Consumer Governance in Electricity Markets - DRAFT

Toby Daglish*

April 28, 2014

Abstract

This paper examines switching decisions by households in the MainPower distribution area of New Zealand. The paper measures the extent to which customers switched in response to information about directors' bonuses, marketing surrounding firm ownership, and work by the New Zealand Electricity Authority to promote switching behaviour. The first two events demonstrate the magnitude of consumer concerns about firm governance in an Electricity market. The latter provides a measure of search costs in a market where no central switching service is provided.

Retail customers play an important role in the risk-management strategies of gentailer companies. Firms who have retail market shares equal to their production shares are less inclined to exert market power in wholesale markets, and are also, given the fixed prices negotiated with customers, relatively immune to fluctuations in wholesale prices. Risk management may encourage gentailers to target a particular market share. More aggressive firms may choose to take a position that leaves them as net buyers or sellers in the wholesale market. In either case, however, a firm will frequently have a desired level of retail market penetration.

A regulator concerned with market power, in contrast, may desire firms' market shares to align with their productive capacity. The regulator may also want to see customers

*New Zealand Institute for the Study of Competition and Regulation.

exhibiting elastic demand for electricity, thereby moving oligopolistic supply in the market closer to competitive equilibria. These two objectives encourage a regulator to first encourage hedging by firms (whether through derivative contracts or vertical integration) and second to encourage customers to move retailers in response to price competition.

The behaviour of customer switching in electricity markets is thus of interest to both firms who are targeting one particular market share and also regulators who may be targeting another particular set of market shares, and hoping to achieve a healthy level of "churn" amongst customers. This paper seeks to explore the motivations behind electricity retail customer movements.

We hypothesise that retail customers are motivated by several factors in making a decision to switch retailers. First, we assume that customers are motivated by price concerns. If a competitor offers a lower price, customers will be inclined to switch retailer. This is mitigated by search costs, and so customers may not move if the gains from switching are small. Secondly, however, customers may be motivated by their opinions of the companies concerned. Electricity is a homogeneous product, but electricity retailers may need to be concerned about their corporate image. Thirdly, many customers may be unaware of the possibility of switching, or may have partial information regarding the benefits that can be gained. Hence we might expect that marketing on the part of a regulator who makes this information available to customers may result in more fluid switching behaviour.

This paper makes use of an extensive data set covering the North Canterbury region of New Zealand, provided by the local Lines Company, MainPower. The New Zealand electricity market separates retail and generation activities from ownership of distribution networks. Retailers compete for customers in a region, but the lines company has a monopoly on distribution activities. As such, MainPower observes all switching activity in the region.

We examine the transfers between retailers of ICPs (individual meters) to changes in retail prices. We also examine the responses of customers to three events. First, we examine the response of customers to Contact Energy's Directors' remuneration. In

September 2008, Contact announced that it was jointly raising retail prices, and also paying substantial bonuses to its Directors. We examine whether this event caused increased switching activity amongst customers; were customers concerned with the governance of Contact's board? Second, we examine a marketing campaign, in which Trustpower marketed itself as being more desirable on the strength of being a trust (as opposed to a company, as is the case for most other retailers). Did customer response to this campaign indicate a preference over ownership structure for their retailer? Lastly, we examine the introduction of the "What's my Number?" campaign by the Electricity Authority. In this campaign, the market regulator provided a website to help customers estimate the savings they could achieve by switching retailer. By examining this event, we see whether educational work by the regulator can lower switching costs and achieve a higher rate of customer movement.

Existing empirical work on electricity customer switching behaviour has been sparse. Giulietti, Waddams, and Waterson (2005) examine behaviour of gas customers in the United Kingdom, who face the opportunity of switching from British Gas to new entrants in the market. Hortaçsu, Madanizadeh, and Puller (2011) study the switching behaviour of Texas residents in the wake of deregulation.

The layout of the remainder of this paper is as follows. Section 1 outlines our methodology. Section 2 describes our data set. Section 3 presents the empirical results of our work, while Section 4 concludes.

