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The Impact of Price Comparison Tools on Electricity Retailer Choices

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Abstract

We estimate a structural model of electricity retailer choices accommodating various sources of consumer inertia, including inattention, limited information, switching costs, and product differentiation. The model disentangles the relative importance of different frictions. We estimate our model using individual-level data of all retailer switches and queries on a price comparison website in New Zealand. We find that price comparison tools strongly impact market structure and consumer surplus. However, mandating all consumers search for alternatives has stronger effects on market structure and consumer surplus gains. Our results help policymakers design policies that improve consumer choices and effective competition in retail markets.

Keywords: consumer inertia, consumer search, retail electricity markets, structural demand estimation

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1 Introduction

Limited information about alternative products can prevent consumers from making optimal choices. Coupled with other sources of inertia, this threatens the success of policies trying to improve competition in markets with entrenched incumbents. These issues are especially acute in retail electricity markets. Numerous countries have opened these markets to competition, but most remain highly concentrated. Moreover, policymakers in many countries try to promote time-varying electricity tariffs that can help deal with supply-side volatility and ease the transition towards renewable generation.

Price comparison tools are a promising way of reducing information frictions. These tools allow consumers to learn about all available products and their prices and attributes. Price comparison tools have been implemented to help consumers compare products such as gasoline, mobile phone plans, and electricity contracts. However, such markets are often marred by several frictions: many consumers do not actively consider other retailers and switching costs are often high.

In this article, we study how price comparison tools affect retailer choices in the New Zealand electricity market. Using a unique data set comprising all retailer switches and visits to a price comparison tool from January 2018 to May 2022, we explore how price comparison tools affect the substitution patterns between incumbents and new entrants, market structure, and welfare. Our model allows us to disentangle the information friction from other sources of consumer inertia: consumer inattention, which results in a failure to search for other retailers at all; switching costs, which make it costly to change retailers even when attentive and informed; and product differentiation, which makes it possible that consumers prefer more expensive retailers. The estimated model allows us to study how price comparison tools reduce information frictions, identify which consumers benefit from them, and how effective they are in fostering effective competition. We find that the price comparison tool has an important impact on market structure and consumer surplus. However, the tool's impact is limited because of other frictions, most notably the fact that some consumers are inattentive and never consider switching in the first place.

The main contribution of this article is to explicitly disentangle information frictions from other sources of consumer inertia. We are therefore able to quantify the impact of price comparison tools on removing information frictions relative to the impact of removing other frictions, such as consumer inattention, switching costs, and product differentiation. Previous literature has estimated the extent of consumer inattention (Heiss et al., 2021; Hortaçsu et al., 2017) without accounting for how different types of searches may lead to different choices sets and thus have information frictions. Other literature has disentangled information frictions and switching costs (Dressler and Weiergraeber, 2023), assuming all consumers are active and attentive. We are able to disentangle the different sources of consumer inertia by using a rich individual-level dataset for the New Zealand retail electricity market (which has been appropriately anonymized). We observe all retailer switches from January 2018 to May 2022. In addition, for each household, our dataset allows us to link retailer switches to queries on a price comparison website (powerswitch.org.nz, Powerswitch henceforth). These two sources combined allow us to directly observe whether a household used the price comparison tool and their subsequent switching behavior. In addition, we have access to retail prices and detailed census data on different demographic characteristics.

In the first step, we use our rich panel of switching and searching data to present descriptive statistics and reduced form regression results, in order to analyze how the price comparison tool impacts switching flows. We find that consumers who accessed the price comparison tool prior to switching are substantially more likely to switch to smaller retailers, whereas consumers who did not access the tool are more likely to choose another large incumbent. These findings suggest that the price comparison tool is relatively effective in informing consumers about alternatives. We also exploit quasi-random variation in the information that consumers gain when using the price comparison tool: Electric Kiwi, one of the new entrants into the market, suddenly and unexpectedly dropped off the price comparison tool in June 2020 before returning just as suddenly and unexpectedly in January 2021. We find that the share of switchers captured by Electric Kiwi plummeted by a factor of five. This suggests that consumers becoming informed about smaller entrants via a price comparison tool is crucial for these small entrants' market share. We corroborate these descriptive findings via a difference-in-differences style analysis.

In the second step, we build and estimate a structural model of consumer retailer choice that contains a decision to search and a decision to switch. The model allows us to disentangle the role of inattention, limited information, switching costs, and product differentiation in choosing between retailers. In the model, consumers first decide whether to become active and search for retailers other than their current one. This decision depends on whether the consumer experienced a bill shock in the previous month. Conditional on deciding to search actively, consumers then either access the price comparison tool or use some other means to learn about (some of) the other retailers; consumers may have different choice sets, depending partly on whether they accessed the price comparison tool. Then, consumers choose either a new or their current retailer. In choosing a retailer, a consumer takes into account a switching cost that they incur if they opt for a retailer different from their current one.

In the third step, we use the estimated model to quantify the effects of different frictions. We find that the price comparison tool has a strong impact on market structure and benefits consumers: The collective market share of small entrant retailers would be 3.5 percentage points higher if all searchers accessed the price comparison tool, a 20% increase. Consumer surplus would increase by NZD 2.98 per consumer per month, which amounts to an increase in total yearly consumer surplus of NZD 67.7 million. However, price comparison tools are no silver bullet. In particular, the fact that many consumers are inattentive and do not actively search is a friction of similar importance. If all consumers became active in searching for other retailers at least once a year, the market share of small entrant retailers would increase by around 4 percentage points or 24%. Consumer surplus would increase by NZD 9.64 per consumer per month, amounting to a total of NZD 219.2 annually. These results are informative for policymakers wishing to improve effective competition in markets marred by the frictions we disentangle and analyze. For instance, the New Zealand Electricity Authority recently started a consultation on how to make electricity retailer comparisons easier (see New Zealand Electricity Authority, 2024).

We contribute to the literature that has examined and quantified different sources of consumer inertia. Heiss et al. (2021) study limited attention and switching costs in the US health care market. Ho et al. (2017) focus on supply-side responses to the existence of such frictions. Hortaçsu et al. (2017) examine consumer inertia in the Texas retail electricity market and disentangle consumer inattention from incumbent brand preferences. Dressler and Weiergraeber (2023) study the Belgian retail market, disentangling limited information, switching costs, and consumer preferences. The novelty of our article is to combine an information acquisition stage with a model that allows for limited attention and switching costs. Our unique individual-level data on price comparison tool usage allows us to model and separately identify inattention, limited information, switching costs, and product differentiation.

The closest article to ours is probably Dressler and Weiergraeber (2023). However, we depart from their analysis in at least two respects. First, to identify their search cost parameters, Dressler and Weiergraeber (2023) rely on survey data on search behavior that is not directly linked to their data on retailer choice. In contrast, we directly observe searches for all households in New Zealand, allowing us to link retailer switches directly to observed searches. The considerable variation in choices conditional on accessing or not accessing the price comparison tool allows us to directly identify the parameters determining the decision to search. Second, our model explicitly allows households to be inattentive in a period – that is, not to consider a switch at all. In doing so, we can disentangle not only information frictions from retailer differentiation but also estimate the proportion of households who are "asleep" and do not consider any other retailer apart from their current one. We show that accounting for this friction is crucial as it has a similar impact on market structure and a larger impact on consumer surplus than the information friction.

We also connect and contribute to the literature on competition and tariff choice in retail electricity markets. Giulietti et al. (2014) analyze the UK market, estimating a search model in which they assume products are homogenous. Fowlie et al. (2021) and Ito et al. (2023) study consumer adoption of time-varying electricity tariffs. Poletti and Wright (2020) study the impact of adopting real-time pricing on market power. Pébereau and Remmy (2023) study the introduction of real-time pricing tariffs in New Zealand and identify barriers preventing widespread adoption.

Finally, we relate to a wider literature studying the effects of information, transaction frictions, and price transparency on consumer choices. Transaction and information frictions have been studied in the PC industry (Sovinsky Goeree, 2008), the banking industry (Honka et al., 2017), the television industry (Shcherbakov, 2016), for hospital choices (Gaynor et al., 2016), health care choices (Ho et al., 2017), retirement plans (Luco, 2019a), and in online markets (Jolivet and Turon, 2019; Kim et al., 2017; Santos et al., 2012, 2017). Price transparency policies have been studied in health insurance markets (Brown and Goolsbee, 2002), retail gasoline markets (Luco, 2019b; Martin, 2020), and supermarkets (Ater and Rigbi, 2023).

2 Data

We build a detailed household-level panel data set containing information on a household's current retailer, whether they search the price comparison tool, demographic information, and prices of the retailer's "standard" tariff. Our data is monthly, covering the period from January 2018 to May 2022. We restrict our attention to 28 out of the 39 "network reporting regions" in New Zealand (as defined by the Electricity Authority); these 28 include all the largest regions. We also focus on the ten largest retailers, lumping the others into the outside option; throughout our period, these ten account for over 94 per cent of the market. This section summarises some key features of our data; further information about our dataset is provided in Appendix C.

Retailer choices. We use detailed data on retailer choices provided by the Electricity Authority ("EA"). This data is at the household connection point (ICP) level. We construct a panel dataset for all ICPs (suitably anonymized) in our 28 regions across the period from January 2018 to May 2022 by combining (i) two snapshots of all ICPs and their current retailer in January, 2018 and June, 2022 with (ii) monthly data on all switches occurring between those two points of time. In this dataset, there are two principal types of switches: "move-in" switches occurring when a new household occupies the ICP and "trader" switches when a household switches retailers. We only consider trader switches in the empirical analysis as those are the types of switches we are interested in modeling. We define households as follows. If, for a given ICP, we do not observe any moves in the course of our time period, then the ICP is associated with a single household. When we observe a move-in switch at an ICP, we assume the current household ceases to exist and a new household is created; we are forced to do so because, unfortunately, when a household moves, we do not observe the ICP to which it moves.

