (e.g., Cai et al., 1998; Goett, 1998; Goett et al., 2000; Revelt & Train, 2000).

The growing interest in understanding consumer switching has seen a slight increase in analysis of consumer preferences for the attributes of electricity services (e.g., Abdullah & Mariel, 2010; Amador et al., 2013; Hensher, Shore, & Train, 2014; Kaenzig et al., 2013; Yang, 2014). The focus of these studies differs depending on the main objective. While some studies identify important determinants of supplier choice or switching by valuing the attributes of electricity suppliers (Amador et al., 2013; Cai et al., 1998; Goett et al., 2000; Hensher et al., 2014; Kaenzig et al., 2013; Revelt & Train, 2000), others focus on: (1) attitudes that motivate or prevent consumers from switching (e.g., Gamble et al., 2009); (2) barriers to switching (Electricity Authority, 2010, 2012a, 2016; Gamble et al., 2007; Gärling et al., 2008; Giulietti et al., 2014;

Ministry of Economic Development, 2005a); and (3) determinants of WTP for the attributes (Abdullah & Mariel, 2010; Amador et al., 2013). While results from these studies show that attributes of electricity suppliers such as price, length of contract, reliability of supply, share of renewables, discounts, and type of supplier (e.g., Goett et al., 2000; Hensher et al., 2014) are important determinants of supplier choice, other factors such as attitudes, past experience, perceived barriers, and socio-demographic characteristics of consumers also play an important role in consumer switching (Electricity Authority, 2010; Gamble et al., 2007, 2009).

In this paper we model consumer switching in retail electricity markets in New Zealand to: (1) identify important determinants of switching and estimate WTP for a selected subset of non-price attributes of electricity services, namely, call waiting time, length of fixed rate contract, proportion of renewables in the fuel mix, loyalty rewards, ownership of supplier, and supplier type; (2) explore the existence of market segments with clearly distinct preferences for the attributes and use a psychological construct based on the theory of planned behaviour to explain preference heterogeneity across preference classes; and (3) explain switching inertia in terms of the status quo effect and preferences for non-price attributes. A novel latent class approach to modelling consumer switching is adopted where sensitivity to power bill savings is allowed to vary within and across the latent preference classes. This is achieved by specifying utility as a piecewise linear function of the savings variable. In this regard, this paper contributes to the limited literature on consumer switching in retail electricity markets and increases our understanding of consumer preferences for the attributes of electricity services.

The remainder of this paper is arranged as follows: Section 2 provides a brief literature review. Section 3 briefly describes the "What's My Number" campaign used to promote switching in New Zealand. Section 4 describes the method and provides a brief overview of choice experiment approach and describes in detail our choice experiment and survey development. Section 5 presents the empirical results, and Section 6 outlines our main conclusions.

2. Literature review

Early studies of consumer switching or preferences and WTP for the attributes of electricity services were conducted during the initial stages of deregulation of retail electricity markets. Their main objective was to provide insight on the attributes that would influence consumer switching, and how new entrants would affect incumbent retailer's market share (e.g., Cai et al., 1998; Goett, 1998; Goett et al., 2000; Revelt & Train, 2000). Since the market data required for this type of analysis was nonexistent, these studies relied on stated preference data generated from choice experiments (CEs), where each respondent was presented with several hypothetical, yet realistic offers by energy suppliers and asked to choose his/her preferred offer.

The stated preference approach has also been adopted in recent studies of consumer switching (e.g., Amador et al., 2013; Bae & Rishi, 2018; Cardella et al., 2017; Hensher et al., 2014; Kaenzig et al., 2013). However, some recent studies have adopted a different approach by using revealed preference data on consumers actual behaviour to investigate consumer switching in deregulated markets (e.g., Daglish, 2016; Giulietti et al., 2014; Hortaçsu et al., 2017; Rutter et al., 2018). The motivation for recent studies stems from observed consumer inertia across all jurisdictions with deregulated electricity markets, where switching rates are below expectation despite large price differences and reduced search costs (Giulietti et al., 2014). Both stated preference and revealed preference studies find that consumers attach significant value to non-price attributes which may play an important role in consumers' switching decisions. However, no stated preference study on consumer switching based on CEs has been conducted in New Zealand, a jurisdiction with the highest switching rates in the world.

The advantage of revealed preference over stated preference studies is that they use market data rather than responses to hypothetical questions. However, the main drawback of revealed preference studies on consumer switching is that market data on some relevant attributes is limited or missing, and variability of the data is also limited resulting in large sample sizes required to estimate the individual effects of the attributes. For example, data on consumer switching is often at an aggregate rather than individual-level and may not include all relevant attribute information considered by consumers in making their switching decisions, and/or individual-level socio-demographic characteristics of the consumers. Furthermore, revealed preference data does not include attitudinal data, such as, consumers' attitudes, perceptions and experiences which have been shown to be important determinants of consumer switching (see, Gamble et al., 2009). Consequently, revealed preference studies have focused mainly on price, brand value, search cost, market share, and average consumption. Although some revealed preference studies have included socio-demographic characteristics obtained by linking electricity meter addresses to census block group data (e.g., Daglish, 2016; Hortaçsu et al., 2017), none of these studies have included attitudinal variables in choice models.

Through carefully designed survey instruments, stated preference studies can cover a wider range of attributes, and collect accurate individual-level information on socio-demographic characteristics and attitudes (Johnston et al., 2017). However, few CE studies of consumer switching have included attitudinal data in the estimated models despite the wide acceptance of the notion that attitudes influence consumer behaviour. For example, Amador et al. (2013) use a Likert-type scale to measure "concern" about greenhouse gas emissions from electricity generation, and interact this variable with an attribute measuring the proportion of renewables in the fuel mix to explain differences in WTP for green electricity. The theoretical basis for this measure of "concern" and how the relevant attitudinal question is developed is unclear. Strazzera et al. (2012) combine data from a CE with psychometric scales to identify and explain factors that explain support for wind energy development. As in Amador et al. (2013), the statements used are not linked to any specific theory, which questions the validity of the attitudinal measures. However, a latent class analysis of their data shows that membership to preference classes depends on psychometric variables.

Hawcroft and Milfont (2010) show that the use of arbitrary constructs is pervasive and argue that this practice limits comparability of results from different studies. Our paper differs from these studies by using a psychological contract based on a well-established attitude-behaviour theory (see section 4.2). However, we adopt a similar approach to Strazzera et al. (2012) by estimating a latent class model in which attitudinal responses are used as explanatory variables in the class membership model rather than interactions with the attributes of alternatives.

Recent valuation studies in other fields show that measurement errors occur when scores/indicators obtained from Likert-type scales are used as direct measures of latent variables. The direct use of these indicators in choice models as interactions with design attributes raises endogeneity concerns (Hess & Beharry-Borg, 2012). The state-of-the-art approach to integrating attitudinal and choice data in discrete choice models involves the estimation of hybrid choice models. These models overcome the endogeneity problem by treating responses to attitudinal and choice questions as dependent variables driven by the same underlying latent variable(s) but are complex and come at a high computational cost.[2]

3. Consumer switching in New Zealand retail electricity markets

New Zealand introduced retail competition in 1998, under the Electricity Industry Reform Act 1998. The main objective of the Act was "to increase consumer choice, encourage innovation,

[2] A detailed discussion of hybrid model such as the integrated choice and latent variable model is beyond the scope of this paper. Readers interested in these models may refer to Hess and Beharry-Borg (2012), Ben-Akiva et al. (2002) for detailed discussions.

and ultimately result in lower prices than would otherwise be charged" (Electricity Authority, 2010, p. 3). In 2009, a ministerial review of the performance of the electricity market determined that consumer switching rates were insufficient to curb non-competitive behaviour by retailers and that the full benefits of retail competition had not yet been realised, particularly for domestic customers (Electricity Authority, 2010). It was observed that most electricity customers exhibited a tendency to stay with their default retailers even when cheaper competitors were available. The ministerial review also determined that consumers could be better off by as much as NZ$150 million per annum, in total savings, if they switched to the cheapest available retailer (Electricity Authority, 2011). The estimated welfare benefits from switching were large enough to justify the establishment of a public funded "Consumer Switching Fund" for NZ$15 million to promote switching (Electricity Authority, 2010) through the "What's My Number" campaign and related activities. In 2010 the estimated total benefit from switching to the cheapest retailer was NZ$240 million, reflecting rapidly increasing retail price differences. However, the above welfare benefit estimates were based on the seemingly unrealistic assumption of price convergence in retail electricity markets.

From 2011 to 2014 the "What's My Number" campaign was used as the main instrument for promoting switching. During this campaign period, consumers were made aware of their ability to switch and of the benefits (savings) from switching. The publicized benefits averaged NZ$150 per customer per year (Electricity Authority, 2011, 2012b). An independent one-stop-shop website called "Powerswitch" was revamped to provide consumers easy access to a single central switching service (Electricity Authority, 2010).

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

Several local studies were commissioned under the "Consumer Switching Fund" to provide Electricity Authority and Ministry of Consumer Affairs with research that underpins the Fund (see, Electricity Authority, 2010), and to assess the performance of the "What's My Number" campaign and "Powerswitch" website (Electricity Authority, 2011, 2012a, 2012b, 2013a, 2013b). These studies indicate that annual switching rates in New Zealand increased from

10.5% in 2009 to 20.8% in 2013. By 2011, New Zealand had the second highest switching rates in the world after Victoria, Australia, and became first in 2012-2014 (VaasaETT, 2013). New Zealand authorities attribute this increase in switching to the "What's My Number" campaign and related regulation, and to the market entry by several new suppliers. In New Zealand consumers can choose among 8 to 18 retailer brands depending on their region.