1 Methodology

This paper makes use of the Conditional Logit model (McFadden (1973)) to explain household switching behaviour. We assume that household i in month t receives utility from retailer j according to the following equation

$$U_{i,j,t} = \sum_k \beta_k X_{i,j,t,k} + \epsilon_{i,j,t},$$

where $X_{i,j,t}$ are a set of characteristics that vary across households, retailers and time. These are observable to the econometrician. $\epsilon_{i,j,t}$ is a term that is unobservable to the econometrician, but assumed to be logistically distributed. As such, we can evaluate the probability that a household chooses a particular retailer (j) as

$$\frac{e^{\sum_k \beta_k X_{i,j,t,k}}}{\sum_{j'} e^{\sum_k \beta_k X_{i,j',t,k}}}.$$

With this set of probabilities, the parameters (β_k) can be found by maximising the likelihood that a household chooses the particular retailer observed in a particular month, i.e.:

$$\max_{\beta_1,\ldots,\beta_N} \prod_i \prod_t \frac{e^{\sum_k \beta_k X_{i,j(i,t),t,k}}}{\sum_{j'} e^{\sum_k \beta_k X_{i,j',t,k}}}$$

where $j(i,t)$ is household i's observed time t choice of retailer. In our estimation of standard errors, we allow for clustering across households, following Cameron, Gelbach, and Miller (2011).

1.1 Price effects

We assume that households have a preference for cheaper retail rates, so our first explanatory variable is relative price:

$$X_{i,j,t,1} = \frac{P_{j,t}}{P_{j(i,t-1),t}},$$

i.e. the price of a competitor relative to the household's incumbent retailer. This effect is offset by search costs, ans we therefore allow our second term to be a preference for the household's incumbent retailer:

$$X_{i,j,t,2} = \begin{cases} 1 & \text{if } j = j(i,t-1) \\ 0 & \text{otherwise.} \end{cases}$$

A high estimate for β_2 therefore represents higher search costs, manifested as greater inertia amongst customers. By interacting demographic or time series variables with $X_{i,j,t,2}$

we can examine the effect of variables that might increase/decrease inertia (such as the "What's my number?" campaign). By interacting variables with $X_{i,j,t,1}$ we can examine variables that might increase a household's sensitivity to prices (such as seasonal/weather variables that might proxy for a household having experienced high power bills).

2 Data

Switching data covers the period May 2007-April 2012, while electricity usage data covers the period May 2007-December 2012. The data used in this project can be split into four subsets: switching data, electricity usage, demographics and weather information.

2.1 Switching

Switching information is provided by MainPower, the lines company who provides distribution services in North Canterbury. Data is anonymised by meshblock, and covers all connections and terminations.

Figure 1 shows the dispersion of ICPs across the region, and provides an idea of the demographic character of North Canterbury. The region contains some urban areas in the South: Rangiora and Kaiapoi. There are also some smaller towns scattered across the region: Kaikoura, Waipara, and Culverden. The region is also characterised by large rural areas. North Canterbury has varied terrain; the region is dominated by the Canterbury plain, but in the West is bounded by the Southern Alps, and in the North by the hills surrounding Kaikoura.

The region is divided into seven Grid Exit Points (GXPs) where each ICP is assigned to one GXP (see 1). Ashley11 includes a direct connection to the transmission network by a fibre board factory. We exclude Ashley11 from our work on electricity usage, since its offtake is dominated by the fibre board factory. However, since many small ICPs are also connected, we include Ashley11 ICPs in our switching work.

There are 38 880 ICPs in the region, and we observe 16 674 switches during the period. A histogram of number of switches observed for each ICP is given in figure 2.

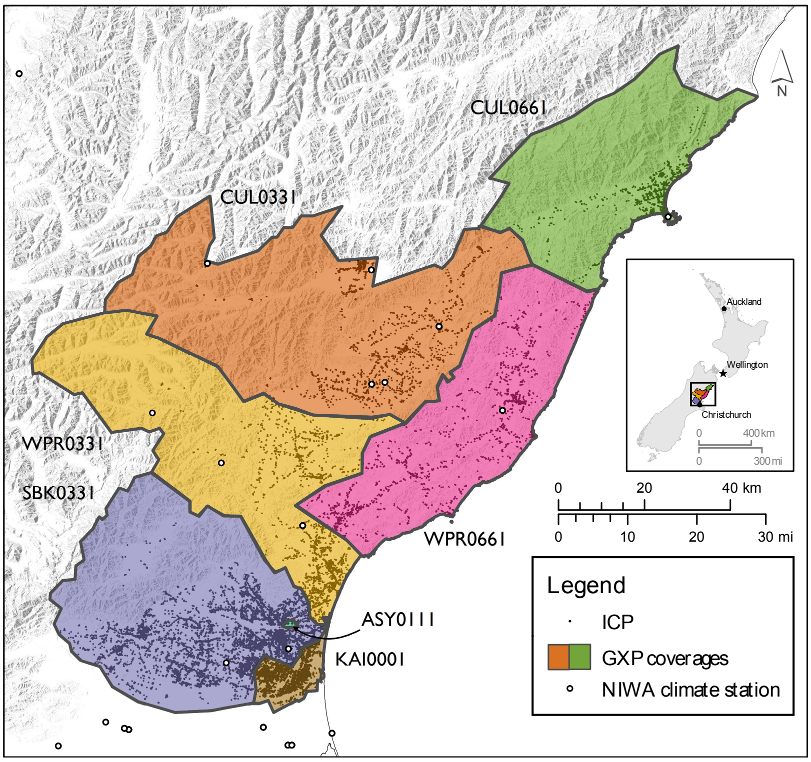

Figure 1: The MainPower region.