Searches on the government-sponsored price comparison website We match the retailer choice data with data on API requests to the price comparison website *powerswitch.org.nz* ("Powerswitch"). Powerswitch was created by Consumer NZ, a consumer protection agency. Whereas there are other price comparison websites in New Zealand, Powerswitch is the only price comparison website that receives funds from (and is overseen by) the Electricity Authority.[1] After data cleaning, we observe over 630,000 visits to Powerswitch between January 2018 and May 2022 alone.[2] The API data gives us information on who executed a search on the ICP level and the search date. We are able to match, for each household, this data to our retailer choice data.

Retailer prices. From Powerswitch, we obtained monthly tariff data for a large number of plans offered by the major retailers. As noted above, we focus on the 10 largest retailers and 28 "network reporting regions". For each of the 28 regions and each of the 10 retailers, we construct a monthly price series for one plan – a relatively standard plan for that region and that retailer. Our method for selecting the standard plan is described in Gibbard and Grubb (2024), as is our method for constructing a monthly price from Powerswitch's data on the variable and fixed components of the price. We calculate a household's monthly bill on the assumption that it consumes 596.4 kWh per month, which is the average monthly consumption in New Zealand over the period from 2018 to 2021.

Further data. We use EA data on the monthly consumption by region. Our demographic data is obtained from the 2018 census. This data primarily comes at the census tract ("Statistical Area 1") level. There are 29,889 census tracts containing around 150 households each.

Table 1 presents summary statistics. At the observation (household-year-month) level, we see that around 0.5% of them involve a retailer switch, and around 0.9% involve an observed search (defined as the household using the price comparison tool). Households pay an average of NZD

[1] In December 2019, there was a merger between the EA's website "What's my number" and Powerswitch, with the former ceasing to operate and its traffic being redirected to Powerswitch. Subsequently, Powerswitch received funding from the EA. See https://www.consumer.org.nz/articles/electricity-authority-and-consumer-nz-merge-price-comparison-websites-whatsmynumber-org-nz-and-powerswitch-org-nz.

[2] Note that we consider 28 out of 39 network reporting regions and delete some visits to Powerswitch, such as two searches by the same household in a single month. See Appendix C for more details on the data cleaning process.

0.27 per kWh, but important heterogeneity exists in the price paid, suggesting that incentives to switch exist. The variable “bill shock”, which measures the percentage change between the previous two months’ bills, underscores the existence of these incentives: Some consumers face large changes in their bills month-to-month, which may be motivation to search for alternative retailers (Heiss et al., 2021; Hortaçsu et al., 2017). At the household level, the switching and searching distributions are heavily skewed: although around 19% of households have switched and 26% of households have used the price comparison tool, most households never switch or search. In contrast, some households search and switch retailers multiple times. We also see substantial heterogeneity across census tracts regarding income, age, educational attainment, and ethnicity.

Table 2 dives deeper into switching and searching rates in our sample. The upper part of the Table shows that consumers are considerably more likely to switch retailers conditional on having recently visited the price comparison website. The effect is still substantial even if the consumer visited the website three months ago. These numbers suggest that using the price comparison tool plays an important role in switching behavior. The lower part of the Table shows that, conversely, the likelihood of observing a search (i.e. using the price comparison tool) is much higher conditional on observing a switch.

New Zealand started the process of liberalizing electricity markets in the late 1980s. This process created regulated monopolies in transmission and distribution but introduced competitive generation and retail markets. However, the retail market in the late 2010s was still dominated by the “Big 5”, the five historical incumbents.[3] The market share panel of Table 1 suggests that the retail market in New Zealand is still concentrated, with the largest five retailers having enjoyed an average combined market share of over 75%. The “Small 5”, who are the next five largest retailers, have only gained around 20% of the market. Figure 1 sheds more light on the evolution of the retail market from 2018-2022. Market shares of the Big 5 retailers are high but fall throughout the sample period, whereas the market shares of some small retailers rise from low levels. The right panel of Figure 1 plots the percentage of consumers that use the

[3]The Big 5 retailers are Contact Energy, Genesis Energy, Mercury Energy, TrustPower, and Meridian Energy. Note that, at the end of our time period, the parent companies of TrustPower and Mercury merged; moreover, in the middle of 2023, the retail brand of TrustPower changed to Mercury.

price comparison tool in any given month against the average bill paid. The figure suggests that search rates often spike when bills increase (which is mainly due to seasonal consumption patterns), suggesting that bill shocks may prompt consumers to search. As might be expected, the average search rate on Powerswitch rose after its merger with the EA's website, which occurred in December 2019.

Switching behavior

How does using the price comparison tool affect consumer switching? Such a tool ensures that consumers are informed about all products and prices. Not using the tool may force the consumer to trade off choosing within a restricted choice set or spend time and effort learning about all products and prices individually. Table 3 shows aggregate switching behavior across and within retailer groups.[4] In this table, the "Outside Option" (OO) refers to those fringe retailers that are not among the 10 largest – that is, they are not in the Big 5 nor the Small 5. The table contrasts two types of switches: switches that took place "with the price comparison tool" (switches that occurred within three months of using the tool); and those that took place without the tool. The entries in the table record the fraction of switches from the retail group in the row that went to the retail group in the column. For example, the top left entry in the table records that, of the switches from Big 5 retailers that took place with the price comparison tool, 37.67% were switches to a Big 5 retailer.

There are striking differences between the behavior of those who use the price comparison tool and those who don't. Among those who use the tool, most households leaving a Big 5 retailer choose one of the small retailers. Among those who do not use the tool, most households leaving a Big 5 retailer go to another Big 5 retailer instead. The same pattern holds for households leaving small retailers. Tables 7 and 8 in Appendix A provide more granularity on the winners and losers of the price comparison tool: The biggest loser among Big 5 retailers is Genesis: among households who do not use the tool, about 14% switch to Genesis; among those who don't use it, only 8% switch to Genesis. The biggest winners from the Small 5 retailers are Powershop and Electric Kiwi: among households that do not use the tool, Powershop and Electric Kiwi

[4] Tables 7 and 8 in Appendix A document switching behavior broken up by retailer.

(EK) each capture less than 10% of the switches; among those who use the tool, this fraction shoots up to 15% for Powershop and 21% for Electric Kiwi.

Electric Kiwi is an interesting case. In mid-2021, Electric Kiwi withdrew permission to be featured on Powerswitch, partly on account of fees charged by Powerswitch. They returned in January 2022 after both parties reached an agreement. Table 9 in Appendix A shows the share of switchers among Powerswitch users that were captured by Electric Kiwi from June to December of 2021 (when households did not see Electric Kiwi as a potential choice on Powerswitch). During this period, Electric Kiwi's capture rate among those who use the tool plummeted to a quarter of the rates in Table 7, comparable to its capture rate among those who do not use the tool. These numbers suggest that being featured on the price comparison website is crucial for Electric Kiwi's market share.

Reduced-form evidence

Who uses the price comparison tools, and who switches retailers? This section presents reduced-form evidence to shed some light on these questions. Columns 2-4 of Table 4 report regressions where we regress an indicator that a household accessed the price comparison tool in a given month on demographics, information about the current retailer, previous search behavior, and previous choices. So the dependent variable indicates whether the household has engaged in a search for electricity providers using the price comparison website. We see that wealthier and younger households are more likely to search. In contrast to the switching decisions, search decisions are unaffected by the price paid. However, experiencing a bill shock does make searching likelier, suggesting that households "wake up" and go look for alternatives when their bill goes up. Being with a Big 5 retailer is associated with a lower probability of searching, highlighting the presence of consumer inertia. Whether a household ever switched retailers or ever searched previously also makes searching much more likely, when including them individually. However, the effect of ever having switched on searching becomes negative when controlling for both of these variables. Both results suggest that a subsample of the population is substantially more active than the rest.

The last three columns of Table 4 report results from a regression where we regress a monthly indicator of whether a household switched retailers on similar regressors as in the searching regressions. The Table shows that households that switch tend to be younger on average. In contrast to the decision to search, income is no longer positively correlated with the probability of switching, perhaps suggesting that lower-income households are more price sensitive. Searching is positively correlated with the probability of switching retailers, as expected (where "search" here is defined as the household having accessed the price comparison tool in the previous three months). Being with a Big 5 retailer is associated with a reduced probability of switching, on the other hand. This negative correlation could indicate inertia or strong brand attachment to Big 5 retailers. We will disentangle these forces in the structural model. Columns 6 and 7 also suggest that, although the price paid at the current retailer correlates with more switching, experiencing a bill shock is not an important driver of switching, as evidenced by the statistically insignificant coefficient on *bill shock*. We also see that households who have previously switched are substantially more likely to switch again, reflecting the skewed distribution of switches across the population.

Table 5 investigates the impact of Electric Kiwi leaving the price comparison tool in June 2021 for six months. We do so by running a difference-in-differences-style strategy. In the first two columns, we regress an indicator that a household switches to Electric Kiwi on a search indicator (*Search*), an indicator that Electric Kiwi is off the price comparison tool (*EK off*), and their interaction, along with further controls (the same ones we used in the previous regressions). In the third and fourth columns, the dependent variable is instead an indicator that a household switches to any Small 5 retailer, which is regressed on the same set of regressors; in columns five and six, we use an indicator that a household switches to a Big 5 retailer. If Electric Kiwi is negatively impacted by no longer being featured on the price comparison tool, we would expect the interaction term between *Search* and *EK off* to be negative in the first two columns. In the third to sixth columns, this interaction indicates where switches to Electric Kiwi were diverted to. If the interaction term was zero in columns three and four (where the dependent variable is a Switch to any Small 5 retailer), it would indicate that all switches instead went to other Small 5 retailers. If it is negative, it would suggest that some retailers instead chose non-Small 5 retailers. The first two columns show that Electric Kiwi dropping off the search platform substantially reduces switching to Electric Kiwi, as evidenced by the negative and statistically significant coefficient on the interaction term. This result corroborates the descriptive evidence in Table 9: being visible on the price comparison tool is crucial for Electric Kiwi's market share. Who gains the market share that Electric Kiwi loses? Columns three and four show that the overall market share of the Small 5 retailers dropped, suggesting that Electric Kiwi dropping off the price comparison tool generated diversion to non-Small 5 retailers. The last two columns confirm this, as the interaction term there is positive, suggesting that Electric Kiwi dropping off the price comparison tool led to more switching towards Big 5 retailers.