Although the above studies show an increase in switching activity during the campaign period, they also show that around 80% of consumers did not switch in any particular year, despite substantial savings in the market (see Table 1). Furthermore, the combined market share for the top five retailers (the 'Big 5') has remained high at 95%, similarly to most jurisdictions in Europe (see, Defeuilley, 2009; Giulietti et al., 2010) suggesting that consumer switching has been mainly between the 'Big 5'.

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

	Year			
	2011	2012	2013	2014
Average annual household savings (NZ$)	$165	$175	$155	$162
Switching rate	20.7%	19.1%	20.8%	22.7%
Potential national savings (NZ$ million)[1]	$280	$295	$267	$275

[1]Based on the assumption that all customers switched to the cheapest available retailer in their region (Source: Electricity Authority, 2013c, 2016)

At the time of this research, the Electricity Authority was consulting on ways to increase consumer propensity to switch, which indicated a need for more research into consumer preferences. Assuming reduced search cost due to "What's My Number" campaign and "Powerswitch" website and, high potential savings from switching, lower than expected switching rates, and results from reviewed international literature, we hypothesize that non-price attributes of electricity services are important determinants of switching (*Hypothesis I*). Cai et al. (1998) show that consumers switch supplier at different discount thresholds suggesting that a consumer will switch supplier when potential or perceived economic benefits exceed a certain threshold. Based on these findings, we postulate a non-linear marginal utility structure for power bill savings (*Hypothesis II*), which may, in part explain why some consumers have not switched supplier.

4. Methods.

In this paper we adopt a stated preference approach because market data is unavailable. The main stated preference approaches used in previous valuation studies are the contingent valuation method (CVM) and stated choice experiments (CEs). Both approaches elicit consumer preferences through hypothetical choices elicited by asking respondents to choose their preferred option among alternatives described in terms of attribute levels and price.

The stated CE technique is preferred to the CVM given the multi-attribute valuation context and objectives of this paper. This technique has been used in previous studies investigating WTP for the attributes of electricity services (e.g., Abdullah & Mariel, 2010; Amador et al., 2013; Goett et al., 2000; Kaenzig et al., 2013).

The model of consumer switching developed in this paper includes, among other variables, a psychological construct based on the theory of planned behaviour (Ajzen, 1988, 1991) to explain preference heterogeneity across preference classes. The theory of planned behaviour and its application is discussed in section 4.2.

4.1. An overview of choice experiments (CEs).

Stated CEs are widely used to study individual preferences in the fields of transportation, marketing, health and environmental economics, because of their ability to mimic decisions observed in real markets. Studies employing CEs provide insight regarding the determinants of consumer choice and allow researchers to introduce new attributes or even vary attribute levels beyond those available in the market.

Stated preferences are elicited using a series of constructed hypothetical choice situations in which two or more alternatives are described in terms of attribute levels and respondents are asked to select their preferred option (Adamowicz et al., 1995; Hanley et al., 2001; Louviere et al., 2000). The attribute levels of the alternatives, except for the status quo, are varied by the researcher, based on an experimental design, to provide the variation needed for estimating the underlying preference parameters.

To allow for the estimation of marginal WTP values for the attributes, a cost attribute is included in each alternative. By selecting the preferred alternative in each choice task, a respondent implicitly makes trade-offs between the attribute levels of alternatives (Bennett &

Adamowicz, 2001; Hensher et al., 2005; Louviere et al., 2000). The series of choices made by respondents give rise to a panel of discrete choices used in model estimation. Previous valuation literature provide evidence that experimental choice-based methodologies can produce accurate predictions of actual choice decisions (e.g., Burke et al., 1992; Huber & Zwerina, 1996; List et al., 2006).

Stated CEs allow researchers to uncover respondents' preferences for the attributes of a scenario rather than preferences for a specific scenario as a whole. Adamowicz et al. (1995) argue that the CE technique provides a richer description of the attribute trade-offs that individuals are willing to make compared to the CVM. The CE technique has a number of advantages over the CVM such as, smaller sample sizes, reduced strategic behaviour and "yea-saying", avoids explicit elicitation of respondents' WTP, and provides an internal scope test (see, Hanley et al., 2001; Holmes & Adamowicz, 2003; Willis, 2006). Its drawbacks include placing a heavier cognitive burden on respondents, as they are required to evaluate larger or more complex choice sets, and the high level of complexity involved in the experimental design. Cognitive burden on respondents may affect the quality of responses, which in turn affects the validity and reliability of the results.

A challenge with the CE technique involves the design of the CEs. Experimental design is the way in which the attribute levels of alternatives are set and structured into the choice sets (Bennett & Adamowicz, 2001). Experimental design is complex, time consuming, and can heavily influence the outcomes (validity and reliability) and conclusions of the research (see, Hensher et al., 2005; Louviere et al., 2008). Researchers rely on literature review, expert opinion and focus groups in developing their experimental designs (Johnston et al., 2017).

4.2. The theory of planned behaviour

We use a psychological construct based on the theory of planned behaviour to explain differences in switching behaviour among residential electricity consumers. The theory of planned behaviour posits that, a person's intention to perform a behaviour (behavioural intention, or BI) is the immediate determinant of that behaviour (Ajzen, 1988, 1991). Ajzen (1988, 2005) and, Ajzen and Fishbein (1980) provide a detailed discussion of the theory of planned behaviour. Based on this theory we postulate that an electricity consumer's intention to switch supplier (BI) is the immediate determinant of switching (i.e. behaviour), that is, we expect BI, among other variables, to explain differences in switching behaviour in the sampled population (*Hypothesis III*).

To develop the question and statement used to measure BI we followed the procedure recommended by Ajzen and Fishbein (1980) and (Ajzen, 1988). The question and statement used to assess BI are presented in Table 2. Response categories were points on a 7-point bipolar Likert scale.

Table 2: Question and statement used to measure behavioural intentions (BI).[1]

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

[1]Likert scale points were marked as "extremely unlikely, quite unlikely, slightly unlikely, neither likely nor unlikely, slightly likely, quite likely, extremely likely", and "strongly disagree, quite disagree, slightly disagree, neither agree nor disagree, slightly agree, quite agree, strongly agree" for 1 and 2 respectively. These points were coded as -3, -2, -1, 0, 1, 2, and 3, respectively.

4.3. Study design

4.3.1. Survey questionnaire

An online questionnaire was developed to collect the data required for this research. The first part of the questionnaire consisted of an introduction and screening questions. This was followed by questions eliciting information on socio-demographic characteristics, BI, and sensitivity to power bill savings, among others. BI was measured using a question and a statement, with responses marked on an evaluative semantic differential scale (see Table 2.) Sensitivity to power bill savings refers to the stated minimum level of power bill savings that would have been sufficient to induce switching supplier(s) in the past 24 months.

Sensitivity to power bill savings was ascertained for each respondent based on a series of questions similar to those used in the iterative bidding game format in contingent valuation studies. Initially all respondents were asked if they would have switched supplier in the past 24 months if they could have saved NZ$100 per year on their power bills. Respondents who answered "*No*" were progressively presented with NZ$100 increments in power bill savings as shown in Table 3. A set of indicator variables $Switch_d$ = ($Switch_1$, $Switch_2$, $Switch_3$, $Switch_4$) was used to capture responses (1 if *Yes,* 0 if *No*) to questions, 1, 2, 3, and 4, respectively.

Table 3: Consumer sensitivity to power bill savings.

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

Figure 1 shows the distribution of average annual power bill savings across 16 main regions in New Zealand during 2014. The selected range of values used to test sensitivity to power bill savings spans over the range of values achievable at the time the survey was conducted. Although the highest average savings was below NZ$350, higher values of NZ$400 and NZ$500 were used to test sensitivity of the most reluctant switchers.

The third part of the survey questionnaire elicited information on respondents' choices among experimentally designed alternatives followed by a debriefing section.