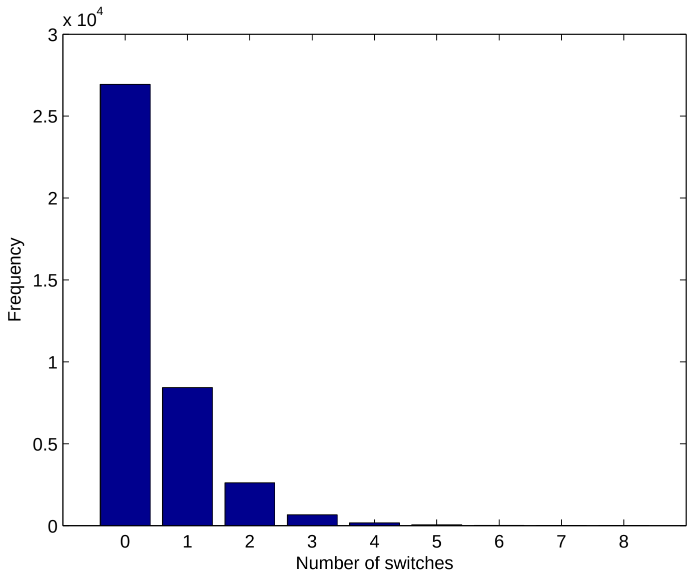

Figure 2: Histogram of number of switches for an ICP in the MainPower region.

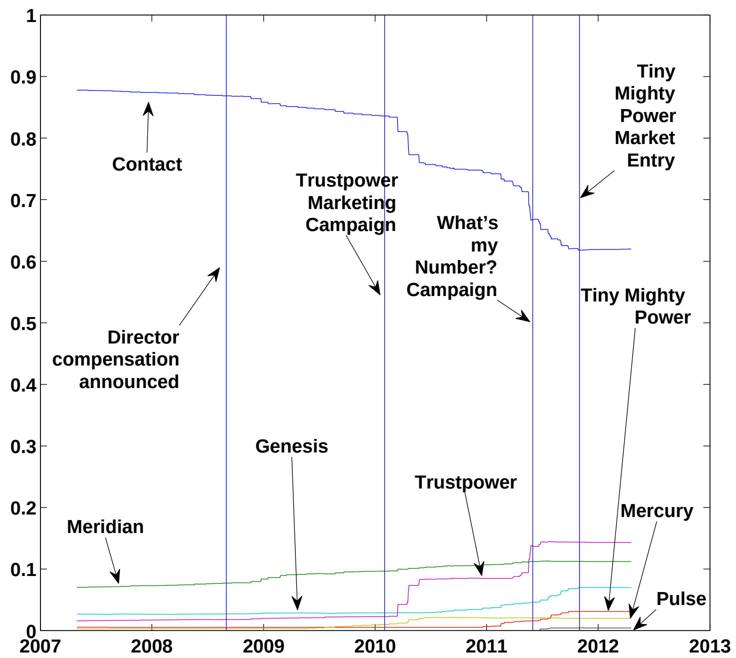

Figure 3: Market shares (as percentage) for the MainPower region.

Contact Energy is the incumbent firm from deregulation, and at the start of the sample, accounts for roughly 90% of ICPs in the region. Over the course of the sample period, this portion declines and the retail shares become more evenly distributed across retailers, see figure 3.

2.2 Electricity Usage

Electricity offtakes are available at a Grid Exit Point (GXP) level (see figure 1). We aggregate daily offtakes into monthly observations (see figures 4 and 5). Electricity use fluctuates in most areas, and often shows strong seasonal patterns. These patterns can exhibit high mid-year (winter) usage (see for example Kaiapoi11) or high year end (summer) usage (see for example Waipara33).

2.3 Demographics

Since our data is anonymised at a Meshblock level, we can connect our switching data to Statistics New Zealand data concerning house sizes, and general demographic information for the area.

We further create GXP level information by weighting meshblock information according to the number of ICPs attached to a particular GXP that lie in each meshblock. GXP level information is used for electricity usage estimation (see section 3.1) while meshblock level information is used for switching estimation (see section 3.2).