3 Model

To disentangle the different frictions facing consumers when choosing retailers, we build and estimate a structural model of retailer choice. The model includes two stages: consumers first decide whether to search for alternative tariffs. If they search, they decide which retailer to use.

Probability of searching

The probability of searching is modeled as depending on demographic variables and also the bill shock in the previous period. As defined in the previous section, the bill shock of household h in month t, $b_{h,t}$, is the percentage change between the bill in month t and the bill in the previous month. The five demographic variables were described in the previous section: for household h, household income is denoted by z_h^1; age by z_h^2; Maori share by z_h^3, Pacifica share by z_h^4; and education (share with Bachelor degree or higher) by z_h^5. We use a standard binary logit model. In particular, the probability that household h searches in period t is given by:

$$S_{ht}(\lambda) = \frac{e^{W_{ht}}}{1+e^{W_{ht}}} \tag{1}$$

where

$$W_{ht} = \lambda^1 + \lambda^2 b_{h,t-1} + \lambda^3 z_h^1 + \lambda^4 z_h^2, \lambda^5 z_h^3 + \lambda^6 z_h^4 + \lambda^7 z_h^5 \tag{2}$$

and λ is the vector $(\lambda_1, \ldots, \lambda_7)$. Equation (1) is interpreted as a reduced form representation of the determinants of inattention. Our modeling of the first stage of the decision process is similar to that in (Heiss et al., 2021; Hortaçsu et al., 2017). The idea is that consumers are passive and inattentive, not searching at all until they are "awoken", in which case they search a subset of the alternatives. By way of contrast, in the model of (Dressler and Weiergraeber, 2023), consumers are active and awake in every period.

The dependency of choice sets on the type of search

If a search is undertaken, it can take two forms: a Powerswitch search and a non-Powerswitch search. The probability that a search occurs on Powerswitch depends on whether the search was undertaken before or after the merger in December 2019 of Powerswitch with the EA's price comparison website. ψ_1 denotes the probability of a Powerswitch search conditional on a search being undertaken before the merger; ψ_2 denotes the conditional probability after the merger. ψ_1 and ψ_2 are assumed to be exogenous parameters, which reflect consumers' awareness of Powerswitch, as well as the availability of alternative methods of search. The expectation is that ψ_2 is greater than ψ_1, which is consistent with the observation that the average search rate on Powerswitch increased post-merger (see the right panel of Figure 1). ψ denotes the vector (ψ_1, ψ_2). For period t, we define the scalar ψ^t to be such that $\psi^t = \psi_1$ if t is before the merger and $\psi^t = \psi_2$ otherwise.

What is the choice set of consumers after searching? Hortaçsu et al. (2017) and Heiss et al. (2021) assume that after searching, consumers consider all the alternatives. In our model, this would mean that the choice set comprises eleven retailers – the Big 5, the Small 5 and the outside option. However, Table 3 shows that the propensity to switch to Small 5 retailers is substantially higher after a Powerswitch search than a non-Powerswitch search. We accommodate this by restricting the choice set following a non-Powerswitch search. We assume that, after a non-Powerswitch search, with probability π, a consumer's choice set is restricted to the Big 5 together with the consumer's retailer in the previous period. We denote the restricted choice set of household h in period t by $C^R_{ht} := \{1, \ldots, 5\} \cup \{m_{h,t-1}\}$, where m_{ht} is household h's retailer in period t.[5] However, after a non-Powerswitch search, with probability $1-\pi$, the consumer has the full choice set $C^F := \{1,\ldots,11\}$. This may be the case, for example, if the consumer searches a non-Powerswitch price comparison website. By way of contrast, we assume that, with a probability of 1, the household has the full choice set C^F in periods where they undertake a Powerswitch search.

Table 2 suggests that a Powerswitch search not only has an effect on the switching rate in the same period but also in the next few periods, although that effect diminishes over time. Accordingly, our model allows for a Powerswitch search to generate a full choice set C^F not only in the same month (with probability 1) but also a full choice set in the following three months with probability δ_τ, with $\tau \in \{1,2,3\}$. We would expect that $\delta_1 > \delta_2 > \delta_3$.

To summarize, Figure 2 depicts the paths to forming the various possible choice sets in our model, along with the associated probabilities.

Retailer choice

The utility of household h from choosing retailer m depends upon three factors. First, households view retailers as providing differentiated products. Their assessment of retailer m's value is captured by a retailer-specific constant α_m in their utility function, with the constant for the outside option being normalized to zero. Second, household h's utility from retailer m is affected by h's price for that retailer, p^m_{ht}. Consistent with the reduced-form results, we allow for a consumer's price sensitivity to depend on their income. In particular, we specify the price coefficient for household h to be $\beta^h = \beta_1 + \beta_2 z^1_h$. If $\beta^h < 0$ and poorer households tend to be more price sensitive, then $\beta_2 > 0$. Third, there is assumed to be a switching cost of γ, which is interpreted as incorporating either a monetary cost or a (non-monetary) effort cost from switching. Accordingly, household h's utility from choosing retailer m at time t is given by:

$$U^m_{ht} \equiv V^m_{ht} + \varepsilon^m_{ht}, \tag{3}$$

[5] In our model, the universe of retailers is 11 firms. The Big 5 are denoted by $1,\ldots,5$; the Small 5 by $6,\ldots,10$; and the outside option by 11.

where ε_{ht}^{m} is an i.i.d. Gumbel random variable and

$$V_{ht}^{m} \equiv \alpha_m + \beta^h p_{ht}^{m} + \gamma \mathbf{1}_{m \neq m_{h,t-1}} \tag{4}$$

where $\mathbf{1}_{m \neq m_{h,t-1}}$ is an indicator variable with a value of one if $m \neq m_{h,t-1}$ and zero otherwise. For month t and household h, conditional on the choice set $C \subset \{1,\ldots,11\}$, household h chooses retailer i if and only if the utility from i, U_{ht}^{i}, is the maximum of the utilities for the various alternatives in the choice set C. So the probability of household h choosing i at time t conditional on choice set C is:

$$Q_{ht}^{i}(\alpha,\beta,\gamma|C) = \frac{e^{V_{ht}^{i}}}{\sum_{m \in C} e^{V_{ht}^{m}}} \tag{5}$$

where α is the vector $(\alpha_1,\ldots,\alpha_{10})$ and β is the vector (β_1,β_2).

4 Estimation

We estimate the model via a maximum likelihood procedure. We first describe how we calculate the choice probabilities from the model. Second, we explain how the choice probabilities are used to specify the likelihood function. Third, we discuss the identification of the model.

Choice probabilities

An observation for household h in period t must fall into one of the following six cases.

Case (1): h undertakes a Powerswitch search in period t.

Case (2): h switches in period t, having undertaken a Powerswitch search in one of the three previous periods.

Case (3): h does not switch in period t, having undertaken a Powerswitch search in one of the three previous periods.

Case (4): h switches to a Big 5 retailer in period t, having not undertaken a Powerswitch search in period t nor in the three previous periods.

Case (5): h switches to a Small 5 retailer or the outside option in period t, having not undertaken a Powerswitch search in period t nor in the three previous periods.

Case (6): h does not switch in period t, having not undertaken a Powerswitch search in period t nor in the three previous periods.

For each of these six cases, we provide an expression for the choice probability below. Note that the probability for time period t should be interpreted as being conditional on the events in previous periods.

Case 1: h undertakes a Powerswitch search in period t.

Suppose that in period t, household h searches on Powerswitch and then chooses retailer m (which may or may not constitute a switch). There is only one way in which this event can happen. First, the household decides to search, with probability $S_{ht}(\lambda)$, given by equation (1). Second, the search is a Powerswitch search, which (conditional on there being a search) occurs with probability ψ^t. Third, the choice set is then the full set $C^F = \{1,\ldots,11\}$. Fourth, conditional on this choice set, the household chooses retailer m, with probability $Q^m_{ht}(\alpha,\beta,\gamma|C^F)$, given by equation (5).

Hence, the choice probability is:

$$P_{ht}(\alpha,\beta,\gamma,\lambda,\psi) = \psi^t S_{ht}(\lambda) Q^m_{ht}(\alpha,\beta,\gamma|C^F)$$

Case 2: h switches in period t, having undertaken a Powerswitch search in one of the three previous periods.

Suppose that in period t, household h switches to retailer m, having been observed to undertake a Powerswitch search s months ago, where $s \in \{1,2,3\}$. There is only one way in which the event can occur. First, the household is awake after the search s months ago, which occurs with a probability δ_s. Thus the choice set is the full set of retailers $C^F = \{1,\ldots,11\}$. Third, conditional on this choice set, the household chooses retailer m, with probability $Q^m_{ht}(\alpha,\beta,\gamma|C^F)$, given by equation (5). So the choice probability is:

$$P_{ht}(\alpha,\beta,\gamma,\delta) = \delta_s Q^m_{ht}(\alpha,\beta,\gamma|C^F)$$

Case 3: h does not switch in period t, having undertaken a Powerswitch search in one of the three previous periods.

Suppose that in period t, household h sticks with its retailer m from the previous period, having been observed to undertake a Powerswitch search s months ago, where $s \in \{1,2,3\}$. There are two broad ways in which this can occur. The first way is if, despite the Powerswitch search s months ago, the household is no longer awake. This occurs with probability $1-\delta_s$. The second way is as follows. The household is awake after the search s months ago, with probability δ_s. So the choice set is the full set of retailers $C^F = \{1,\ldots,11\}$. Conditional on this choice set, the household chooses m, with probability $Q^m_{ht}(\alpha,\beta,\gamma|C^F)$, given by equation (5). So the choice probability is:

$$P_{ht}(\alpha,\beta,\gamma,\delta) = (1-\delta_s) + \delta_s Q^m_{ht}(\alpha,\beta,\gamma|C^F)$$

Case 4: h switches to a Big 5 retailer in period t, having not undertaken a Powerswitch search in period t nor in the three previous periods.