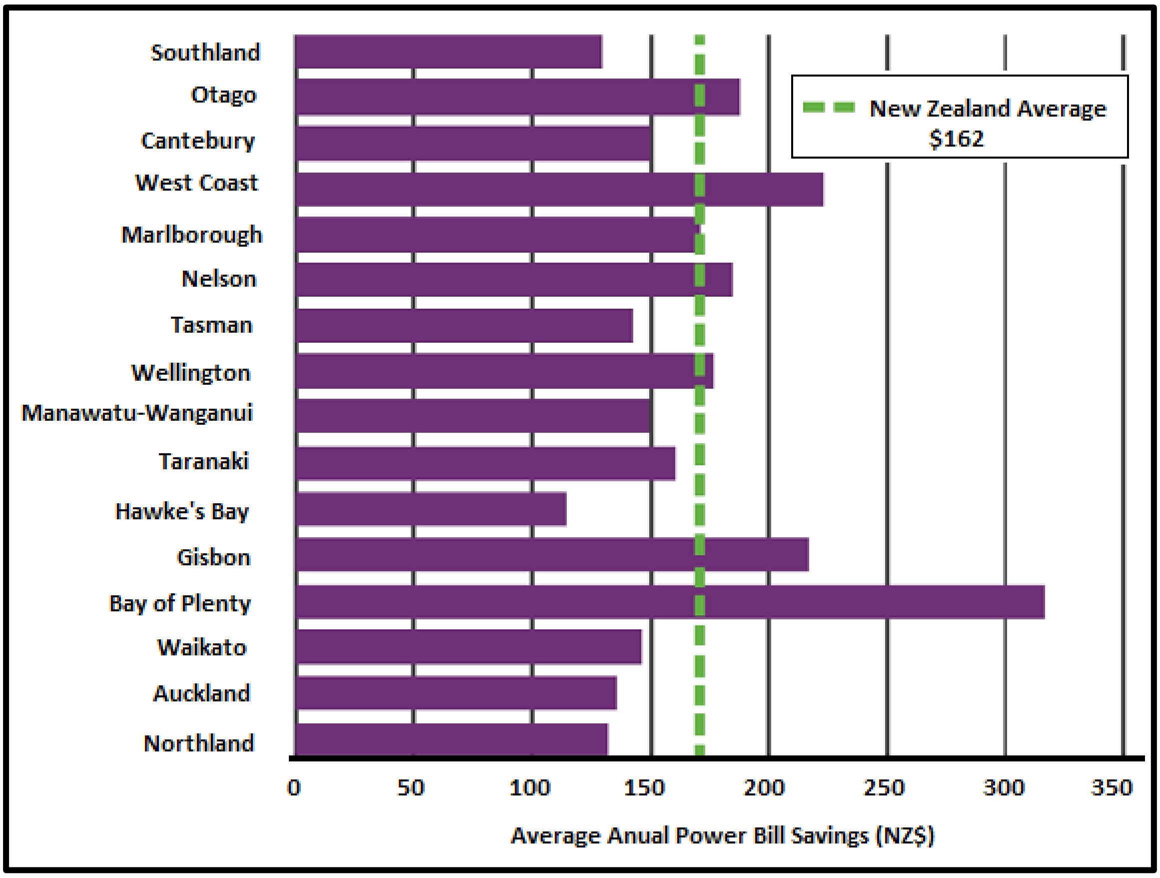

Figure 1: Average annual residential power bill savings in New Zealand during 2014.

(Source: Adapted from Electricity Authority, 2016).

4.3.2. Attribute selection and experimental design

In this study, residential electricity customers were presented with a series of 12 choice tasks, which were the same for all respondents. Each choice task consisted of three alternatives, a reference alternative (status quo) represented by an incumbent traditional retailer and two experimentally designed generic alternatives representing competitors, who were either new non-traditional entrants or other traditional retailers. Each task required respondents to decide whether to switch or not given the attribute levels of the alternatives.

The identification and selection of important attributes and attribute levels used in the experimental design (see Table 4) was based on previous New Zealand studies (e.g., Electricity Authority, 2010, 2011, 2012a; Ministry of Economic Development, 2005a), international literature review and four focus groups.[3] Results from the latter were similar to those from the nation-wide surveys. These studies used importance statements to identify and rank 15 most important attributes of electricity services considered by consumers in deciding to switch. The attributes used in the experimental design were selected from the 10 most important attributes identified in these studies and focus groups. The selected attributes fall into the following categories representing potential key drivers of switching in New Zealand: pricing and contract, loyalty rewards, local ownership of supplier, green energy attributes, customer service (call waiting time - *Time*), and supplier type. International literature also provides support for the selection of the attributes in our final list (e.g., Amador et al., 2013; Goett et al., 2000; Kaenzig et al., 2013).

[3] Focus groups consisted of 8-10 participants recruited through interception by the lead author at two locations in Hamilton East, New Zealand. To qualify, participants had to be at least 18 years old and be responsible for paying their power bills or have a say in choosing their electricity supplier.

Table 4: Attributes, attribute levels and design codes used to develop the experimental design.

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

Non-experimental design variables used in model estimation

Savings	Continuous variable measuring implied savings from switching from current supplier to a competitor
$Switch_1$*_Savings*	Interaction term between *Savings* and $Switch_1$
$Switch_2$*_Savings*	Interaction term between *Savings* and $Switch_2$
$Switch_3$*_Savings*	Interaction term between *Savings* and $Switch_3$
$Switch_4$*_Savings*	Interaction term between *Savings* and $Switch_4$
Behavioural Intention	This variable is the average score for BI as defined in Table 2

The attribute level range for each of the selected attributes was based on publicly available information on electricity retailers' websites. A list of these attributes was sent to all the major retailers who were asked to provide levels for each attribute. A unanimous response from retailers was that all attribute level information (except *Time*) was available on their respective websites. The range for *Time* was ascertained through repeated calls to retailers' customer service and recoding the time (minutes) it took to speak to a customer service representative. Average *Time* for each retailer was recorded, which provided the range used in the experimental design. The attribute level units for all attributes are based on similar previous studies. For example, the share of generation from renewables was measured as a percentage of the fuel mix (e.g., Amador et al., 2013; Borchers et al., 2007; Goett et al., 2000; Kaenzig et al., 2013), cost was measured as monthly power bill (e.g., Amador et al., 2013; Goett et al., 2000). Discount (e.g., Goett et al., 2000) and ownership (e.g., Electricity Authority, 2011) were measured as percentages, while fixed price contract was measured in months, and supplier type (e.g., Kaenzig et al., 2013) and loyalty rewards were dummy coded.

A sequential orthogonal design with three unlabelled alternatives was developed as an initial design using NGENE 1.1.0 software and tested on a focus group.[4] Experimental design literature provides detailed discussions of different types of designs and their pros and cons (e.g., Bennett & Adamowicz, 2001; Burgess & Street, 2003, 2005; Huber & Zwerina, 1996; Louviere et al., 2000).

An advantage of orthogonal designs is that they do not require any prior information about the parameters of the model. Their drawback is that they fail to utilize available information such as estimates of parameters from related studies (see, Ferrini & Scarpa, 2007; Huber & Zwerina, 1996; Scarpa & Rose, 2008) and plausible assumptions about the signs of the parameters. In this paper this design strategy is only used at the initial stage, later made more efficient by a sequential updating process in which a series of designs are generated and tested based on the cumulative information available at each stage. The sequential updating of the experimental design used a D-error minimizing homogenous pivot design for an MNL model where each

[4] A sequential orthogonal design is an orthogonal fractional factorial design approach where an orthogonal design for the first alternative is created and subsequent alternatives are generated by re-arranging the rows of the first alternative in such a way that the levels of any two attributes of an alternative are uncorrelated, i.e., orthogonal (ChoiceMetrics, 2012). A design is orthogonal if the sum of the inner product of any two design columns (or attributes) is zero, i.e., the attributes of the design are independent of each other or uncorrelated (Bliemer & Rose, 2011; ChoiceMetrics, 2012).

respondent faces the same reference alternative.[5] The design was tested on a pilot sample of 70 respondents drawn from an online panel of bill-payers. Data from the pilot survey was used to estimate an MNL model. For the final survey, the parameter estimates from the pilot survey were used as priors in a Bayesian D-error minimizing main effects design consisting of seven attributes with four levels each and one attribute with two levels[6]. A fractional factorial design was used to reduce the number of choice sets from 32,768 ($4^7 x 2^1$) to 12, which satisfied the degrees of freedom (11) for the design. Ferrini and Scarpa (2007) and Scarpa and Rose (2008) contend that Bayesian efficient designs are less sensitive to misspecification of the priors compared to designs based on fixed priors.

The final survey was administered in January 2014 to bill-payers sampled from an online panel managed by a leading market research company in New Zealand. A target sample of 224 usable responses was achieved overnight highlighting one of the appeals of crowd sourcing or online labour pools.[7] The experimental design described above was optimized for our sample size, which was constrained by a limited data collection budget. However, we took advantage of repeated sampling i.e., each respondent provided 12 data points resulting in 2,688 choice responses. Simulation of the experimental design revealed that a sample size of 200 was adequate for the identification of the individual effects of the attributes.

A drawback for online surveys is the incomplete and potentially biased sample frame since panel members are originally recruited through non-probabilistic methods, and the exclusion of large sections of the population particularly where internet penetration rates are low. New Zealand has an internet penetration rate of more than 84.5% and is ranked 12th in the world (Internet World Stats, 2012), which justifies the use of an online labour pool for this study[8]. Screening questions were used to ensure that participants met the following criteria: New Zealand resident, at least 18 years old, and responsible for paying the bills or had a say in choosing their electricity supplier. Quotas were set for age, gender, income, regional population

[5] Focus groups and pre-test revealed that participants had difficulty figuring out the exact attribute levels for their current supplier and that a homogeneous pivot design with a reference alternative described using the market average for the attribute levels would reduce the complexity of the choice tasks.
[6] Main effects designs do not include interaction terms.
[7] Usable responses include answers to the choice questions. Respondents who did not meet the screening criteria to participate were screed out before answering the choice questions. Their incomplete responses are not usable and are excluded from the sample.
[8] For detailed discussions on the pros and cons of crowd sourcing, interested readers are referred to recent studies such as Casey et al., (2017), Gosling and Mason (2015), Sharpe et al. (2017).

and ethnicity to ensure that a representative sample, based on NZ 2006 Census statistics, was drawn from the online panel.

Before answering the choice questions, respondents were advised that the scenarios were used to understand how people would switch from their electricity suppliers under different conditions. In each scenario, respondents were asked to compare two experimentally designed alternative suppliers, "Supplier A" and "Supplier B", with the status quo labelled as "Your Current Supplier", and indicate whether they would switch if conditions described in each scenario were to occur in a real choice situation. Figure 2 presents an example of a choice task.

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

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

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

4.4. Model specification

We use the multinomial logit (MNL) and latent class (LC) models to analyse the choice data (MNL is used as a base model). These models are based on the random utility maximization (RUM) theory (McFadden, 1974). Although integrated choice and latent variable models and mixed logit models account for unobserved heterogeneity of preferences, they do not identify preference classes. We use the LC choice model to identify latent groups with similar preferences. 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. When C = 1, the LC model collapses into an MNL.