2.4 Weather

Weather information is available from the National Institute of Water and Atmospheric Research (NIWA). NIWA has a range of weather stations scattered across the North Canterbury region (see figure 1). For each ICP, we take the weather reading from the closest weather station. We then generate an average across all ICPs associated with a particular GXP to generate GXP level weather parameters. This provides us with two data-sets. As with demographic data, GXP level data is used for electricity demand estimation, while meshblock level data is used for switching estimation.

3 Results

We first investigate the electricity offtakes in the MainPower/North Canterbury region. Then we turn our attention to the actual switching decisions of the ICPs.

3.1 Electricity Demand

We use our panel data on GXP offtakes and the demographic information to explore the sensitivity of electricity demand to household characteristics and weather.

In Table 1 we aggregate across GXPs. This allows us to explore the effect of demographic variables, which vary in the cross-section. We find that rain and soil moisture have a negative impact on electricity usage, while temperature and hours of sunlight have

Variable	Coeff.	T-stat	Coeff	T-stat
Constant	2977.1077	3.0188	2481.4082	2.6657
Rain	-0.42172231	-0.417	0.28806895	0.31715
Sun	0.65279703	0.37923	2.4509189	2.3701
Soil Moisture	-22.523171	-1.7264	-33.299149	-3.5615
Temperature	16.080464	1.1728	4.5756082	0.37651
ICP Density	-7545.9209	-7.7247	-7572.5424	-7.6161
Proportion Four Bedroom House	-312.17372	-7.9881	-310.44548	-7.7723
Proportion Household Income 100001+	578.78461	7.0055	575.96347	6.8205
Proportion Age 65+	181.72713	2.9826	186.33366	2.9911
Dummy Feb	-462.11331	-2.3525		
Dummy Mar	-516.56403	-2.6182		
Dummy Apr	-662.01083	-2.9868		
Dummy May	-681.33873	-2.8033		
Dummy Jun	-610.3638	-2.0214		
Dummy Jul	-420.72073	-1.4164		
Dummy Aug	-497.21565	-1.6702		
Dummy Sep	-705.22995	-2.5437		
Dummy Oct	-607.16922	-2.4692		
Dummy Nov	-300.98275	-1.5325		
Dummy Dec	-64.083451	-0.35779		
Soil Moisture*ICP Density	76.639945	4.044	80.697296	4.2628
R^2	0.441		0.394	

Table 1: Whole sample model for electricity usage. Dependent variable is GXP offtake in a given month. Two specifications are fit, one including dummy variables for months, and the other without. Variables described as Proportions refer to the proportion of census respondents in a meshblock who answered affirmatively; i.e. Proportion Four Bedroom House refers to the proportion of census respondents who live in a four bedroom house.

a positive impact. This supports the hypothesis that electricity usage in the region is significantly impacted by use of irrigation, predominately a dry weather activity. Seasonal dummy variables suggest that peak electricity usage is in December and January.

Demographically, we find that higher incomes and greater numbers of retirees increase electricity usage. Interestingly, the proportion of four bedroom place of dwelling in a meshblock (a proxy for the prevalence of larger houses, since most dwellings in the region are 1-4 bedrooms) has a negative impact on electricity usage.

Lastly, by interacting ICP density with soil moisture, we uncover a positive term, indicating that electricity usage is less sensitive to soil moisture in more urbanised GXPs.

We next break the sample into individual GXPs. Table 2 shows the results of this.

Since we have disaggregated the cross-sectional element of the data, we can no longer estimate demographic effects. However, it is interesting to examine the effects of weather variables.

Figure 4 shows the results of trying to explain electricity usage with weather variables alone. For Culverden33, Waipara33 and Kaiapoi11, the regular seasonal patterns in the data are well explained by seasonal patterns in weather. However, for Culverden66/Kaikoura33, Waipara66 and Southbrook33, performance is considerably weaker. Figure 5 shows results once monthly seasonal dummies are incorporated. Culverden66/Kaikoura33, in particular shows a much improved estimation, suggesting that seasonal tourist visitors in December/January can explain much of the fluctuations in usage.

3.2 Switching Behaviour

We next turn our attention to customer switching behaviour. Given that our electricity demand results suggest that customers may have varying electricity usage based upon weather effects and demography, we include these explanatory variables as factors that may make a customer more or less likely to switch. Specifically, we interact these variables with relative pricing, so that customers who potentially have high power bills are more likely to switch retailers when prices are materially different.

Given Contact's preponderance in the region, we also include dummy variables for each of the retailers, effectively allowing customers to have a preference for a particular firm over others.