Suppose that in period t, household h switches to a Big 5 retailer m, despite not undertaking a Powerswitch search in periods $t-s$, for $s \in \{0,1,2,3\}$. This event must occur as follows. First, the household decides to search, with probability $S_{ht}(\lambda)$, given by equation (1). Second, the search is a non-Powerswitch search, which (conditional on there being a search) occurs with probability $1-\psi^t$. This can affect consideration in two ways. Either the non-Powerswitch search yields a restricted choice set $C^R_{ht} = \{1,\ldots,5\} \cup \{m_{h,t-1}\}$, which occurs with probability π, or, with probability $1-\pi$, it yields the full choice set C^F. In the first case, the choice probability conditional on the choice set is $Q^m_{ht}(\alpha,\beta,\gamma|C^R_{ht})$ and in the second case, it is $Q^m_{ht}(\alpha,\beta,\gamma|C^F)$. So the choice probability is:

$$P_{ht}(\alpha,\beta,\gamma,\lambda,\pi,\psi) = S_{ht}(\lambda)(1-\psi^t)\Big(\pi Q^m_{ht}(\alpha,\beta,\gamma|C^R_{ht}) + (1-\pi)Q^m_{ht}(\alpha,\beta,\gamma|C^F)\Big)$$

Case 5: h **switches to s Small 5 retailer or the outside option in period** t**, having not undertaken a Powerswitch search in period** t **nor in the three previous periods.**

Let m denote a Small 5 retailer or the outside option. Suppose that in period t, household h switches to m, despite not undertaking a Powerswitch search in periods $t-s$, for $s \in \{0,1,2,3\}$. This event must occur as follows. First, the household decides to search, with probability $S_{ht}(\lambda)$, given by equation (1). Second, the search is a non-Powerswitch search, which, conditional on there being a search, occurs with probability $1-\psi^t$. As the switch is to a Small 5 retailer or the outside option, the non-Powerswitch search does not yield the restricted choice set; so it must generate the full choice set C^F, which has a probability of $1-\pi$. In this case, the choice probability conditional on the choice set is $Q^m_{ht}(\alpha,\beta,\gamma|C^F)$. So the choice probability is:

$$P_{ht}(\alpha,\beta,\gamma,\lambda,\pi,\psi) = S_{ht}(\lambda)(1-\psi^t)(1-\pi)Q^m_{ht}(\alpha,\beta,\gamma|C^F)$$

Case 6: h **does not switch in period** t**, having not undertaken a Powerswitch search in period** t **nor in the three previous periods.**

Suppose that in period t, household h remains with its retailer m from the previous period and does not undertake a Powerswitch search in periods $t-s$, for $s \in \{0,1,2,3\}$. There are two general ways in which this event can occur: either the household decides not to search, which occurs with probability $1-S_{ht}(\lambda)$ or it decides to search, with probability $S_{ht}(\lambda)$. In the second case, the search is a non-Powerswitch search, which, conditional on there being a search, occurs with probability $1-\psi^t$. This can generate two types of choice sets. With probability π, the non-Powerswitch search yields the restricted choice set $C^R_{ht} = \{1,\ldots,5\} \cup \{m_{h,t-1}\}$ and, with probability $1-\pi$, it generates a full choice set C^F. In the first scenario, the choice probability conditional on the choice set is $Q^m_{ht}(\alpha,\beta,\gamma|C^R_{ht})$ and in the second scenario, it is $Q^m_{ht}(\alpha,\beta,\gamma|C^F)$. The choice probability is then given by:

$$\begin{aligned}&P_{ht}(\alpha,\beta,\gamma,\lambda,\pi,\psi) = \\ &(1-S_{ht}(\lambda)) + S_{ht}(\lambda)(1-\psi^t)\Big(\pi Q^m_{ht}(\alpha,\beta,\gamma|C^R_{ht}) + (1-\pi)Q^m_{ht}(\alpha,\beta,\gamma|C^F)\Big)\end{aligned}$$

The likelihood function

To simplify the estimation procedure and diminish the computational expense, we reduce the size of our dataset as follows. First, we remove the three regions in which Electric Kiwi only entered in June 2020, leaving 25 regions in our dataset. Second, given that, in several other regions, Electric Kiwi had not entered the first two months of our time period (January and February 2018), we also removed those periods from our dataset. In the final dataset, the first period, $t = 1$, is March 2018; the final period, $T = 51$, is May 2022. Third, from the set of households that do not move throughout our period, we randomly select $N = 100,000$ households, which we use to estimate the structural model. In the previous section, the choice probabilities that we specified for period t are conditional on choices in the previous three months. Hence we estimate the parameters determining the households' choices for months $t = 4$ to month T, conditioning on choices in months $t = 1,2,3$. Accordingly, using the choice probabilities P_{ht} specified in the previous section, we can write the log-likelihood function as follows:

$$\mathscr{L}(\alpha,\beta,\gamma,\delta,\lambda,\pi,\psi) = \sum_{h=1}^{N}\sum_{t=4}^{T} \log P_{ht}(\alpha,\beta,\gamma,\delta,\lambda,\pi,\psi)$$

Identification

As a substantial fraction of searches are observed in our dataset, the explanation for the identification of our estimators is more straightforward than in other models of two-stage decision processes where searches are not observed, such as Heiss et al. (2021) and Hortaçsu et al. (2017). The values of the parameters in the vector λ are identified by the extent to which demographic variables and bill shocks affect the probability of an *observed* search. Identification of α, β, and γ follows from standard identification arguments for logit models with no choice set restrictions. Identification of ψ comes from variation in Powerswitch searches and switch rates; in particular, the fact that we observe more switches when there are more Powerswitch searches in a given month (Table 2). The parameter π is identified from variation in the propensity to switch to Small 5 retailers between Powerswitch and non-Powerswitch users. In particular, recall that Table 3 displayed the discrepancy between the fraction of switches to the Small 5 after a Powerswitch search and the fraction of switches to the Small 5 after a non-Powerswitch search. Consider the following thought experiment: assume that this discrepancy increases. The model will rationalize this via a higher value of π. To see why the parameters in the vector δ are identified, consider, for example, the first member of the vector δ_1. This parameter will be higher, all else equal, the greater is the fraction of Powerswitch searches that are followed by a switch one month later, relative to the fraction of Powerswitch searches that are accompanied by a switch in the same month – these fractions are presented in Table 2.

In order to check whether the model can recover the parameters of interest, we create a simulated dataset with $N = 100,000$ households and $T = 51$ time periods. The values of the prices, bill shocks, and demographic variables are generated by draws from a standard normal distribution; the decisions to search and choose retailers are then generated by our model, using values for the parameters substantially different from our estimates. We find that our maximum likelihood estimation procedure is able to recover the true values of the parameters. Importantly, all estimates are close to the true values. The results of the simulation exercise are presented in Appendix B.

5 Results

Table 6 reports the maximum likelihood estimates for the structural model. The top panel of the left column presents the parameters that determine the decision to search, λ. We see that experiencing a bill shock induces consumers to search for a new retailer, a result that is consistent with previous studies (Hortaçsu et al., 2017). We also find that higher-income individuals are more likely to search. This result is in line with findings by Byrne and Martin (2021), who review the literature on search and find that search tends to increase with income[6]. We also see that consumers residing in older census tracts search less, which could be explained by lower access to, or less ease with, technology. The results from the structural model are also broadly in line with the reduced-form findings we presented in Table 4.

The right column of Table 6 reports the results regarding the retailer choice stage. We see that higher-income consumers are less price-responsive, underlining an interesting pattern between

[6]For retail electricity in Australia, they find an inverse U-shaped relationship, with search intensity decreasing again in the uppermost income bracket.

income and consumer choices: whereas lower-income households are more price-sensitive, they are less likely to search, thus severely restricting their choice sets. We estimate a switching cost of about NZD 266 (around USD 170), which lies on the higher end of what previous studies have found for retail electricity, even though it is in line with what has been found for TV subscriptions in the US (see Shcherbakov, 2016). The average monthly electricity bill in New Zealand is about NZD 169, so we estimate switching costs to represent around 157% of monthly electricity expenditure. Further, households exhibit substantial brand heterogeneity, as evidenced by the retailer-specific constants reported in the bottom panel of the Table. With the exception of Electric Kiwi, consumers have a strong preference for contracting with a Big 5 retailer rather than a Small 5 retailer. Relative to the outside option, consumers are willing to pay about NZD 18 to contract with Genesis, one of the incumbent, vertically integrated retailers.

The bottom panel of the left column specifies the estimates of the parameters that determine the probabilities of choice sets conditional on search. We estimate around 13.5-15% of searches are on Powerswitch; this is close to the fraction of switches that occur in the same month as a Powerswitch search, presented in Table 2. Note that the probability of a search being on Powerswitch is higher after its merger with the EA's price comparison website ($\psi_2 > \psi_1$). As expected, the probability of being awake after a Powerswitch search declines with time: from 48% after one period to 22% after two periods and 16% after three periods. Note that these probabilities approximately correspond to the rate of decline, reported in Table 2, in the probabilities of switching conditional on a search observed in the same month, one month earlier, two months earlier and three months earlier. Of non-Powerswitch searches, a substantial fraction (29 per cent) yield restricted choice sets, which explains the considerable difference, described in Table 3, between (i) the propensity to switch to a Small 5 retailer following a Powerswitch search and (ii) the propensity following a non-Powerswitch search. To assess the fit of our model, we use our estimated parameters to generate a simulated set of choices for the $N = 100,000$ households in our dataset for the months from $t = 4$ to $T = 51$. As specified in our model, these simulated choices depend on the choices made by the households for the months $t = 1,2,3$. The simulated decisions to search are generated by taking draws from a standard logistic distribution, and the simulated choices of retailers (conditional on search) are obtained by drawing from a standard Gumbel distribution. As depicted in Figure 3, our model has a good fit. Figure 3 compares the actual market shares of the Big 5 and Small 5 retailers to the simulated market shares. Our simulation captures accurately the decline in the market share of the Big 5, as well as the rise in the market share of the Small 5.