We follow standard procedure and specify a class-specific utility function consisting of a deterministic component ($\boldsymbol{\beta}'_c \boldsymbol{x}_{int}$) related to the attributes of the supplier, which include the cost element, and a random component ($\varepsilon_{int|c}$) as follows (see, Boxall & Adamowicz, 2002; Walker & Ben-Akiva, 2002):

$$U_{int|c} = \boldsymbol{\beta}'_c \boldsymbol{x}_{int} + \varepsilon_{int|c} \quad (1)$$

where $U_{int|c}$ is the utility of supplier i to individual n in choice situation t conditional on class c membership; $\boldsymbol{x}_{int}$ is a matrix of all attributes of suppliers and socio-demographic characteristics that appear in all utility functions including an alternative-specific constant for the status quo (incumbent traditional supplier); $\varepsilon_{int|c}$ 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 supplier i in choice situation t conditional on class c membership; and $\boldsymbol{\beta}'_c$ is a class-specific parameter vector to be estimated.[9] Equation (1) assumes that respondents in each class have the same marginal utility of income and similar preferences with respect to non-price attributes. Omitting the subscript c from Equation (1) provides a utility function for the MNL.

The parameters of a standard 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 switches to supplier i can be expressed as a product of two probabilities (Kamakura & Russell):

$$P_{in} = \sum_{c=1}^{C} \left[\frac{\exp(\boldsymbol{\alpha}'_c \boldsymbol{S}_n)}{\sum_{\mathrm{c=1}}^{\mathrm{C}} \exp(\boldsymbol{\alpha}'_c \boldsymbol{S}_n)}\right] \left[\frac{\exp(\boldsymbol{\beta}'_c \boldsymbol{x}_i)}{\sum_{\mathrm{j=1}}^{\mathrm{J}} \exp(\boldsymbol{\beta}'_c \boldsymbol{x}_j)}\right], \text{ c} = 1, 2, \ldots, C; \; \alpha_C = 0; \; \forall \; i \neq j \quad (2)$$

where $\frac{\exp(\boldsymbol{\alpha}'_c \boldsymbol{S}_n)}{\sum_{\mathrm{c=1}}^{\mathrm{C}} \exp(\boldsymbol{\alpha}'_c \boldsymbol{S}_n)}$ is the c^{th} class membership probability of individual n with socio-demographic characteristics S_n including *BI*, defined parametrically using a multinomial logit as membership equation; $\boldsymbol{\alpha}'_c$ is a vector of class-specific parameters, which is a zero vector for

[9] Socio-demographic characteristics may enter the utility function as interactions with choice attributes or alternative-specific constants.

class C for identification; $\frac{\exp(\boldsymbol{\beta}'_c \boldsymbol{x}_i)}{\sum_{j=1}^{J} \exp(\boldsymbol{\beta}'_c \boldsymbol{x}_j)}$ represents the conditional probability of an individual n in class c switching to supplier i, and $\boldsymbol{\beta}'_c$ as defined before. Following Morey et al. (2006), we assume that class membership is a function of socio-demographic characteristics including behavioural intention (*BI*).[10] However, based on the basic Heckman and Singer model, the class-specific probabilities may be a set of fixed constants if no observable characteristics that help in class separation are observed (Heckman & Singer, 1984). The second term in Equation (2) provides the logit choice probability for the MNL model where subscript c is suppressed and the first term is equal to 1 since C = 1 in the case of an MNL model.[11]

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

$$\ln L = \sum_{n=1}^{N} ln \left[\sum_{c=1}^{C} \frac{\exp(\boldsymbol{\alpha}'_c \boldsymbol{S}_n)}{\sum_{c=1}^{C} \exp(\boldsymbol{\alpha}'_c \boldsymbol{S}_n)} \prod_{t=1}^{T} \frac{\exp(\boldsymbol{\beta}'_c \boldsymbol{x}_i)}{\sum_{j=1}^{J} \exp(\boldsymbol{\beta}'_c \boldsymbol{x}_j)} \right] \tag{3}$$

We maximize the likelihood with respect to the C structural parameter vector $\boldsymbol{\beta}'_c$ and the C-1 latent class parameter vector $\boldsymbol{\alpha}'_c$. Since the $\boldsymbol{\beta}_c$'s which include the coefficient of the cost element (monthly power bill) vary across classes, the LC model identifies heterogeneity in the consumers' values of the attributes of the suppliers, 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). 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.

To capture the systematic effect of consumer sensitivity to the level of savings on switching behaviour we modify the utility function in Equation (1) by employing an indirect utility specification similar to that suggested by Morey et al. (2003), which uses a piecewise linear formulation for the power bill savings parameter. In this formulation, the utility of savings is

[10] Including *BI* in the class membership probability in Equation (2) may introduce endogeneity bias. This is investigated by estimating an alternative model using a two-stage sequential approach in which fitted values of *BI* are used in the class membership model (e.g., Strazzera et al., 2012).
[11] All corresponding equations for the MNL model may be obtained from the LC model equations in this manner.

assumed to be a step function of power bill savings. This approach allows us to explore differences in preferences for consumers with different power bill savings sensitivities instead of estimating a single parameter for the savings variable, which would imply homogeneous preferences among customers (*Hypothesis II*). Nonlinear effects of continuous variables such as income have been studied in the past and the evidence suggests that incorporating such effects in random utility maximization models improves model fit and provides estimates of marginal utility of income that are more intuitive than assuming constant marginal utility (see, Goett et al., 2000; Herriges & Kling, 1999; Layton & Lee, 2006).

For respondent *n* in class *c* in choice situation *t*, the indirect utility function of supplier *i* is re-specified as:

$$U_{int|c} = \begin{cases} \gamma_{1c} Switch_1\_Savings_{int} + \boldsymbol{\beta}'_c \boldsymbol{x}_{int} + \varepsilon_{int|c} & if\ Switch_1 = 1;\ \forall\ Switch_d = 0 \\ \gamma_{2c} Switch_2\_Savings_{int} + \boldsymbol{\beta}'_c \boldsymbol{x}_{int} + \varepsilon_{int|c} & if\ Switch_2 = 1;\ \forall\ Switch_d = 0 \\ \gamma_{3c} Switch_3\_Savings_{int} + \boldsymbol{\beta}'_c \boldsymbol{x}_{int} + \varepsilon_{int|c} & if\ Switch_3 = 1;\ \forall\ Switch_d = 0 \\ \gamma_{4c} Switch_4\_Savings_{int} + \boldsymbol{\beta}'_c \boldsymbol{x}_{int} + \varepsilon_{int|c} & if\ Switch_4 = 1;\ \forall\ Switch_d = 0 \end{cases} \quad (1')$$

where $\gamma_{1c}, \ldots, \gamma_{4c}$ are the class-specific marginal utilities of savings for respondents who would switch supplier at NZ$100, NZ$200, NZ$300 and NZ$400+ levels of savings, respectively (see Table 3), $\boldsymbol{x}$ is a K×1 vector of non-price attributes including $x = 1$ for the alternative specific constant for the status quo alternative, $\boldsymbol{\beta}'_c$ and $\varepsilon_{int|c}$ are as defined before, and $d = 1, 2, 3, 4$.

Based on Equation (1′), we re-specify Equation (2) and (3) as follows:

$$P_{in} = \sum_{c=1}^{C} \left[\frac{\exp(\boldsymbol{\alpha}'_c \boldsymbol{S}_n)}{\sum_{c=1}^{C} \exp(\boldsymbol{\alpha}'_c \boldsymbol{S}_n)} \right] \left[\frac{\exp(\gamma_{dc} Switch_d\_Savings_i + \boldsymbol{\beta}'_c \boldsymbol{x}_i)}{\sum_{j=1}^{J} \exp(\gamma_{dc} Switch_d\_Savings_i + \boldsymbol{\beta}'_c \boldsymbol{x}_i)} \right],\ \mathrm{d} = 1, 2, 3, 4 \quad (2')$$

$$\ln L = \sum_{n=1}^{N} ln \left[\sum_{c=1}^{C} \frac{\exp(\boldsymbol{\alpha}'_c \boldsymbol{S}_n)}{\sum_{c=1}^{C} \exp(\boldsymbol{\alpha}'_c \boldsymbol{S}_n)} \prod_{t=1}^{T} \frac{\exp(\gamma_{dc} Switch_d\_Savings_i + \boldsymbol{\beta}'_c \boldsymbol{x}_i)}{\sum_{j=1}^{J} \exp(\gamma_{dc} Switch_d\_Savings_i + \boldsymbol{\beta}'_c \boldsymbol{x}_i)} \right] \quad (3')$$

5. Results

5.1. Sample statistics and behavioural intentions

Key demographic and income characteristics of our sample are presented in Table 5. Our sample resembles the national population in terms of gender, age-group, and income-group. The average personal income of respondents (NZ$45,000) is higher than the national average of NZ$37,500. The difference may be due to the inclusion of a low-income age-group (15-17 years) in the national average. In terms of ethnicity, *Maori* are under-represented whilst *NZ Europeans* are over-represented, which may also explain the higher sample average income as *NZ Europeans* are likely to earn more. The sample average monthly electricity bill is lower than the national average, which is expected as the national average is over winter and summer months, whereas the survey was conducted in summer.

Table 5: Sample statistics versus national population.