Table 3 contains our results. Our basic result is that customers have a very strong preference for remaining with their incumbent retailer. With a coefficient for incumbent retailer of 5.9828, we can infer that if all prices were identical, a customer has probability $e^{-5.9828} = 0.0025$ of switching to a given competing retailer. Our index of -11.7842 on price says that if an incumbent faced a competitor who was 10% cheaper, a customer would have probability $e^{-5.9828+0.1\times 11.7842} = 0.0080$ of switching; price competition has significant impact on customer churn.

Variable	Culverden33		Kaiapoi11		Culverden66/ Kaikoura33		Southbrook33		Waipara33		Waipara66	
	Coeff.	T-stat	Coeff.	T-stat	Coeff.	T-stat	Coeff.	T-stat	Coeff.	T-stat	Coeff.	T-stat
Constant	5134.145	4.339	1978.702	7.077	1799.153	5.695	2539.375	7.370	1869.021	6.354	2034.989	2.731
Rain	2.628	1.273	-0.426	-0.488	0.523	1.052	-0.331	-0.349	-0.030	-0.042	0.898	0.554
Sun	9.537	3.286	-3.171	-4.316	2.536	3.280	-0.056	-0.062	-0.121	-0.171	1.965	1.018
Soil Moisture	-125.150	-5.824	25.345	7.606	3.271	0.747	-0.794	-0.186	-15.838	-4.405	3.281	0.323
Temperature	-31.021	-1.123	18.133	1.839	1.951	0.218	-4.441	-0.374	-9.528	-1.145	-8.471	-0.400
R^2		0.723		0.754		0.211		0.006		0.458		0.041
Constant	6670.075	4.738	1607.671	10.456	2310.307	7.110	2939.198	9.677	2091.035	6.356	2329.813	2.987
Rain	-0.858	-0.417	0.555	1.234	0.803	1.987	0.024	0.031	-0.308	-0.390	2.692	1.661
Sun	-1.442	-0.317	0.676	1.245	1.585	1.534	-0.281	-0.266	-0.038	-0.036	2.334	0.881
Soil Moisture	-59.253	-1.960	2.927	0.905	-11.649	-1.872	-22.826	-3.369	-18.015	-2.519	-36.707	-2.362
Temperature	5.937	0.219	9.653	2.017	18.629	2.339	7.946	0.860	-9.661	-1.170	23.082	1.106
Dummy Feb	-860.962	-1.907	-126.858	-1.850	-530.442	-5.183	-450.526	-3.408	-153.088	-1.413	-505.097	-1.796
Dummy Mar	-1105.406	-2.402	86.355	1.232	-438.265	-4.368	-354.775	-2.629	-233.546	-2.135	-507.881	-1.832
Dummy Apr	-2109.565	-3.991	208.835	2.751	-356.744	-2.995	-405.320	-2.762	-318.788	-2.590	-548.930	-1.732
Dummy May	-2604.374	-4.495	598.523	7.190	-212.690	-1.641	-29.488	-0.181	-232.118	-1.616	57.526	0.161
Dummy Jun	-2584.416	-3.700	904.323	8.368	-73.466	-0.479	319.857	1.508	-82.990	-0.413	730.047	1.624
Dummy Jul	-2106.581	-3.197	1085.318	9.424	79.074	0.525	636.218	2.805	12.046	0.062	1019.215	2.475
Dummy Aug	-2039.999	-3.166	889.873	7.740	49.603	0.329	563.108	2.482	-59.390	-0.298	1055.539	2.419
Dummy Sep	-2013.115	-3.324	411.357	3.841	-31.611	-0.226	198.564	0.949	-209.356	-1.109	613.759	1.475
Dummy Oct	-1600.611	-2.806	258.330	2.847	55.397	0.432	153.993	0.871	-212.194	-1.344	379.928	1.013
Dummy Nov	-567.619	-1.247	89.862	1.270	-174.642	-1.758	142.831	1.052	-288.000	-2.488	242.743	0.847
Dummy Dec	-177.651	-0.435	60.269	0.952	-44.016	-0.473	84.762	0.698	-95.549	-0.975	265.321	1.052
R^2		0.847		0.963		0.666		0.618		0.690		0.518

Table 2: Individual GXP demand regressions. Columns are GXPs under consideration. For each GXP, we consider two specifications: one including monthly dummy variables and the other excluding them.