6 Counterfactuals

We run four sets of counterfactuals to assess the role of price comparison tools in imperfectly competitive markets. First, we analyze the effects of removing the price comparison tool. Second, we consider the effects of making every consumer access the price comparison tool. Then we compare these results to a scenario where, instead, every consumer is forced to search once a year. Finally, we consider the effects of a Small 5 retailer losing access to the price comparison tool.

We calculate each counterfactual by generating a simulation of the 100,000 households in our dataset using the simulation method described above that was used to generate the fitted values. In order to assess how search frictions and information frictions affect welfare, we calculate the effect on consumer surplus per household per month. We use the same method for obtaining *ex-ante* consumer surplus as Dressler and Weiergraeber (2023).[7] For a household h which, in period t, has a choice set of C_{ht}, its *ex ante* consumer surplus is given by

$$CS_{ht} = \frac{1}{\beta^h} \log\Big(\sum_{m \in C_{ht}} \exp(V_{ht}^m)\Big) + K$$

where V_{ht}^m was specified in equation (4) and K is an unknown constant.[8] First, we assess the effect of Powerswitch ceasing to operate. The counterfactual simulation is generated by setting to zero the parameter ψ^t, which represents the probability that, conditional on a search taking place, the search is on Powerswitch. Figure 4 shows the impact of removing the price comparison tool on the market shares of the Big 5 and Small 5 retailers, respectively. The light blue line

[7] For a discussion of the *ex-ante* measure of consumer surplus in the broader literature on discrete choice, see Train (2009).

[8] For the purpose of this equation, the choice set of a household h that does not search in month t is simply given by the singleton set containing their retailer from the previous month.

traces the observed market share, the dark blue line traces the fitted market share, and the red line traces the counterfactual market share. Here and in all further scenarios, we will compare actual (light blue) to counterfactual (red) outcomes. We can see that, in the counterfactual where Powerswitch is removed, the fall in the Big 5's market share would have been less pronounced. Accordingly, the market share of the Small 5 retailers would have been somewhat lower by the end of the sample period, even though the effect is not large: collectively, the Small 5 would hold 0.5 percentage points less of the market. In addition, not having access to Powerswitch would have hurt consumers. We estimate that consumer surplus would have been lower by NZD 0.60 per consumer per month. The total annual consumer surplus would have decreased by NZD 13.7 million.[9]

In the second counterfactual, we simulate the effect of all searches taking place on Powerswitch. This simulation is obtained by setting $\psi^t = 1$. Note that merely all searchers now access the price comparison tool, not all consumers. The effects we find in this counterfactual hold failure to search constant. Only the subset of searchers now has a full choice set when making their retailer choice.

Figure 5 shows the impact on Big 5 and Small 5 market shares. The effects are more pronounced compared to the first counterfactual and unsurprisingly go in the opposite direction. The Big 5 market would be lower by around 4.5 percentage points, whereas the market share of Small 5 retailers would be 3.5 percentage points higher by the end of the sample period. The impact on consumer surplus is positive: consumer surplus would increase by NZD 2.98 per consumer per month; the total annual increase would have been NZD 68.2 million. However, this counterfactual also shows that price comparison tools are no magic bullet for reducing the market share of incumbent retailers. Although non-negligible, the effects on market structure and consumer surplus are not large.

The third counterfactual quantifies the effect of removing the inattention friction – the friction that consumers search infrequently. The goal of this counterfactual is to compare the importance of this friction to the information friction quantified above. We operationalize the third counterfactual by mandating that consumers search in December of each year. Doing

[9]There were 1,906,322 residential electricity connection points in New Zealand in May 2022. We use this number as the total number of households in order to calculate the changes total consumer surplus.

so boils down to undertaking a simulation where the probability of searching is set to one in December of each year. For other months, the probability of searching is unchanged and given by $S_{ht}(\lambda)$.

Figure 6 shows the impact of all consumers searching at least once per year on market shares. By May 2022, the Big 5 market share has decreased by 5.6 percentage points, whereas the Small 5 market share has increased by 4.2 percentage points. Big 5 (Small 5) market shares decrease (increase) by around 1 percentage point more compared to the scenario where every searcher accesses the price comparison tool. This result drives home the takeaway that price comparison tools are not a magic bullet: other frictions exist that are of similar importance to the information friction, and that cannot be solved by deploying price comparison tools alone. The welfare impacts underline this: mandating an annual search increases consumer surplus by NZD 9.64 per consumer per month, which across all households over a whole year amounts to an increase of NZD 220.5 million. Intuitively, it makes sense that removing the inattention friction has a larger impact: it impacts more households. Expanding access to the price comparison tool only affects those households who actively decide to search in the first place, and so it only benefits these households.

Finally, the fourth counterfactual assesses the average effect of a Small 5 retailer removing itself from Powerswitch, as Electric Kiwi did in 2021. The goal of this exercise is to get an idea of the importance of providing consumers with a variety of choices. The results in Table 6 suggest that consumers exhibit strong brand preferences, and the results in Table 5 suggest that a Small 5 retailer being not present on the price comparison tool can have important implications on aggregate switching behavior. We undertake five simulations, each of which corresponds to one retailer from the Small 5 being removed from Powerswitch. In each simulation, we modify the choice set generated by a Powerswitch search to be the full choice set C^F less the relevant retailer that is removed from Powerswitch. We then average across these five simulations to obtain the effect on market shares depicted in Figure 7. The market share of a Small 5 retailer would be hurt substantially by such a move- on average, the market share would be around .4 percentage points lower, which amounts to a 10% drop in market share by the end of our period. This suggests that being present on the price comparison platform is indeed important for small entrants to gain market share.

Overall, the counterfactuals reveal that price comparison tools bring substantial benefits to consumers and can be an effective tool for increasing the market share of small entrant retailers. However, their effectiveness is limited by other frictions. Notably, many consumers fail to search in the first place and never “make it to” the price comparison tool. Removing this friction has a larger impact on consumer welfare and market structure than directly expanding the usage of price comparison tools. These findings are relevant to policymakers wishing to improve effective competition in markets suffering from the frictions we study in this article. In fact, the New Zealand Electricity Authority has started a consultation process with the goal of finding interventions that would make retailer comparisons easier and increase consumer switching rates (see New Zealand Electricity Authority, 2024).

7 Conclusion

Retail electricity markets are characterized by consumer inertia, resulting in part from inattention, informational frictions, switching costs as well as perceived product differentiation. We develop a model of electricity retailer choice that allows us to disentangle the effects of these four sources of consumer inertia. We estimate the model using a unique data set of household retailer switches in New Zealand from January 2018 to May 2022 and household queries on a price comparison website that we can link to the resulting switches.

The raw data reveals substantial differences in switching behavior between households who used the price comparison tool and those who did not. The former are substantially more likely to choose one of the small, younger retailers as opposed to a large incumbent. An episode in which one of the small retailers dropped off the price comparison website led to a substantial drop in switching towards that retailer, underlying the importance of the price comparison tool for new entrants.

In the estimation of the structural model, we find that an increase in the monthly electricity bill makes it more likely that consumers decide to actively search for alternative retailers. Higher-income households are also more likely to actively search, all else equal. On the other hand, these households are less price-sensitive. Younger households are also more likely to search.

Households exhibit substantial switching costs, on the order of around NZD 266.

We use the estimated model to perform a series of counterfactuals aimed at quantifying the impact of price comparison tools on market structure and consumers and compare it to the removal of other frictions. We find that expanding usage of the price comparison tool to all households that search reduces incumbent market share and increases switching to smaller, younger retailers. Consumer surplus increases by almost NZD 3 per consumer per month.

However, the price comparison tool only impacts consumers who decided to search in the first place. We find that making all consumers search for alternative retailers at least once a year has a slightly larger impact on market structure and increases consumer surplus by more than 9.5 NZD per consumer per month.

Our results have implications for policymakers. They suggest that merely increasing awareness about price comparison tools and making them easier use is no magic cure in a market where many frictions co-exist. Our results suggest that a policy that encourages more consumers to actively search should go hand in hand with encouraging usage of price comparison tools. In doing so, more consumers can make more informed choices.

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Tables

Table 1. Summary statistics

	Mean	Median	Min	Max
Observation level				
Switch	0.005	0.000	0.000	1.000
Search	0.009	0.000	0.000	1.000
Has ever switched	0.112	0.000	0.000	1.000
Has ever searched	0.150	0.000	0.000	1.000
Price (in NZD/kWh)	0.272	0.266	0.179	0.431
Bill shock (in %)	0.775	-1.010	-39.488	76.617
Household level				
Switch	0.186	0.000	0.000	1.000
Search	0.261	0.000	0.000	1.000
Demographics				
Income (in NZD 100k)	0.825	0.786	0.023	1.500
Age (in 100 years)	0.401	0.385	0.161	0.883
Share Bachelor degree or higher	0.291	0.265	0.000	0.889
Ethnicity				
Share Maori	0.155	0.111	0.000	1.000
Share Pacifica	0.068	0.029	0.000	1.000
Market shares				
Big 5				
Contact Energy	0.207	0.207	0.203	0.215
Genesis Energy	0.183	0.182	0.172	0.196
Mercury Energy	0.169	0.169	0.157	0.184
TrustPower	0.121	0.120	0.118	0.128
Meridian Energy	0.080	0.081	0.077	0.084
Small 5				
Powershop	0.040	0.040	0.029	0.050
Frank Energy	0.047	0.047	0.045	0.048
Nova Energy	0.031	0.031	0.026	0.036
Pulse Energy	0.041	0.040	0.036	0.044
Electric Kiwi	0.028	0.029	0.010	0.041
Other				
Fringe retailers	0.055	0.055	0.047	0.059
Sample sizes				
Number of observations	78,122,701			
Number of households	1,894,688			
Number of time periods	53			

Table 2. Average monthly probability of switches and searches

Type	Percentage
Switch	
Unconditional	0.54
Conditional on:	
search same month	7.4
search 1 month ago	3.8
search 2 months ago	1.8
search 3 months ago	1.4
Search	
Unconditional	0.95
Conditional on:	
switch same month	12.9
switch same month or subsequent month	19.3
switch same month or subsequent 2 months	22.5
switch same month or subsequent 3 months	24.9