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

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

Responses to the behavioural intention (BI) statements listed in Table 2 are summarized in Figure 3. The results show that at least 31% of respondents expressed no intentions of switching supplier in the next 12 months indicating the presence of “consumer stickiness”. On average, 38% intended to switch. This percentage is slightly higher than the most recent observed switching rate of 30% indicating a possibility for higher switching rates in the future. Only 21% of respondents had switched supplier in the past 24 months. The average score for BI is -0.02, indicating that on average respondents are neutral to switching and that higher switching rates may be achieved through switching campaigns aimed at changing consumers' behavioural intentions towards switching. In the next subsection, the individual BI scores are used in the class membership equation and improve the LC model.[12]

1. How likely or unlikely is it that you will switch to a supplier offering a better package of price and services in the next 12 months?	2. I intend to switch to a supplier offering a better package of price and services in the next 12 months.

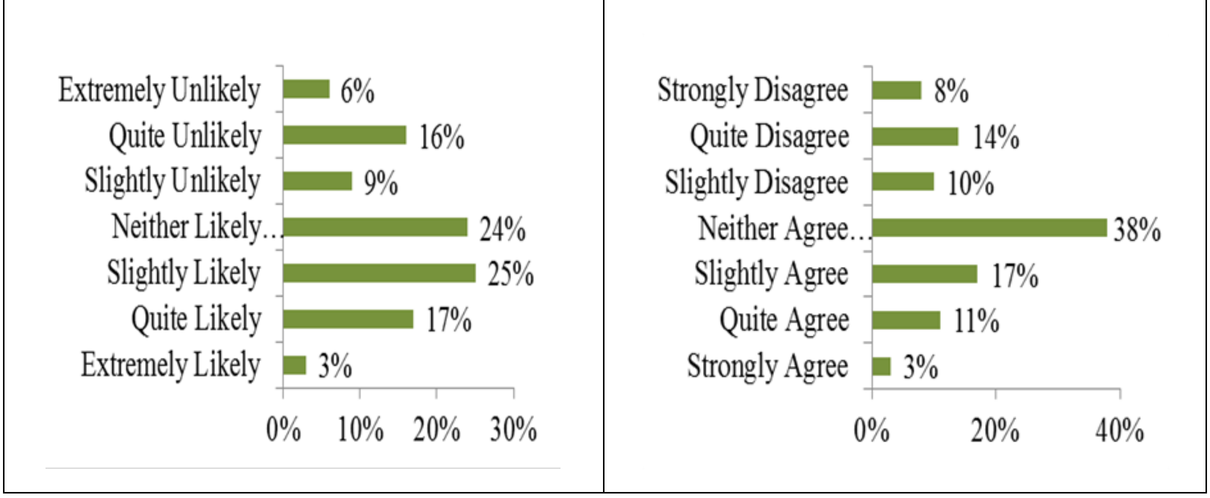

Figure 3: Distribution of responses on behavioural intentions (BI).

5.2. Estimation results

Preliminary estimations of the LC models with socio-demographic characteristics in the class membership model revealed that these variables are poor predictors of membership of preference class. Estimation results for the final estimated models are presented in Table 6. Model (M1) is the standard MNL model. Models (M2) and (M3) are LC models. M2 and M3 differ in that the class membership sub-model in M2 is the Heckman and Singer (1984) model, which assumes that all parameters are the same across classes except for the class-specific constants, whilst the psychological construct BI is used to sharpen class membership in M3. Models M1 and M2 are used for comparison purposes and testing hypotheses *II* and *III*. All three models are based on the utility function specified in Equation (1′) to account for individual sensitivity to power bill savings.[13]

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[12] To account for the panel nature of the choice dataset, a panel LC model is estimated. The log-likelihood maximized is for the panel of discrete responses, which are hence correlated by the same utility coefficients, so correlation across responses by the same individual is accounted for and no clustering is necessary.
[13] The results of an MNL model (M0) and LC model (M4) based on the utility function specified in Equation (1) which assumes a single parameter for power bill savings are presented in Table B.1 in the Appendix.

The models were estimated using NLOGIT 5 software, and the data was coded for attribute non-attendance to account for ignored attributes as recommended in the literature (see, Hensher et al., 2012).

As previously noted, the number of classes retained in a latent class model "is exogenously defined and outside the space of estimable parameters" (Scarpa & Thiene, 2005, p. 434), hence we base our model selection on information criteria and other factors such as the pattern of significant parameters and relative signs, ease of interpreting the results, parsimony and the need to avoid over-fitting the model. Information criteria indicate the presence of three or four classes with clearly distinct preferences for the attributes of electricity services. The CAIC and BIC indicate that only three classes may be retained whilst Hannan-Quinn information criterion (HQC), AIC, crAIC and CAIC3 indicate four classes (see Appendix A). The model with three classes is selected based on CAIC and BIC, which have been found to have a tendency of lower over-fitting rate (Andrews & Currim, 2003).

The models fit the data well with pseudo-R^2 values ranging from 0.294 to 0.431. M3 performs better than M1 and M2 in terms of LL, AIC, pseudo-R^2, and the likelihood ratio test ($\chi^2_{(30\text{ d.f.})} = 788$ and $\chi^2_{(2\text{ d.f.})} = 10.30$ against M1 and M2 respectively), but performs marginally worse than M2 based on BIC. Better performance of M3 over M2 indicates that the inclusion of behavioural intention (*BI)* in the class membership sub-model significantly improves model fit and provides support for inclusion of *BI* information.

Models M1 and M2 with nonlinear effects specification for *Savings* perform better than their counterpart linear effects models M0 and M4, respectively. These results provide strong support for the utility specification presented in Equation (1′). Considering M1 and M0, the null Hypothesis II of a single coefficient for *Savings* is rejected based on the Wald test of linear restrictions with χ^2 = 123.62 and p-value = .0001. Furthermore, M3 out-performs its counterpart M5 with a utility function specified in Equation (1).[14]

To address endogeneity concerns due to the use of *BI* in the class membership equation in M3, an alternative LC model M6 was estimated using fitted values for *BI* obtained from an ordered Probit model with socio-demographic characteristics as explanatory variables. Socio-demographic characteristics were found to be poor predictors of *BI.* The coefficients of *BI* are all highly insignificant in M6, which performs worse than M3, the preferred model.

[14] Results for M5 and M6 are presented in Table B.2 in the Appendix.

Table 6: MNL and LC model regression results (t values are in parentheses) (N =224)

	MNL (M1)	LC Model (M2)			LC Model with BI (M3)		
		Class			*Class*		
		1	2	3	1	2	3
ASC_SQ (traditional supplier)	0.608^{c}	0.832^{c}	0.088	2.854^{c}	1.053^{c}	0.102	2.550^{c}
	(7.97)	(2.58)	(0.77)	(6.36)	(2.60)	(0.90)	(6.68)
Time	-0.041^{c}	-0.090^{c}	-0.027^{c}	-0.074^{b}	-0.096^{c}	-0.029^{c}	-0.033
	(-5.50)	(-2.83)	(-2.89)	(-2.06)	(-2.80)	(-2.96)	(-1.12)
Fixed	0.005^{b}	0.023^{b}	0.007^{b}	-0.023^{a}	0.021^{b}	0.009^{c}	-0.028^{b}
	(2.46)	(2.41)	(2.20)	(-1.91)	(2.11)	(2.97)	(-2.25)
Rewards	0.409^{c}	0.142	0.491^{c}	0.881^{b}	0.035	0.479^{c}	1.076^{c}
	(5.67)	(0.59)	(4.53)	(2.42)	(0.15)	(4.51)	(2.85)
Renewables	0.009^{c}	0.006	0.013^{c}	0.016^{c}	0.005	0.013^{c}	0.013^{b}
	(7.29)	(1.45)	(7.81)	(2.58)	(0.95)	(7.84)	(2.19)
Ownership	0.009^{c}	0.020^{c}	0.012^{c}	0.033^{c}	0.020^{c}	0.012^{c}	0.025^{c}
	(6.96)	(4.36)	(6.35)	(3.83)	(4.01)	(6.46)	(3.31)
New electricity company	-0.364^{c}	-0.317	-0.221	-1.158^{b}	-0.483	-0.172	-0.641^{a}
	(-3.77)	(-0.94)	(-1.60)	(-2.32)	(-1.29)	(-1.24)	(-1.67)
New non-electricity company	-0.667^{c}	-0.052	-0.745^{c}	-2.397^{c}	-0.136	-0.663^{c}	-1.538^{b}
	(-5.35)	(-0.13)	(-4.34)	(-2.94)	(-0.33)	(-3.85)	(-2.49)
Well-known non-electricity company	-0.386^{c}	0.250	-0.336^{b}	-1.080^{b}	0.155	-0.271^{a}	-0.573
	(-3.32)	(0.48)	(-2.18)	(-2.01)	(0.26)	(-1.74)	(-1.16)
Switch$_1$_Savings [γ_1]	0.033^{c}	0.097^{c}	0.024^{c}	0.025^{c}	0.101^{c}	0.024^{c}	0.021^{c}
	(30.02)	(9.37)	(13.91)	(4.01)	(8.69)	(14.23)	(3.60)
Switch$_2$_Savings [γ_2]	0.025^{c}	0.083^{c}	0.016^{c}	0.038^{c}	0.085^{c}	0.013^{c}	0.045^{c}
	(16.86)	(7.15)	(7.76)	(5.43)	(6.78)	(5.95)	(7.53)
Switch$_3$_Savings [γ_3]	0.019^{c}	0.057^{c}	0.009^{b}	0.028^{c}	0.072^{c}	0.013^{c}	0.022^{c}
	(9.10)	(5.43)	(2.17)	(3.13)	(3.91)	(3.54)	(2.73)
Switch$_4$_Savings [γ_4]	0.013^{c}	0.052^{c}	0.011^{c}	0.004	0.054^{c}	0.012^{c}	0.001
	(7.18)	(6.11)	(3.00)	(0.52)	(5.31)	(3.09)	(0.14)
Class probability model							
Constant					1.240^{c}	1.339^{c}	0.0
					(4.71)	(5.04)	(Fixed)
Behavioural Intention (BI)					0.372^{b}	0.569^{c}	0.0
					(2.06)	(3.05)	(Fixed)
Class Probability		0.416^{c}	0.459^{c}	0.125^{c}	0.405	0.456	0.139
Model fit							
K	13		41			43	
LL	-2075.05		-1686.19			-1681.04	
AIC	4176.1		3454.4			3448.1	
CAIC	4265.8		3455.7			3744.6	
BIC	4252.8		3696.1			3701.6	
McFadden Pseudo-R^2	0.294		0.429			0.431	

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

All parameters for non-price attributes are significant at the 5% level in at least one of the classes in M3 indicating that non-price attributes are significant determinants of switching. The null Hypothesis I is rejected at the 5% level of significance. The results from all the models show how each attribute contributes to explaining the variation in choices observed within the sample. M3 results show that each class has its own set of utility functions, which differ from other classes in terms of the values and/or signs of parameter estimates and the variables that enter the utility functions – i.e., choices are determined by different sets of variables with their corresponding class-specific parameters. Membership probabilities for classes 1, 2, and 3 are about 40%, 46%, and 14%, respectively. Membership is probabilistic rather than deterministic and all results and following discussion should be interpreted in this perspective.