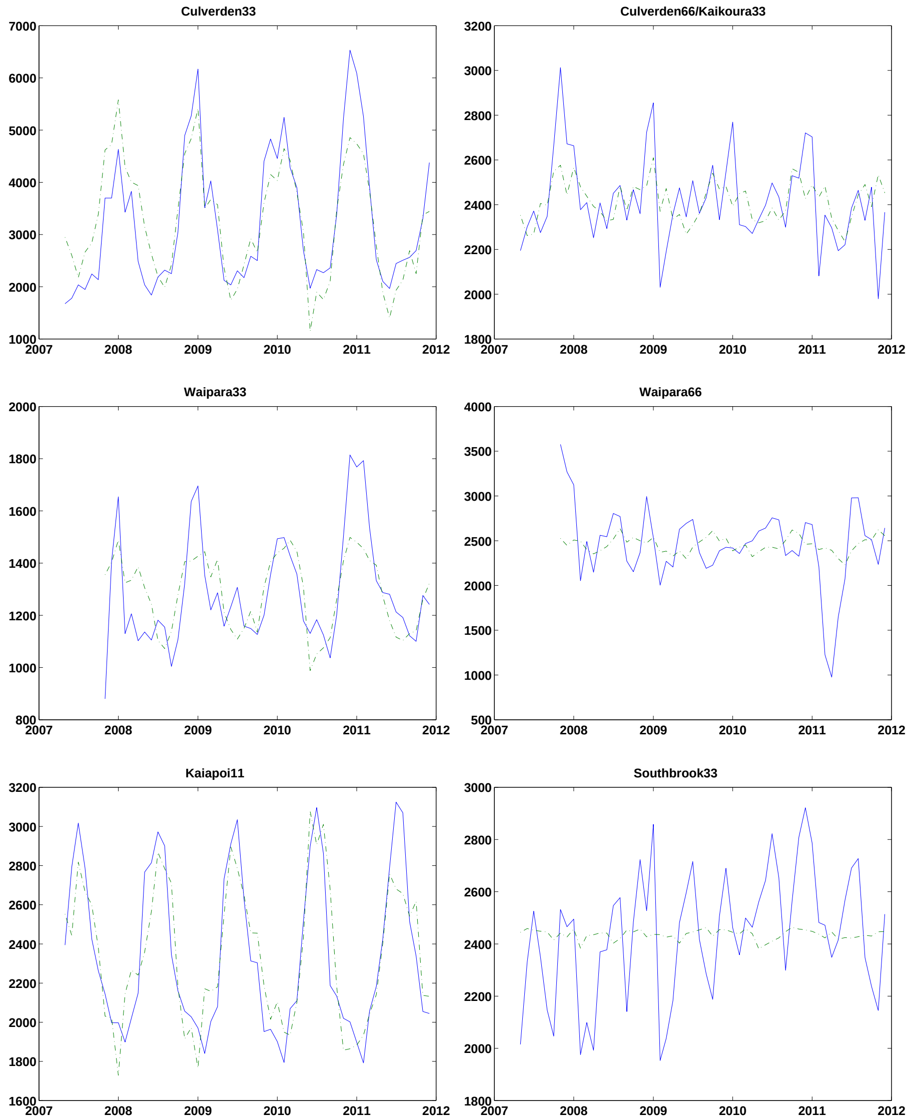

Figure 4: Electricity offtakes by Grid Exit Point. Solid line represents observed offtakes, dashed line represents fitted offtakes explained by weather variables.