Table 3. Aggregate switching behavior

	With price comparison tool			Without price comparison tool		
From \ To	BIG 5	SMALL 5	OO	BIG 5	SMALL 5	OO
BIG 5	0.3767	0.5075	0.1159	0.5063	0.2961	0.1976
SMALL 5	0.4311	0.4255	0.1434	0.5024	0.2585	0.2391
OO	0.3811	0.5126	0.1063	0.4397	0.3119	0.2485

Table 4. Reduced form evidence: searching and switching

Dependent Variable:	Search			Switch		
Variables						
Search				2.305***	2.285***	2.275***
				(0.0427)	(0.0421)	(0.0418)
Price	-0.0461	-0.1523	0.2965	6.068***	5.880***	5.962***
	(1.153)	(1.145)	(0.9734)	(1.651)	(1.583)	(1.590)
Bill shock	0.0049***	0.0048***	0.0047***			0.0015
	(0.0010)	(0.0010)	(0.0010)			(0.0011)
Big 5	-0.2944***	-0.2618***	-0.2370***	-0.5175***	-0.4690***	-0.4673***
	(0.0345)	(0.0365)	(0.0289)	(0.0553)	(0.0524)	(0.0525)
Income	0.4220***	0.4147***	0.3274***	-5.6×10^{-5}	-0.0097	-0.0113
	(0.0497)	(0.0488)	(0.0390)	(0.0225)	(0.0218)	(0.0225)
Age	-1.181***	-1.172***	-1.032***	-1.210***	-1.200***	-1.200***
	(0.1164)	(0.1156)	(0.0962)	(0.1636)	(0.1593)	(0.1571)
Education	0.0003	0.0124	-0.0056	-0.2335	-0.2172	-0.2113
	(0.2191)	(0.2159)	(0.1668)	(0.1647)	(0.1566)	(0.1567)
Share Maori	-0.6132***	-0.6101***	-0.5128***	-0.0064	-0.0037	0.0013
	(0.1380)	(0.1386)	(0.1206)	(0.0768)	(0.0750)	(0.0775)
Share Pacifica	-0.5955***	-0.6016***	-0.5408***	0.4550***	0.4508***	0.4573***
	(0.1964)	(0.1956)	(0.1683)	(0.0839)	(0.0819)	(0.0802)
Ever switched		0.1869***	-0.0652***		0.2665***	0.2689***
		(0.0234)	(0.0179)		(0.0355)	(0.0346)
Ever searched			0.9946***			
			(0.0505)			
Fixed-effects						
Region	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	74,992,860	74,992,860	74,992,860	78,122,701	78,122,701	75,363,098
Pseudo R^2	0.01867	0.01942	0.05661	0.05807	0.05873	0.05931

Clustered (Region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5. Logit regression: Electric Kiwi leaving Powerswitch

Dependent Variables:	Switch to EK		Switch to Small 5		Switch to Big 5	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
EK off	-0.4917***	-0.5940***	-0.3394***	-0.4359***	0.0399	0.1709*
	(0.0338)	(0.0409)	(0.0585)	(0.0542)	(0.0736)	(0.0910)
Search	3.479***	3.463***	2.920***	2.883***	1.912***	1.813***
	(0.0801)	(0.0859)	(0.0485)	(0.0502)	(0.0391)	(0.0431)
I(EK off × Search)	-1.253***	-1.262***	-0.2259***	-0.2309***	0.2613***	0.2725***
	(0.0713)	(0.0744)	(0.0622)	(0.0644)	(0.0284)	(0.0281)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Region	Yes	Yes	Yes	Yes	Yes	Yes
Year		Yes		Yes		Yes
Month		Yes		Yes		Yes
Fit statistics						
Observations	75,363,098	75,363,098	75,363,098	75,363,098	75,363,098	75,363,098
Pseudo R^2	0.12823	0.13167	0.08462	0.08953	0.20675	0.21479

Clustered (Region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6. Results from the structural model

Stage One: Decision on search			**Stage Two: Decision on retailer**		
Parameter	Estimate	Std. error	Parameter	Estimate	Std. error
Constant (λ_1)	-2.0794***	(0.0280)	Price (β_1)	-0.0198***	(0.0013)
Bill shock (λ_2)	0.0199***	(0.0004)	Price × inc. (β_2)	0.0026*	(0.0014)
Income (λ_3)	0.3119***	(0.0084)	Switching cost (γ)	-4.7877***	(0.0181)
Age (λ_4)	-1.8269***	(0.0261)	*Retailer constant*		
Maori (λ_5)	-0.5804***	(0.0146)	Contact (α_1)	-0.0196	(0.0136)
Pacifica (λ_6)	-0.8241***	(0.0198)	Genesis (α_2)	0.3179***	(0.0148)
Education (λ_7)	-0.1415***	(0.0205)	Mercury (α_3)	-0.1927***	(0.0231)
			TrustPower (α_4)	0.0212*	(0.0119)
Choice set probabilities given search			Meridian (α_5)	-0.2682***	(0.0140)
Probabilities of Powerswitch search			Powershop (α_6)	-0.3083***	(0.0124)
Pre-merger (ψ_1)	0.1350***	(0.0029)	Frank (α_7)	-0.7681***	(0.0177)
Post-merger (ψ_2)	0.1502***	(0.0030)	Nova (α_8)	-0.6179***	(0.0255)
Probabilities awake post-search			Pulse (α_9)	-0.3077***	(0.0175)
At lag 1 (δ_1)	0.4806***	(0.0146)	EK (α_{10})	-0.0581***	(0.0118)
At lag 2 (δ_2)	0.2173***	(0.0090)			
At lag 3 (δ_3)	0.1590***	(0.0069)			
Probabilities given non-Powerswitch search					
Restricted search (π)	0.2877 ***	(0.0144)			

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figures

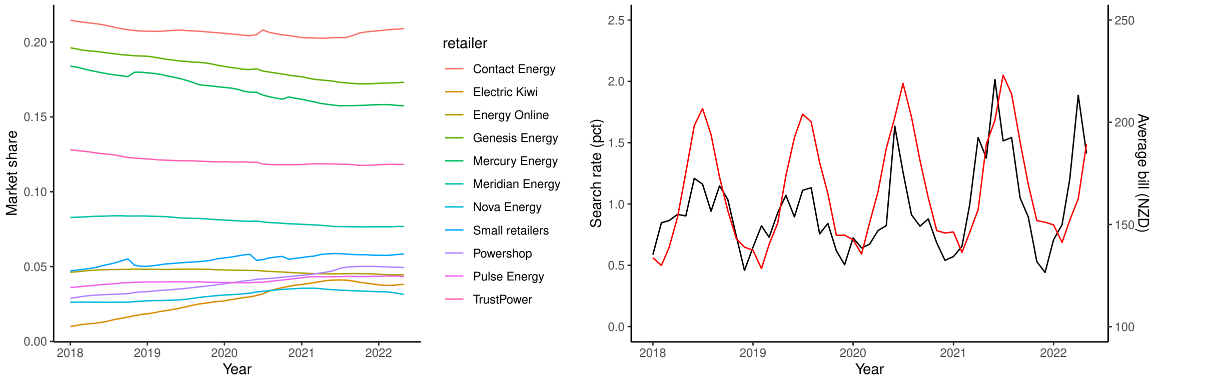
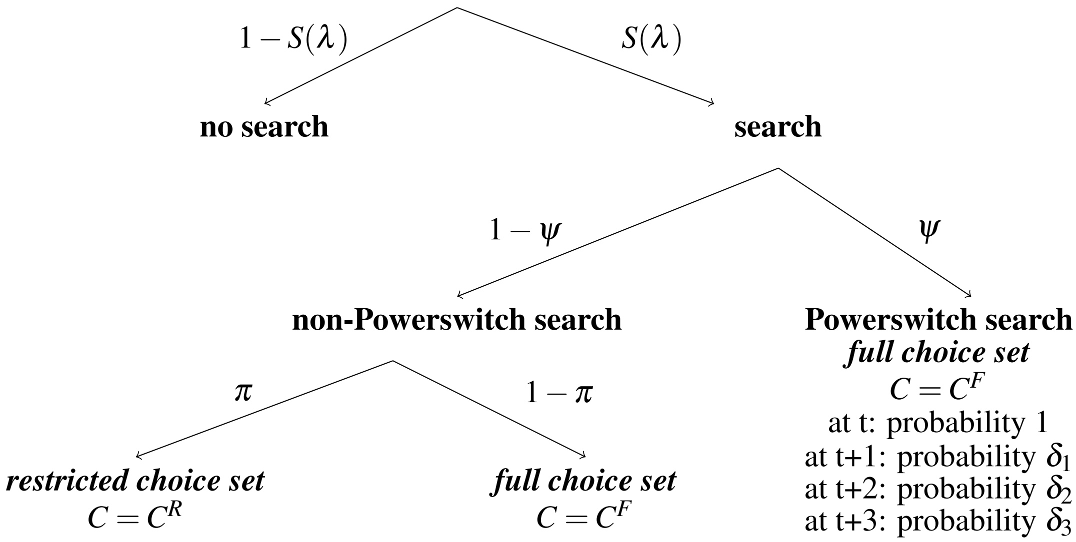
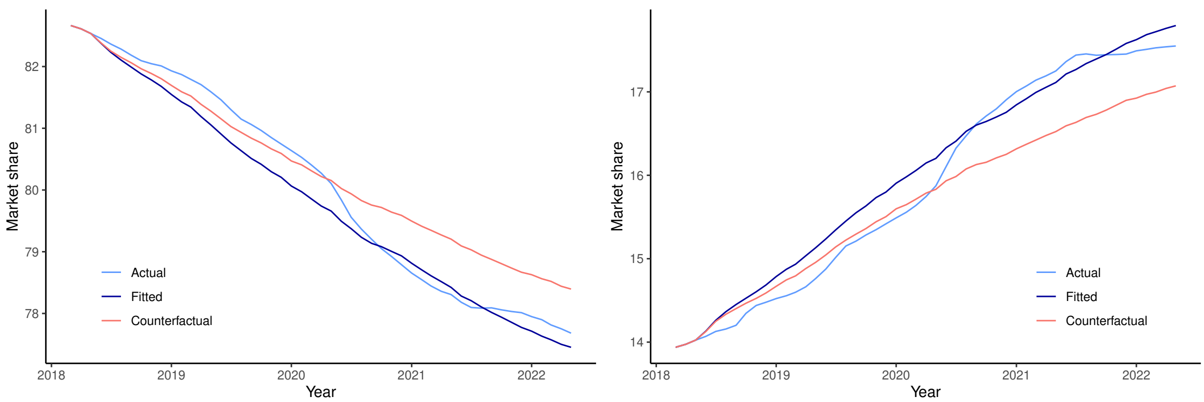