The estimated parameters are interpreted as taste intensities or average marginal effects on the non-stochastic or deterministic component of indirect utility. These are also the same parameters of the nonlinear logit probabilities of alternatives. As such, the parameter estimates have no straightforward behavioural interpretation beyond their significance and signs, which indicate whether a variable of interest has a positive or negative influence on utility or choice probabilities (Hensher et al., 2005).

Taste intensities for *Savings* (γ_1, γ_2, γ_3, and γ_4) decrease in each preference class (except class 3 where $\gamma_2 > \gamma_1$) as sensitivity to power bill savings falls, which provides theoretical validity to the model. The counter intuitive result ($\gamma_2 > \gamma_1$) in class 3 implies that respondents with a higher savings threshold ($200) for switching are more sensitive to power bill savings than respondents with lower savings thresholds ($100). This suggests that respondents in class 3 who answered "*Yes*" to switching at $100 may have displayed a form of "yea saying", because their choices over the choice tasks indicate lower sensitivity to savings as evidenced by a lower value estimate of γ_1. In classes 1 and 2 (at least 86% of the market), the relative magnitudes of the *Savings* coefficients suggest consistency between respondents' choices and responses to the question probing sensitivity to power bill savings. This provides further evidence in support of Hypothesis II that $\gamma_1 > \gamma_2 > \gamma_3 > \gamma_4$; that is, respondents with lower savings thresholds for switching have higher marginal utilities of power bill savings than those with higher savings thresholds.

5.2.1. Class membership and behavioural intentions

All parameter estimates in the class probability model are significant at the 5% level. For identification purposes, all membership equation parameters in class 3 are normalized to zero as they act as a reference point for identification of the coefficients for the other two classes' membership equations. The constants in classes 1 and 2 are positive indicating the average influence of unobserved effects on class membership relative to class 3. The coefficient for behavioural intention (*BI)* is positive in classes 1 and 2 indicating that respondents who intend to switch supplier (potential switchers) have a higher likelihood of belonging to these classes compared to class 3. This makes sense as class 3 is characterized by large inertia and lower sensitivity to power bill savings. Furthermore, the coefficient for *BI* is largest in class 2, implying that potential switchers have the highest likelihood of belonging to this class, indicating consistency between the class probability model and the choice model.

Apart from improving model fit, the inclusion of *BI* in the class membership model influences the relative sizes of the market segments. For example, class membership probabilities of classes 1 and 2 fall slightly by 2.64% and 0.65%, respectively, whilst that of class 3 increases by 11.2%. This higher probability for class 3 brings it closer to estimates from previous studies in New Zealand that identify a similar preference class with a probability of 18-23% (Electricity Authority, 2011, 2012a, 2013a, 2015). A plausible speculation that is consistent with these findings is that the inclusion of *BI*, a psychological construct based on the theory of planned behaviour, improves the characterization of heterogeneity of preferences and that endogeneity effects, if any, caused by the use of *BI* may have been small.

5.2.2. Preference classes for the attributes of electricity services

We label class 1 representing about 40% of the market as "*Bargain hunters*" because they are most sensitive to power bill savings, call waiting time and prefer longer fixed rate contracts on good deals (lower power bills). "*Bargain hunters*" have positive preferences for the status quo (current supplier), which indicates switching inertia - i.e., they will only switch when power bill savings exceed a certain minimum threshold. A positive preference for local ownership of supplier implies that, all things being equal, "*Bargain hunters*" would switch to suppliers with higher local ownership. These consumers are more likely to respond to campaigns like "What's My Number" for higher savings and price guarantee, but would require information on local ownership of supplier to make optimal switching decisions.

Respondents in Class 2, representing 46% of the market are labelled as "*Potentially mobile but discerning*" because they exhibit no loyalty to their current supplier and value all the attributes. They dislike longer call waiting time and non-traditional power companies, and have positive preferences for fixed rate contracts, loyalty rewards, renewables and local ownership of supplier. This potentially mobile market segment is a challenge to retailers who want to retain or increase market shares as more factors influence switching behaviour. On the other hand, this class offers retailers an opportunity to compete in different ways based on marginal rates of substitution between attributes. For example, a supplier may price above competitors and still retain market share by offering commensurate increases (decreases) in non-price attributes for which respondents have a positive (negative) preference. Since all the design attributes influence switching in this market segment, this provides support for Hypothesis I.

Class 3, labeled as "*Captive and loyal*", represents the smallest market segment (14% of the market) characterized by a large inertia or strong preference for the status quo, negative preference for fixed rate contracts and indifference to call waiting time. Large inertia exhibited by "*Captive and loyal*" customers implies that only large changes in non-price attributes or unpleasant experience with the incumbent may induce switching. Some respondents in this class will not switch supplier for any level of power bill savings, i.e., $\gamma_4 = 0$, creating a challenge for regulators and an opportunity for retailers to behave non-competitively.

The observed preference for the status quo by "*Bargain hunters*" and "*Captive and loyal*" customers implies switching inertia and is consistent with reference-dependent utility theories (Kahneman et al., 1991; Kahneman & Tversky, 1979; Samuelson & Zeckhauser, 1988). Other reasons for the status quo effect often proffered in the literature include loss aversion (Kahneman & Tversky, 1979), regret avoidance (Samuelson & Zeckhauser, 1988), loyalty to the incumbent (Gamble et al., 2009; Gärling et al., 2008), and choice task complexity.[15]

5.2.3. Summary of the preference classes and characteristics of respondents

A summary of the three latent preference classes described in the previous is presented in Table 7. Table 8 presents the characteristics of respondents with a high probability of membership in

[15] We expect the effect of choice task complexity to have been small because less than 2% of respondents rated their understanding of the choice tasks below 'fair', while 13% rated "How easy was it to make your choices in scenarios 1 to 12?" as either 'difficult or somewhat difficult', and none rated it as 'very difficult'.

each class. Identifying the socio-demographic characteristics and attitudes of respondents in each segment is important for policy targeting, customer profiling and marketing.

Table 7: Summary of preference classes

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

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

"*Bargain hunters*" consists of younger retail customers (44 years) with the highest average annual personal income (NZ$48,200), highest switching rate (28%) and highest likelihood of having dependent children (48%). They are more likely to have larger households and better education compared to other groups, which may explain the observed high sensitivity to power bill savings and high switching rate. "*Bargain hunters*" have the lowest environmental attitude core, which may explain why they do not care about renewables. It is interesting to note that their average behavioral intention (BI) score of -0.08 is very close to zero and may have been influenced by the higher proportion of respondents who switched supplier in the past two years. This may explain the positive yet relatively weaker preference for the status quo compared to Class 3.

"*Potentially mobile but discerning*" customers exhibit no loyalty to the incumbent, express a positive intention to switch supplier (*BI* = 0.3), and would choose a retailer based on the value of all attributes. This group is dominated by women (54%), has lower average income than "*Bargain hunters*", and has the highest average environmental attitude score (54.03) hence the positive preference for renewables. This is consistent with findings from previous studies that women tend to have stronger pro-environmental attitudes than men (e.g., Clark et al., 2003; Ek & Soderholm, 2008). "*Captive and loyal*" customers exhibit very strong preferences for incumbent traditional supplier, loyalty rewards, and local ownership of supplier. They have the highest average age, lowest income, smallest household size and are least sensitive to power bill savings.

Table 8: Characteristics of respondents in each class

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

In the next section we estimate WTP for non-price attributes based on regression results for models M1 and M3 discussed in section 4.2.

5.3. Estimating WTP for non-price attributes

Based on standard practice, the average marginal WTP for each non-price attribute (k) is calculated as the ratio of the marginal utility of the attribute to the marginal utility of power bill savings as indicated below:

$$WTP_k = \frac{\frac{d}{dx_k}(\lambda\beta_k x_k)}{\frac{d}{dx_S}(\lambda\gamma_d S)} = \frac{\beta_k}{\gamma_d}\ , \qquad d = 1, 2, 3, 4 \tag{4}$$

where S is the *Switch*$_d$*_Savings* variable defined previously and λ is a scale parameter. The marginal utilities of the attributes are the first partial derivatives of the utility function with respect to each attribute, which turn out to be the parameter estimates presented earlier in Table 6 because the non-stochastic component of indirect utility is specified as a linear function. From Equation (4), WTP is scale free and can be compared across models and datasets. Marginal WTP estimates are presented in Table 9. The columns under each model and/or class heading labelled as γ_1, γ_2, γ_3, and γ_4 represent the four groups of respondents who would switch supplier at savings levels of NZ$100, NZ$200, NZ$300, and NZ$400+, respectively. Since there are four parameters for the *Savings* variable, WTP for each attribute is based on each estimate of γ. The delta method was used to compute the standard errors for WTP.