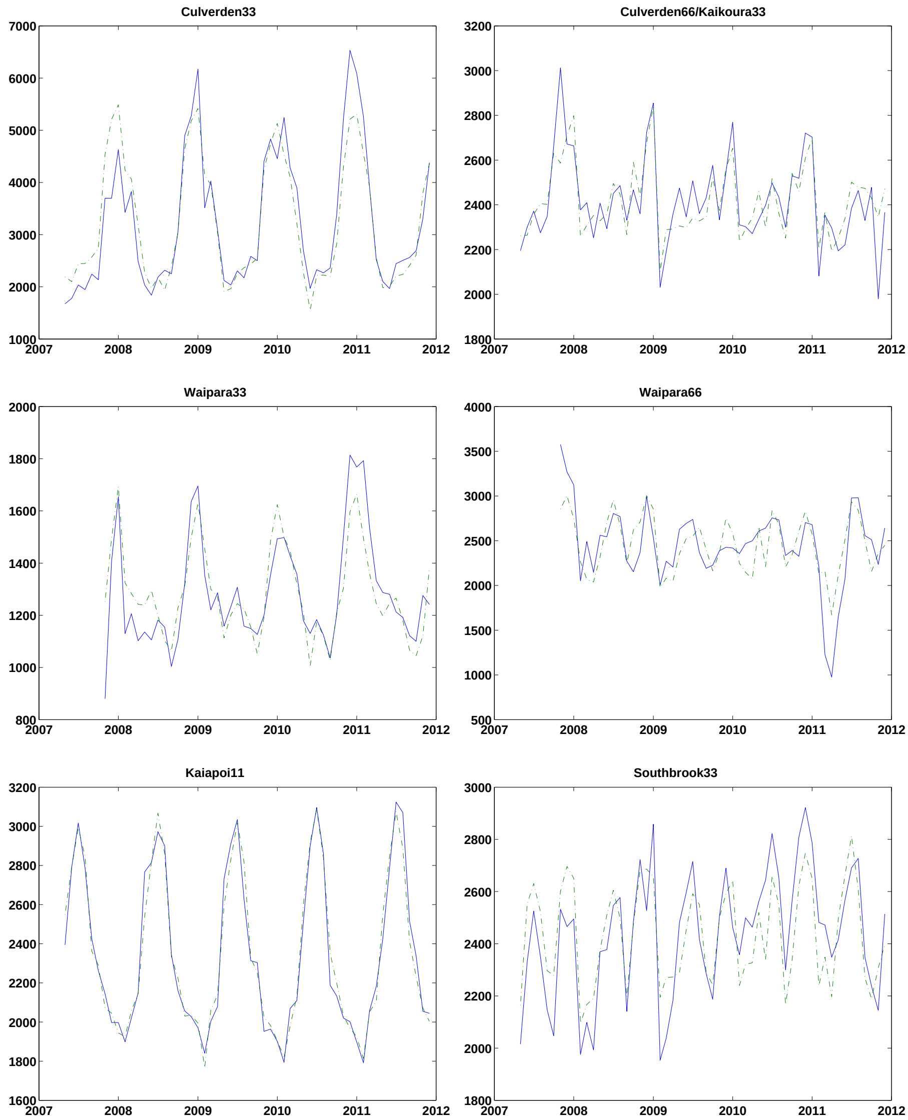

Figure 5: Electricity offtakes by Grid Exit Point. Solid line represents observed offtakes, dashed line represents fitted offtakes explained by weather variables, augmented by monthly dummies.

Examining the Director Remuneration Incident, we find fairly weak effects in terms of customer movements. During the early months (September-November 2008) Contact in fact seemed to have better than usual retention of customers. However, December 2008 and January-March 2009 saw an outflow of customers. Indeed in January, with coefficient -0.8007, we would conclude that the director remuneration effect was the equivalent of a 6.8% price differential. Contact's approaching of former customers to "win them back" had the expected effect of increasing the likelihood of former Contact customers switching back to Contact except in month 6 (February 2009) when former Contact customers were *less* likely than usual to return to Contact. Given that this month follows the largest exodus month (January 2009) this may be seen to be the period in which the Director effect was strongest.

Next we turn our attention to the various marketing campaigns held in the region. The "What's my number?" campaign, unsurprisingly, decreased customer loyalty. Again, translating this to "discount equivalent" terms, this was equivalent in magnitude to a 4.97% price differential.

Interestingly, the largest effect is due to the Trustpower campaign, starting in February 2010, where Trustpower marketed itself as being New Zealand owned and being more desirable due to its trust governance structure. This campaign gave Trustpower the equivalent of a 15% price differential. Graphically, the effect of this campaign can be seen in Figure 3: from February 2010 onward, each winter, Trustpower market shares have risen, largely at the expense of Contact (as the incumbent) market shares.

The effect of Tiny Mighty Power's official "entry" into the market seems to have been largely negative. Examining Figure 3, Tiny Mighty Power had already gained a number of customers in the lead up to their official entry. It appears that their extra marketing around this time had little effect on customer switching.

The two earthquakes had opposite effects on ICP switches. Noting that considerable migration was caused by the two earthquakes, we might expect to see more switching, caused by customers moving into and out of the region. The first Canterbury Earthquake (September 2010) caused a significant *increase* in incumbent effects, while the second earthquake caused a decline in incumbent retention power.

Our company control variables are not surprising. Each of the non-Contact firms has a negative coefficient. Many customers have a strong preference for Contact. Interestingly, Trustpower's number is the most negative, reflecting its small market share prior to the marketing campaign. However, the effect of the campaign is to largely offset this, resulting in Trustpower being the second most popular retailer in the latter part of the sample.

Examining demographic effects, we find that interestingly large households and elderly households exhibit less sensitivity to prices, while high income households are more sensitive. As might be suggested by Figure 3 most switching goes on in the winter, as exhibited by the higher sensitivity to prices during rainy months.