Figure 1. Left panel: Retailer market shares. Right panel: search rate (black line) against consumer bill (red line)

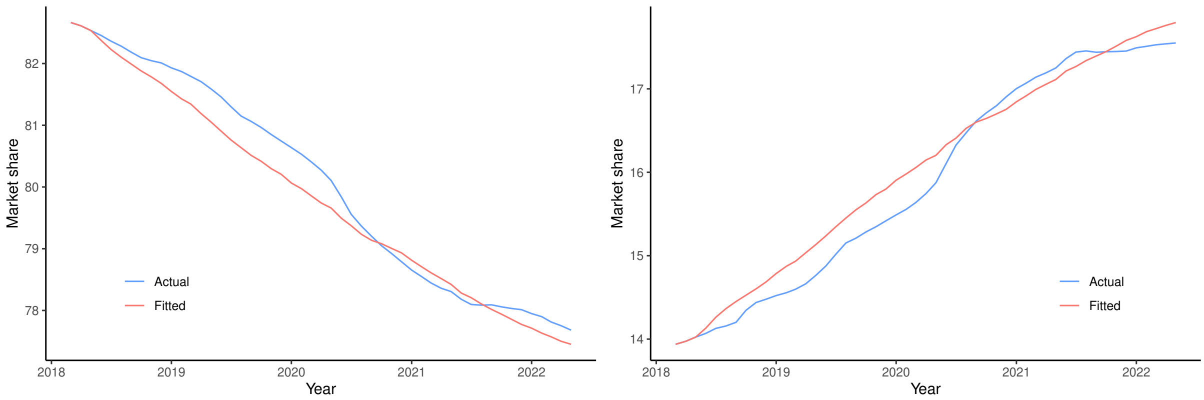
Figure 2. Paths to forming choice sets





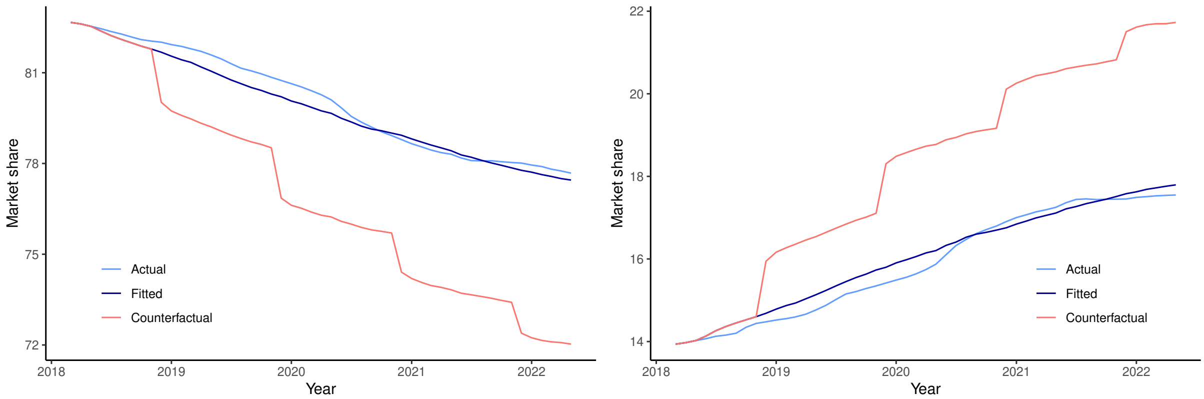
(a) Big 5 **(b)** Small 5

Figure 4. Impact of removing Powerswitch on market shares



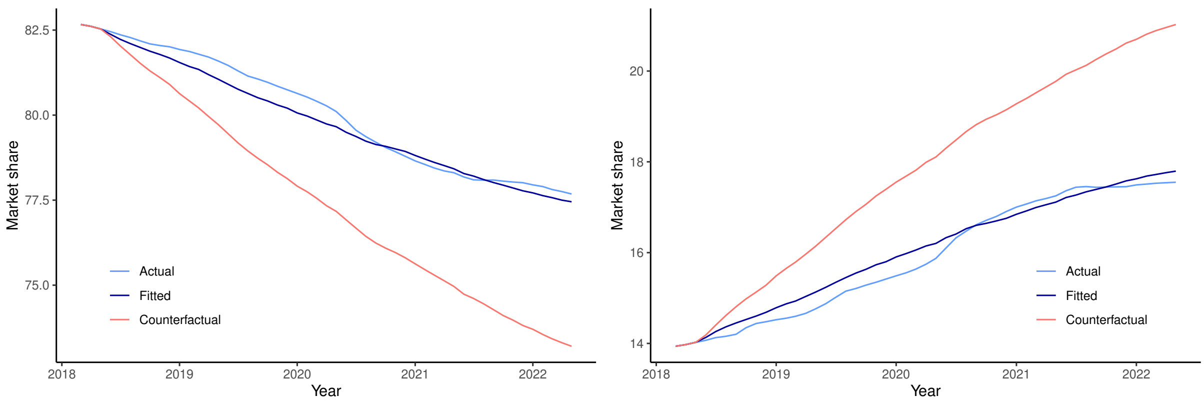
(a) Big 5 **(b)** Small 5

Figure 3. Fitted market shares



(a) Big 5 **(b)** Small 5

Figure 6. Impact of all consumers searching in December on market shares



(a) Big 5 **(b)** Small 5

Figure 5. Impact of all consumers using Powerswitch on market shares

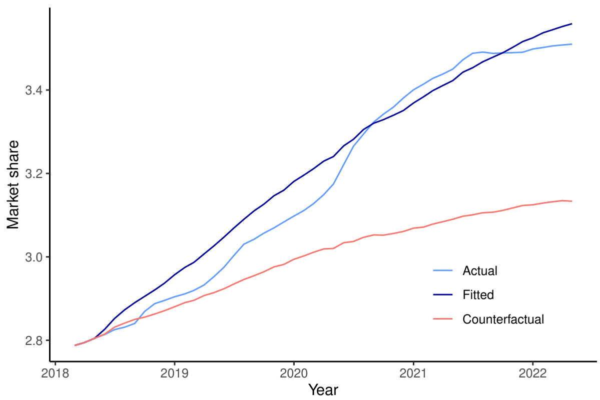


Figure 7. Impact of a Small 5 retailer leaving the price comparison tool

Appendix

A Additional Figures and Tables

Table 7. Switching behavior with price comparison tool

	To Big 5					To Small 5					To OO
	Contact	Genesis	Mercury	TrustPower	Merid.	Powershop	Frank	Nova	Pulse	EK	OO
From Big 5											
Contact	0.0000	0.1069	0.0871	0.0797	0.0712	0.1612	0.0347	0.0605	0.0445	0.2246	0.1297
Genesis	0.1220	0.0000	0.0761	0.0769	0.0747	0.1479	0.0477	0.0709	0.0440	0.2242	0.1156
Mercury	0.1405	0.1058	0.0000	0.0706	0.0862	0.1302	0.0356	0.0464	0.0359	0.2479	0.1010
TrustPower	0.1677	0.0960	0.0876	0.0000	0.0715	0.1571	0.0325	0.0707	0.0472	0.1601	0.1097
Merid.	0.1474	0.0886	0.0651	0.0673	0.0000	0.1581	0.0390	0.0308	0.0295	0.2386	0.1288
From Small 5											
Powershop	0.1467	0.0785	0.0616	0.0695	0.0610	0.0000	0.0631	0.0318	0.0381	0.2755	0.1804
Frank	0.0929	0.0445	0.0744	0.0688	0.0503	0.1558	0.0000	0.0529	0.0441	0.2764	0.1400
Nova	0.1421	0.1498	0.1185	0.0708	0.0449	0.1365	0.0608	0.0000	0.0387	0.1557	0.0821
Pulse	0.1277	0.0925	0.0525	0.0789	0.0499	0.1952	0.0517	0.0231	0.0000	0.2026	0.1259
EK	0.2285	0.0770	0.0722	0.0476	0.0483	0.2419	0.0657	0.0267	0.0295	0.0000	0.1626
From OO											
OO	0.1299	0.0666	0.0557	0.0591	0.0699	0.1575	0.0714	0.0275	0.0210	0.2353	0.1063
From all	0.1226	0.0754	0.0675	0.0613	0.0645	0.1507	0.0446	0.0486	0.0367	0.2089	0.1209

Table 8. Switching behavior without price comparison tool

	To Big 5					To Small 5					To OO
	Contact	Genesis	Mercury	TrustPower	Merid.	Powershop	Frank	Nova	Pulse	EK	OO
From Big 5											
Contact	0.0000	0.1865	0.0937	0.1413	0.0674	0.0652	0.0259	0.0555	0.0941	0.0683	0.2022
Genesis	0.1356	0.0000	0.0991	0.1565	0.0777	0.0590	0.0260	0.0702	0.0900	0.0742	0.2115
Mercury	0.1423	0.2104	0.0000	0.1189	0.0737	0.0470	0.0198	0.0508	0.0782	0.0652	0.1937
TrustPower	0.1621	0.1805	0.1124	0.0000	0.0572	0.0692	0.0253	0.0712	0.0934	0.0554	0.1733
Merid.	0.1607	0.1667	0.0882	0.1146	0.0000	0.0593	0.0217	0.0487	0.0652	0.0695	0.2053
From Small 5											
Powershop	0.1251	0.1151	0.0595	0.1164	0.0399	0.0000	0.0463	0.0360	0.0568	0.1315	0.2760
Frank	0.1087	0.0721	0.0909	0.1285	0.0337	0.0712	0.0000	0.0625	0.0995	0.0900	0.2428
Nova	0.1150	0.2297	0.0924	0.1179	0.0603	0.0577	0.0272	0.0000	0.0965	0.0469	0.1563
Pulse	0.1190	0.1880	0.0757	0.1249	0.0411	0.0776	0.0292	0.0168	0.0000	0.0631	0.2648
EK	0.2166	0.1073	0.0588	0.0795	0.0405	0.1103	0.0492	0.0370	0.0543	0.0000	0.2265
From OO											
OO	0.1122	0.1050	0.0791	0.0914	0.0519	0.0769	0.0442	0.0350	0.0608	0.0950	0.2485
From all	0.1168	0.1379	0.0752	0.1101	0.0572	0.0623	0.0273	0.0512	0.0785	0.0706	0.2127