Table 9: WTP for non-price attributes of electricity services (NZ$$_{2014}$).[1]

	MNL (M1)				Latent Class Model (M3)										
					Class 1 *(Bargain hunters)*				Class 2 *(Mobile and discerning)*				Class 3 *(Captive and loyal)*		
	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3	γ_4	γ_1	γ_2	γ_3
Time	-1.24	-1.61	-2.16	-3.17	-0.95	-1.14	-1.34	-1.78	-1.20	-2.14	-2.29	-2.47	*NS*[2]	*NS*	*NS*
	(0.22)	(0.31)	(0.45)	(0.72)	(0.31)	(0.43)	(0.53)	(0.72)	(0.41)	(0.81)	(1.01)	(1.14)			
Fixed	0.16	0.21	0.28	0.42	0.21	0.25	0.30	0.39[a]	0.39	0.70	0.75	0.81	-1.36	-0.64	-1.30[a]
	(0.07)	(0.09)	(0.12)	(0.18)	(0.10)	(0.13)	(0.16)	(0.22)	(0.14)	(0.28)	(0.33)	(0.37)	(0.67)	(0.27)	(0.70)
Rewards	12.42	16.22	21.73	31.91	*NS*	*NS*	*NS*	*NS*	19.87	35.61	38.07	41.04	51.32	24.17	49.26
	(2.17)	(3.00)	(4.44)	(7.01)					(4.45)	10.01)	(14.06)	(16.80)	(22.84)	(9.35)	(24.59)
Renewables	0.28	0.36	0.48	0.71	*NS*	*NS*	*NS*	*NS*	0.53	0.96	1.02	1.10	0.60	0.28	*0.58*[a]
	(0.04)	(0.05)	(0.08)	(0.14)					(0.08)	(0.19)	(0.32)	(0.38)	(0.31)	(0.13)	*(0.32)*
Ownership	0.29	0.38	0.51	0.75	0.19	0.23	0.27	0.36	0.51	0.91	0.97	1.05	1.17	0.55	1.12
	(0.04)	(0.06)	(0.09)	(0.14)	(0.04)	(0.05)	(0.09)	(0.09)	(0.08)	(0.19)	(0.30)	(0.37)	(0.37)	(0.15)	(0.43)
New electricity	-11.04	-14.41	-19.30	-28.35	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*	*NS*	-30.57[a]	-14.40[a]	-29.35[a]
company	(2.88)	(3.81)	(5.30)	(8.23)									(18.59)	(8.39)	(18.00)
New non-electricity	-20.26	-26.46	-35.44	-52.05	*NS*	*NS*	*NS*	*NS*	-27.50	-49.28	-52.68	-56.78	-73.36	-34.54	-70.40
company.	(3.84)	(5.16)	(7.57)	(12.16)					(7.27)	(14.81)	(20.17)	(23.72)	(33.73)	(13.93)	(35.13)
Well-known non-	-11.74	-15.33	-20.53	-30.15	*NS*	*NS*	*NS*	*NS*	-11.24[a]	-20.15[a]	*NS*	*NS*	*NS*	*NS*	*NS*
electricity company.	(3.51)	(4.65)	(6.44)	(9.95)					(6.46)	(11.99)					
Class Probability					40%				46%				14%		

[1]NZ$1 = US$0.8389. [2]*NS* indicates that WTP is not statistically different from zero based on the respective parameter estimates which are insignificant even at the 10% level. [a] Significant at the 10% level.

Note: figures in parentheses are the standard errors. The column for γ_4 is omitted in class 3 as the coefficient of *Switch$_4$_Savings* is highly insignificant and WTP may not be estimated.

WTP estimates based on the MNL model (M1) are significant at the 5% level, indicating that respondents value all the attributes of electricity services irrespective of the level of sensitivity to savings. Preferences for non-price attributes become stronger as sensitivity to bill savings falls, i.e. respondents who would only switch supplier for at least NZ$400 in power bill savings and those who would not switch based on any of the investigated level of savings value non-price attributes of electricity services the most, followed by those who would switch at NZ$300. The absolute values of WTP for all non-price attributes increase from γ_1 to γ_4.

Model M1 results suggest that respondents with a strong preference for non-price attributes of electricity services are less likely to switch supplier on the basis of power bill savings alone. This has substantive implications for policies designed to promote switching in retail electricity markets. Negative WTP for non-traditional suppliers indicates that these suppliers have to charge lower prices. For example, new electricity companies have to charge at least NZ$133 per year less than traditional suppliers, whilst new non-electricity companies and well-known non-electricity companies have to charge at least NZ$224 and NZ$141 less, respectively. These amounts exclude the status quo effect or incumbent value of NZ$18.42 per month and apply to about 62% of respondents who are the most sensitive to power bill savings. This demonstrates that even where only the most savings-sensitive consumers are considered, price convergence in retail electricity markets is unlikely, and partly explains why switching rates are lower than expected. The incumbent value estimate of NZ$18.42 supports findings by Hortaçsu et al. (2017) where the incumbent value was less than US$16 after five years of deregulation in Texas, USA.

WTP estimates based on the LC model (M3) provide insight into the preferences of consumers in three segments of the retail market and allow for possible product designs and policies targeted at specific market segments. For example, any supplier type offering low call waiting time, longer fixed rate contracts and higher local ownership may target the market segment represented by "*Bargain hunters*" (40%). Estimates of marginal WTP for *Rewards*, *Renewables*, and *Supplier type* are not significantly different to zero for "*Bargain hunters"* indicating that improvements in the levels of these attributes would not induce switching. Furthermore, "*Bargain hunters*" have the lowest WTP for non-price attributes of electricity services. They are willing to pay an extra NZ$4.75 to NZ$9.00 per month to a retailer offering 25% more local ownership compared to NZ$12.75 to NZ$26.25 for "*Potentially mobile but* *discerning*", *ceteris paribus*[16]. These results are consistent with estimates from a revealed preference study by Daglish (2016), which showed that consumers are willing to pay a premium of NZ$16.79 per month for a 50% increase in local ownership.

The upper value for each range of WTP in each class only applies to a small proportion of the market consisting of customers who would only switch supplier at annual savings level of at least NZ$400 and those who would not switch for any level of savings. Campaigns such as "What's My Number" that promote switching based on price differences are likely to be effective when targeted at "*Bargain hunters*".

"*Potentially mobile but discerning*" consumers are willing to pay on average between NZ$19.87 and NZ$41.04 more per month to a supplier offering loyalty rewards and between NZ$5.30 and NZ$11.00 to secure a 10% increase in renewables in their fuel mix. For an increase of 10% in local ownership these respondents are willing to pay between NZ$5.10 and NZ$10.05 more per month. A retailer offering a 24 months fixed rate contract may charge between NZ$9.36 and NZ$19.44 more per month, compared to similar retailers offering variable rate contracts, without losing its customers. Informing these consumers that switching to competitors would save them between NZ$112 and NZ$233 per year would not result in any switches if these competitors are not offering at least 24 months fixed rate contracts.

To attract "*Potentially mobile and discerning*" consumers, non-electricity companies entering the retail market have to charge between NZ$135 and NZ$681 less per year compared to traditional suppliers. A retailer able to reduce call waiting time by 5 minutes may charge between NZ$6 and NZ$12.35 more per month without losing its market share, other things being equal. These results indicate that for 46% of the market, substantial price differences in the retail market may not induce switching as these differences may reflect the value and level of provision of non-price attributes across competitors. These WTP values indicate potential for niche markets where retailers can offer differentiated product services at a premium. Furthermore, these values suggest that switching campaigns that rely mainly on publicizing price differences may be ineffective on at least 46% of the market.

[16] The WTP amounts are obtained by multiplying the marginal WTP estimates presented in Table 9 with the respective changes in the level of the attributes. This assumes constant marginal WTP, which may be criticised as evidence of lack of scope sensitivity, an issue that is well documented in the literature. However, we use relatively small changes which are likely to be realistic and less likely to be seriously affected by lack of scope sensitivity if any.

The absolute values of marginal WTP estimates for "*Captive and loyal*" consumers (14%) tend to be higher than those of respondents in other classes except in the case of renewables in Class 2. This is expected as Class 2 has a higher average environmental attitude score than Class 3. The negative preference for fixed rate contracts means that retailers offering 24-month fixed rate contracts would have to charge between NZ$15.36 and NZ$32.64 less per month to retain customers in this market segment. A new non-electricity company would have to charge between NZ$414 and NZ$880 less per year in order to attract "*Captive and loyal*" customers compared to traditional retailers. These amounts are above the average annual savings publicized during the switching promotion campaign in New Zealand indicating that consumers in this market segment are unlikely to switch supplier under current market conditions.

5.4. Switching Inertia

For 60% of the market (Class 2 and Class 3), the marginal WTP estimates for supplier type clearly indicate that incumbent traditional retailers enjoy large premiums in the market. This offers one possible explanation for the observed price dispersion in the retail electricity markets in New Zealand, and why despite of the entry of more than 18 non-traditional retailers, the "*Big 5*" still dominate the retail electricity markets.