4 Conclusion

This paper examines the effect of consumer sensitivity to governance aspects of retailers/gentailers, over and above responsiveness to price differences. We find that there was a small response by Contact customers to news about Contact's Directors' compensation packages. However, more significant customer movements occurred in response to Trustpower's marketing of itself as having a more desirable governance structure to its competitors. Was this partly made more effective by being preceded by the remuneration incident? It is difficult to say.

Potential areas for future research would be to obtain more disaggregated data for electricity usage, allowing for better control for monthly bill size on switching behaviour. Examining effects in other regions could also be fruitful, since results for North Canterbury may be different due to Contact's dominant position in the retail market there.

References

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller (2011), Robust Inference With Multiway Clustering, *Journal of Business and Economic Statistics* 29, 238–249.

Variable	Coeff.	t-stat	Variable	Coeff.	t-stat
Incumbent	5.9828	262.6488			
Relative Price	-11.7842	-32.6507			
Director Remuneration			**Events**		
Director 1	0.6285	3.1113	What's my number?	-0.5855	-12.051
Director 2	0.7718	3.6778	Trustpower campaign	1.7676	23.353
Director 3	0.7312	3.5517	Contact TP campaign	0.1271	2.5189
Director 4	-0.4102	-3.4103	Tiny Mighty Power	-0.8422	-2.0115
Director 5	-0.8007	-7.8776	Sep. 2010 EQ	0.5812	12.385
Director 6	-0.0573	-0.3906	Feb. 2011 EQ	-0.1623	-2.6498
Director 7	-0.3928	-3.1266			
Director 8	0.4159	2.4221			
Director 9	0.2087	1.3395	**Price Interaction**		
Director 10	0.2427	1.5347	ICP Density	0.0128	0.2623
Director 11	0.4693	2.6545	Prop 4 bedrooms	0.0013	1.4834
Director 12	0.0355	0.2449	Prop 100K+ income	-0.0032	-2.7572
			Prop Age 65+	0.0028	2.9971
Contact recovery of lost customers			Rain	-0.0011	-5.6331
Old Cont. * Dir 1	–	–	Sun	-0.0002	-0.7153
Old Cont. * Dir 2	1.6459	1.1573	Soil Moisture	0.0000	0.0322
Old Cont. * Dir 3	0.8913	0.6283	Temperature	-0.0022	-0.8229
Old Cont. * Dir 4	1.5449	1.8816	ICP Dens.*Soil M.	0.0003	0.2231
Old Cont. * Dir 5	1.0319	1.4429			
Old Cont. * Dir 6	-0.9823	-0.6926	**Firm dummies**		
Old Cont. * Dir 7	-0.0216	-0.0263	Meridan Dummy	-0.6831	-22.2815
Old Cont. * Dir 8	0.3622	0.6723	TMP Dummy	-0.5399	-4.5681
Old Cont. * Dir 9	0.9095	2.2892	Genesis Dummy	-1.7927	-33.1670
Old Cont. * Dir 10	0.3272	0.6471	Trustpower Dummy	-1.9869	-27.8883
Old Cont. * Dir 11	0.6601	1.5970	Mercury Dummy	-0.9539	-15.3394
Old Cont. * Dir 12	0.8324	2.2482	Pulse Dummy	-1.3121	-9.7725

Table 3: Results for customer switching behaviour. Incumbent gives ICP utility from remaining with current retailer. Price multiplied by retailer's price relative to incumbent gives utility from choosing said retailer (incumbent's relative price is 1). Director 1 - Director 12 give utility from choosing Contact from start of Director compensation period to 12 months after. Next coefficients give utility from choosing contact for a customer who left during the Director compensation period (i.e. utility from *returning* to Contact). "What's my number" is a term that affects incumbent retailer during the campaign; a negative term reduces customer loyalty. The Trustpower marketing campaign is considered for effects on Trustpower utility and Contact utility. Demographics and weather characteristics are interacted with relative price; hence a positive number indicates that the characteristic makes a customer *more* price sensitive. Dummy variables for firms capture Contact's position as incumbent retailer; other firms are less popular, ceteris paribus. T-stats are constructed using standard errors that are robust to errors clustered by ICP.

Giulietti, M., C. Waddams, and M. Waterson (2005), Consumer Choice and Industrial Policy: a study of UK Energy Markets, *The Economic Journal* 115, 949–968.

Hortaçsu, A., S. A. Madanizadeh, and S. Puller (2011), Power to Choose: An Analysis of Consumer Behavior in the Texas Retail Electricity Market, Working Paper.

McFadden, D. (1973), Conditional Logit Analysis of Qualitative Choice Behavior, in P. Zarembka, ed., *Frontiers in Econometrics* (Academic Press, New York, USA).