Table 9. Switching behavior with price comparison tool, Jun-Dec 2021

	To Big 5					**To Small 5**					**To OO**
	Contact	Genesis	Mercury	TrustPower	Merid.	Powershop	Frank	Nova	Pulse	EK	OO
From Big 5											
Contact	0.0000	0.0870	0.2313	0.0861	0.0487	0.3127	0.0676	0.0076	0.0222	0.0653	0.0714
Genesis	0.2410	0.0000	0.1722	0.0632	0.0535	0.2429	0.0902	0.0056	0.0311	0.0479	0.0524
Mercury	0.3247	0.0847	0.0000	0.0788	0.0434	0.2401	0.0648	0.0052	0.0376	0.0582	0.0626
TrustPower	0.2795	0.0635	0.1255	0.0000	0.0303	0.2684	0.0553	0.0173	0.0380	0.0553	0.0669
Merid.	0.2877	0.0617	0.1160	0.0790	0.0000	0.2679	0.0617	0.0049	0.0185	0.0407	0.0617
From Small 5											
Powershop	0.3117	0.0684	0.1101	0.0718	0.0394	0.0000	0.1390	0.0035	0.0220	0.1217	0.1124
Frank	0.2011	0.0370	0.1429	0.0882	0.0229	0.3122	0.0000	0.0035	0.0265	0.0688	0.0970
Nova	0.2376	0.0957	0.1089	0.0842	0.0347	0.2426	0.0809	0.0000	0.0314	0.0363	0.0479
Pulse	0.2413	0.0483	0.0753	0.0714	0.0232	0.3301	0.0579	0.0019	0.0000	0.0656	0.0849
EK	0.4179	0.0291	0.0718	0.0361	0.0286	0.2932	0.0586	0.0023	0.0169	0.0000	0.0474
From OO											
OO	0.2758	0.0468	0.1085	0.0526	0.0368	0.2620	0.0770	0.0053	0.0139	0.0789	0.0425
From all	0.2542	0.0509	0.1243	0.0575	0.0371	0.2580	0.0707	0.0063	0.0249	0.0543	0.0620

B Simulation

This appendix describes how we checked the performance of our estimation procedure using simulated data. Simulated data is generated for 51 periods and 100,000 households, which corresponds to the size of the panel in our actual dataset for the structural model. In our model, a household's choices depend on three lags of data, so we generate simulated choices of searches and retailers for periods $t = 4$ to $T = 51$. The choices are generated using the parameters specified in the final column of Table 10. To generate this choice data, we obtain data on prices, bill shocks and demographic variables as draws from a standard normal distribution. A household's region is drawn from a discrete uniform distribution – that is, all 25 regions are assumed to be equally likely. Similarly, for period $t = 4$, a household's retailer for the previous period is drawn from a discrete uniform distribution. In generating the simulated data, it is assumed that no observed searches take place in periods $t = 1, 2, 3$. Applying the estimation procedure described in Section 4 to our simulated dataset, we obtain estimates of the parameters, which are presented in Table 10. This demonstrates that our estimation procedure is able to recover the true values of the parameters – all of our estimates are within two standard errors of the true values.

C Additional information on the dataset

This appendix supplements the information on our dataset provided in Section 2.

Panel of household retailers

First, we construct a monthly panel of retailers for ICPs from January 2018 to May 2022, where the ICPs are suitably anonymized. Our starting point is the following data provided to us by the EA: (1) a cross-section specifying the retailers of all New Zealand ICPs in January of 2018; (2) a similar cross-section for June 2022; and (3) data on all switches in between those two dates – including both standard ("trader") switches and "move-in" switches. We delete all ICPs that are not active in both of the cross-sections. We use the resulting datasets to construct our panel for the ICPs. This data also specifies the "meshblock" in which an ICP is located. (A "meshblock" is a fine-grained statistical region that typically comprises about 50 dwellings.) Using EA data, we

Table 10. Checking model performance with simulated data

Parameter	Estimate	Standard error	True value
Stage One: The decision to search			
Constant (λ_1)	-1.50118	(0.00196)	-1.5
Bill shock (λ_2)	0.49969	(0.00169)	0.5
Income (λ_3)	0.10261	(0.00149)	0.1
Age (λ_4)	-0.10283	(0.00249)	-0.1
Maori share (λ_5)	0.19963	(0.00171)	0.2
Pacifica share (λ_6)	-0.19967	(0.00175)	-0.2
Education (λ_7)	0.30106	(0.00194)	0.3
Choice set probabilities given search			
Pr. restricted choice set (π)	0.39703	(0.00183)	0.4
Pr. search is on Powerswitch			
Pr. in 2018-9 (ψ_1)	0.19977	(0.00075)	0.2
Pr. in 2020-2 (ψ_2)	0.40088	(0.00102)	0.4
Pr. awake after Powerswitch search			
Pr. at lag 1 (δ_1)	0.60104	(0.00142)	0.6
Pr. at lag 2 (δ_2)	0.30006	(0.00117)	0.3
Pr. at lag 3 (δ_3)	0.20056	(0.00106)	0.2
Stage Two: The decision about retailers			
Price (β_1)	-0.29967	(0.00125)	-0.3
Price $\times$ Income (β_2)	0.15035	(0.00118)	0.15
Switching cost (γ)	-0.69162	(0.00659)	-0.7
Retailer constant			
Contact (α_1)	0.19949	(0.01735)	0.2
Genesis (α_2)	1.79926	(0.01424)	1.8
Mercury (α_3)	1.59659	(0.01227)	1.6
TrustPower (α_4)	0.79698	(0.01482)	0.8
Meridian (α_5)	0.99629	(0.00996)	1.0
Powershop (α_6)	1.19131	(0.01161)	1.2
Frank (α_7)	1.39677	(0.01730)	1.4
Nova (α_8)	0.60245	(0.03535)	0.6
Pulse (α_9)	0.39046	(0.01210)	0.4
Electric Kiwi (α_{10})	1.99500	(0.01411)	2.0

are thereby able to ascertain the "network reporting region" in which the ICP is located. Section 2 describes how, from a panel of ICPs, we construct a panel for households.

Panel of household searches on Powerswitch

For the period of our dataset, the EA provided us with data on API requests triggered by a visit to the Powerswitch website: for each API request, we observe the ICP associated with the request and the date. We were thereby able to construct a panel dataset with an indicator, for each ICP and month, of whether the ICP visited Powerswitch at least once in that month. Moreover, we can link the ICP identifiers in this panel to the ICP identifiers in the panel of retailers. We had to clean the dataset to address the following problem: if Powerswitch wishes to obtain data on the behaviour of a particular ICP, it may undertake an action which triggers an API request which, in our dataset, looks identical to an API request triggered by the visit of the household to the Powerswitch website. In consultation with Powerswitch, we were able to clean the data to deal this problem because Powerswitch undertook these actions in two identifiable ways: (i) on certain dates in August 2021; and (ii) from September 2021 onwards, if an ICP visited Powerswitch, then Powerswitch would obtain data on the ICP in each of the three months after the visit, which triggered an API request for the ICP in each of the three months after the visit. We dealt with the problem by (i) deleting API requests made on ten outlier days in August 2021 and (ii) retaining only those API requests where the ICP was not associated with an API request in the previous three months. On the one hand, this means that we are deleting some legitimate visits by households to Powerswitch – for example, if a household visits in November 2021 then again in December 2021, we will only record the first visit. On the other hand, we can interpret the cleaned data as follows – in our example, the November and December visits are viewed as part of the one search, and our panel records the month in which the search begins – that is, November 2021. Our structural model accommodates this feature of the data, allowing a Powerswitch search to have an effect on the household's choice set in the three months after the initial visit to the website.

Price and bill data

As noted in Section 2, we use the same methodology for obtaining the price series as that described in detail in Gibbard and Grubb (2024). They explain why they only obtain price data for 34 of the 39 "network reporting regions" in New Zealand. We only use data for 28 of those 34 regions, dropping the six smallest regions in Gibbard and Grubb (2024). Following the methodology in Gibbard and Grubb (2024), our prices are for the "standard plan" for each retailer in each region. The bill of a household for a particular month is calculated as follows. First, we observe the household's retailer and region and assume that the household is on the "standard plan" for their retailer and region. Second, we also assume that their electricity consumption in the given month is given by the average residential consumption for the given region in the given month. (The data on consumption comes from the table “Residential consumption trends” on the EA’s website – see https://www.emi.ea.govt.nz/Retail/Reports/0YUCE0). We use this consumption data, together with our data on the fixed and variable components of the tariff for the standard plan, in order to calculate the household’s bill.

Demographic data

As noted above, we observe the “meshblock” region in which an ICP is located. A meshblock region typically includes about 50 dwellings. Using 2018 Census data, we obtained the median household income for each meshblock, which we assign to each ICP in that meshblock. For our other demographic variables, the data was incomplete at the meshblock level, possibly because of confidentiality concerns about reporting data for such fine-grained regions. Accordingly, we obtained data for these demographic variables at the next most fine-grained level – “Statistical Area 1” data. In particular, at this level of granularity, from the 2018 Census, we obtained data on (1) the median age (2) the fraction with Maori descent (3) the fraction with Pacifica descent and (4) the fraction with a Bachelors degree or higher.