6. Conclusions

We estimated a discrete choice model of consumer switching in retail electricity markets in New Zealand using data from a choice experiment. Our results are strongly consistent with Hypothesis I, that non-price attributes are important determinants of consumer switching in deregulated electricity markets; clearly price is *not* all that matters. Latent class model results indicate the presence of three preference classes characterised as "*Bargain hunters*" (40%), "*Potentially mobile but discerning*" (46%), and "*Captive and loyal*" (14%). Policy implications of these findings are: (1) switching promotions should provide consumers information on the levels of non-price attributes, and (2) policies may be tailored for specific consumer groups. The presence of market segments provides retailers opportunities to differentiate their products. The results support the specification of a non-linear marginal utility structure in the model used to analyse the data (*Hypothesis II*) which may, in part, explain why some consumers do not switch supplier. For example, consumers with low marginal utility of power bill savings are unlikely to switch at prevailing market average savings.

The inclusion of behavioural intentions (BI) in the class membership sub-model improves both the characterisation of market segments and model fit, highlighting the importance of including attitudes in models of consumer switching (*Hypothesis III*). Respondents with high BI scores are more likely to belong to "*Bargain hunters*" or "*Potentially mobile but discerning*" group compared to "*Captive and loyal*".

When WTP for non-price attributes of electricity services is taken into account, the market average level of savings may be inadequate to induce some respondents to switch from traditional suppliers to new entrants. These findings offer one possible explanation why, despite the increase in the number of new retailers, the top five traditional retailers in New Zealand continue to dominate the retail market. Non-price attributes may partly explain the perceived 'stickiness' or inertia in retail electricity markets where the price or the level of savings are assumed to be the only drivers for consumer switching. Therefore, from a competition policy perspective, price dispersion should be seen as a natural aspect of a market where consumers value non-price attributes, have a preference for the status quo (traditional supplier), and a dislike for new entrants particularly non-traditional suppliers.

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APPENDICES

Appendix A. Information criteria and segment retention for M3

Table A.1. Information criteria used to determine the number of classes in M3

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

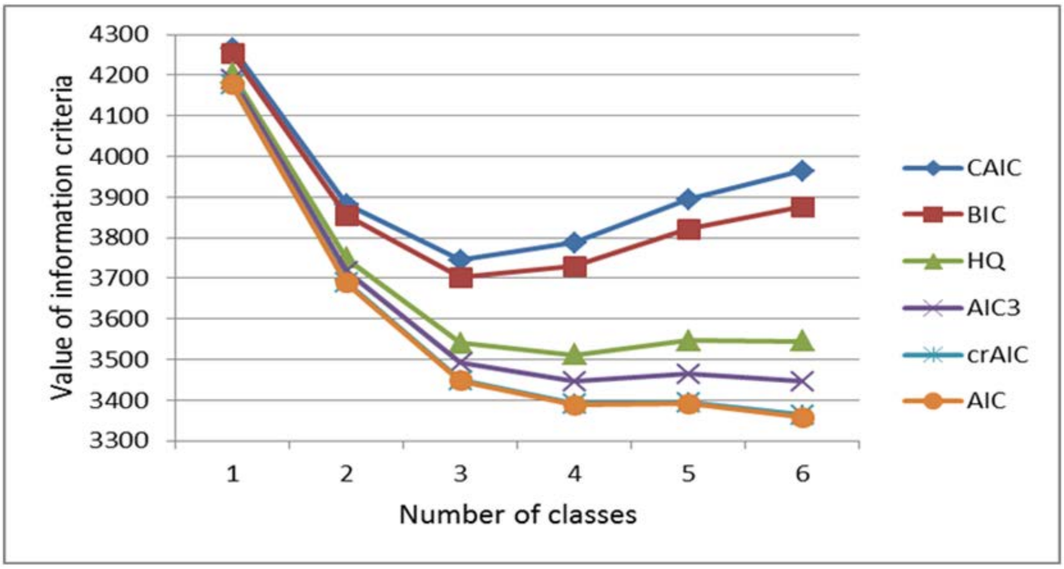

Figure A.1. Information criteria and segment retention for M3

Appendix B. Regression results for MNL model (M0) and LCM model M4

Table B.1. MNL and LCM model results with linear Savings effects

Variable	MNL (M0)	LCM (M4)		
		Class 1	Class 2	Class 3
Alternative-specific constant_Alternative1	0.6124[c]	0.7643[c]	0.1629	3.0451[c]
	(8.09)	(3.10)	(1.41)	(6.18)
Time	-0.0404[c]	-0.0416[b]	-0.0290[c]	-0.0531
	(-5.57)	(-2.08)	(-2.87)	(-1.42)
Fixed	0.0055[b]	0.0016	0.0113[c]	-0.0055
	(2.56)	(0.25)	(3.17)	(-0.40)
Rewards	0.3839[c]	0.2621	0.3835[c]	0.4680
	(5.46)	(1.44)	(3.39)	(1.23)
Renewable	0.0089[c]	0.0054	0.0140[c]	0.0029
	(7.23)	(1.54)	(8.00)	(0.42)
Ownership	0.0092[c]	0.0183[c]	0.0123[c]	0.0152
	(6.68)	(5.50)	(6.06)	(1.59)
New electricity company	-0.3557[c]	-0.1932	-0.1576	-0.7677
	(-3.76)	(-0.79)	(-1.06)	(-1.41)
New non-electricity company	-0.6744[c]	-0.2091	-0.6705[c]	-1.5098[a]
	(-5.49)	(-0.66)	(-3.84)	(-1.84)
Well-known non-electricity company	-0.3891[c]	0.2999	-0.3013[a]	-0.0928
	(-3.41)	(0.71)	(-1.87)	(-0.19)
Savings	0.0272[c]	0.0741[c]	0.0170[c]	0.0178[c]
	(32.72)	(13.73)	(11.54)	(3.16)
Class Probability		0.4886[c]	0.4101[c]	0.1104[c]
K	10		32	
LL	-2136.96		-1703.44	
AIC	4293.9		3470.9	
BIC	4352.9		3659.6	
McFadden Pseudo-R^2	0.2731		0.423	

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

Table B.2. Regression results for LC models M5 and M6 (t values are in parentheses)

	M5 (original BI scores and linear Savings effects)			**M6** (fitted BI and nonlinear Savings effects)		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Alternative-specific constant_SQ	0.771[c]	0.164	3.057[c]	0.833[c]	0.086	2.855[c]
(traditional supplier)	(3.11)	(1.40)	(6.21)	(2.59)	(0.75)	(6.45)
Time	-0.042[b]	-0.029[c]	-0.053	-0.090[c]	-0.027[c]	-0.073[c]
	(-2.07)	(-2.85)	(-1.44)	(-2.82)	(-2.89)	(-2.06)
Fixed	0.002	0.011[c]	-0.005	0.023[b]	0.007[b]	-0.023[a]
	(0.26)	(3.12)	(-0.38)	(2.42)	(2.20)	(-1.91)
Rewards	0.258	0.386[c]	0.453	0.141	0. 492[c]	0.882[c]
	(1.41)	(3.43)	(1.20)	(0.59)	(4.54)	(2.43)
Renewables	0.005	0.014[c]	0.003	0.006	0. 013[c]	0.017[c]
	(1.51)	(8.00)	(0.47)	(1.45)	(7.80)	(2.62)
Ownership	0.0183[c]	0.012[c]	0.015	0.021[c]	0.012[c]	0.033[c]
	(5.44)	(6.08)	(1.63)	(4.36)	(6.34)	(3.87)
New electricity company	-0.196	-0.153	-0.787	-0.316	-0.222	-1.157[b]
	(-0.80)	(-1.03)	(-1.46)	(-0.93)	(-1.61)	(-2.32)
New non-electricity company	-0.208	-0.667[c]	-1.501[a]	-0.501	-0.746[c]	-2.405[c]
	(-0.65)	(-3.80)	(-1.84)	(-0.12)	(-4.35)	(-2.95)
Well-known non-electricity company	0.296	-0.297[a]	-0.078	0.249	-0.337[b]	-1.083[b]
	(0.70)	(-1.85)	(-0.16)	(0.48)	(-2.19)	(-2.02)
Savings	0.0743[c]	0.017[c]	0.018[c]			
	(13.60)	(11.47)	(3.13)			
$Switch_1$_Savings [γ_1]				0. 097[c]	0. 024[c]	0. 025[c]
				(9.36)	(13.87)	(4.02)
$Switch_2$_Savings [γ_2]				0. 083[c]	0. 016[c]	0. 038[c]
				(7.05)	(7.74)	(5.48)
$Switch_3$_Savings [γ_3]				0. 567[c]	0. 010[b]	0. 028[c]
				(5.45)	(2.17)	(3.14)
$Switch_4$_Savings [γ_4]				0. 052[c]	0. 011[c]	0. 004
				(6.10)	(3.00)	(0.52)
Class probability model						
Constant	0.195	0.0	-1.474[c]	1.207[c]	1.301[c]	0.0
	(1.11)	(Fixed)	(-5.39)	(4.28)	(4.60)	(Fixed)
Behavioural Intention (BI)	-0.039	0.0	-0.491[c]	-0.006	-0.007	0.0
	(-0.33)	(Fixed)	(2.72)	(-0.25)	(-0.25)	(Fixed)
Class Probability	0.487	0.402	0.110	0.416	0.458	0.125
Model fit						
K		34			43	
LL		-1698.61			-1685.26	
AIC		3465.1			3456.8	
CAIC		3466.1			3458.0	
BIC		3665.7			3710.1	
McFadden Pseudo-R^2		0.425			0.429	

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