Barriers to real-time electricity pricing: Evidence from New Zealand*

Charles Pébereau† and Kevin Remmy‡

June 6, 2023

Abstract

This paper studies the introduction of real-time electricity pricing in the New Zealand residential retail market to understand why its market share remained below 1.25%. We use rich panel data of all retail switches between 2014 and 2018 and an unexpected wholesale price spike to study adoption and attrition. Exploiting the staggered roll-out of real-time pricing in different locations we find that attrition decreases with experience. We also find that prospective adopters are present biased. The combination of these findings explains why adoption stalled and shows that wholesale price spikes pose a serious threat to widespread adoption of real-time pricing.

JEL Codes: D12, D83, D91, L52, L81, L94, Q41

Keywords: energy, time-varying pricing, consumer behavior, learning

*We would like to thank Mathias Reynaert, Stefan Ambec, Jean Tirole, Christian Bontemps, and Pierre Dubois for their guidance and support. We would also like to thank Heski Bar-Isaac, Steven Berry, Estelle Cantillon, Claude Crampes, Isis Durrmeyer, Daniel Ershov, Natalia Fabra, Rachel Griffith, Thomas-Olivier Léautier, Yassine Lefouili, and Mar Reguant for their helpful comments and suggestions. We would also like to thank participants at the TSE Environmental seminar, TSE student workshop, the 9th Mannheim Conference on Energy and the Environment, and EARIE 2022 for useful comments and suggestions. We are also grateful to the New Zealand Electricity Authority and, in particular, to Phil Bishop and the market analytics team for guiding us through and providing the data used in this study. This research was financially supported by the H2020-MSCA-RISE project GEMCLIME-2020 GA No. 681228. Funding by the German Research Foundation (DFG) through CRC TR 224 (Project A02) is gratefully acknowledged. The authors have no relevant material or financial interests that relate to the research presented in this paper. Correspondence to: K. Remmy, University of Mannheim, L7 3-5, 68161 Mannheim, Mail: remmy@uni-mannheim.de

†Stanford University, charles.pebereau@gmail.com

‡University of Mannheim, remmy@uni-mannheim.de

1 Introduction

Time-varying electricity tariffs are necessary for the energy transition towards intermittent renewable generation, a cornerstone of the fight against climate change, and more generally for the efficiency of retail electricity markets (Ambec and Crampes, 2021). As smart meters are being installed at scale, these tariffs can now be implemented for residential households. A large and growing literature addresses the efficiency and distributional impacts of various types of time-varying tariffs (Joskow and Wolfram, 2012; Borenstein, 2012; Reguant, 2019). Yet, little attention has been paid to how market forces could shape retail electricity markets once time-varying tariffs can be implemented. Using rich panel data of all residential retail switches between 2013 and 2018 in New Zealand, we provide the first observational study of tariff choices in a retail electricity market with a large penetration of smart meters, with a focus on real-time electricity pricing (RTP).

Under RTP, consumers face spot prices and pay the cost of their consumption in real-time rather than some average price, which is efficient. In a frictionless decentralized economy and absent agency costs, all consumers adopt this tariff in equilibrium (Joskow and Tirole, 2006). In theory, the retail electricity market would gradually unravel towards this equilibrium (Borenstein, 2005b). Consumers with the consumption profiles least costly to serve self-select into RTP, increasing the average cost of serving the other consumers. Retailers then increase their rates, making it profitable for a new set of consumers to switch to RTP, creating a self-sustaining spiral. This scenario did not occur in New Zealand where the share of residential consumers on RTP has remained below 1.25% since this tariff was first introduced in 2013.

The purpose of this paper is to examine this puzzle in order to identify barriers to widespread adoption of real-time pricing and their consequences for policies promoting this tariff. We do so using a unique dataset of retailer switches in the residential retail electricity market in New Zealand. We exploit a crisis on the spot market to study how consumers on real-time pricing and prospective adopters react to large and sudden price spikes. Our results suggest that price uncertainty is a serious threat to widespread adoption of real-time pricing because when prices spike unexpectedly and remain high for several weeks, prospective adopters forego adoption and recent adopters switch to another tariff and do not return.

Different policies aimed at fostering the adoption of real-time pricing have been implemented. In the European Union, Directive 2019/944 implements an ”opt-in” policy requiring that large retailers offer real-time pricing by 2025. By contrast, the Spanish government implemented an ”opt-out” policy by defaulting all residential consumers to real-time pricing in 2015 and leaving them the option to switch to another tariff (Fabra et al., 2021). The question of which approach to implement and how to implement it is important because real-time pricing involves trade-offs. On the one hand, real-time pricing increases demand response which can help integrate intermittent renewable energy sources such as wind and solar (Ambec and Crampes, 2021), improve the efficiency of electricity markets by reducing the need to install generation capacity that is only used a few hours each year when demand peaks (Borenstein, 2005a) and preventing producers from abusing their market power (Poletti and Wright, 2020). On the other hand, because spot prices are uncertain and volatile, RTP exposes consumers to the risk of a crisis in electricity wholesale markets[1] which may increase with the share of intermittent electricity sources and by weather changes due to global warming.

The introduction of real-time pricing in New Zealand gives us a unique opportunity to examine what drives adoption and attrition and can therefore inform the debates regarding the implementation of this tariff. While the literature documents consumer behavior with various time-varying electricity tariffs with a fixed price menu, the main specificity of real-time pricing is that it exposes consumers to uncertain spot prices. The fact that the New Zealand retail electricity market did not unravel generates a unique setting because RTP competed with more traditional tariffs over a long period with important spot price variations, including large and unexpected price spikes. We focus most of our attention on a particular event, referred to as the winter 2017 crisis, which occurred more than three years after RTP was first introduced. We address the following questions. Which consumers abandon real-time pricing during the crisis and what drives attrition? How do spot prices affect adoption decisions and do consumers strategically time their adoption?

To address these questions, we use a unique dataset composed of all electricity retailer switches by residential households in New Zealand from January 2013 to June 2018. We also observe each household's monthly electricity consumption, half-hourly spot prices, and detailed census data that we can match to each household. Nearly no consumers who adopted RTP abandoned it until the spark of a crisis in the electricity spot market during the winter of 2017 (hereafter referred to as the crisis). The share of consumers switching to another tariff during this crisis decreased with their time spent on RTP before the crisis and the share of those switching back to RTP afterward increased with time spent on RTP before the crisis. Exploiting the fact that RTP was introduced in different places at different times allows us to rule out that this correlation is due to selection effects. We also study which prices affect adoption. We build several natural predictors for future expected spot prices that consumers may consider and show that recent spot prices better explain adoption decisions. This result holds for predictors of average spot prices over the long run (one year), the medium run (three months), and the short run (one month). Finally, we run a counterfactual exercise to predict how many consumers would have adopted RTP during and after the crisis if it did not occur

[1] For instance, the extreme winter storms that occurred in Texas in February 2021 led spot prices to spike and reach their regulatory ceiling of $9,000, jeopardizing the financial health of consumers who had signed contracts indexed to wholesale market prices. For an overview and a discussion of the events, see `https://www.tse-fr.eu/winter-texas`

and find evidence that most consumers do not strategically time adoption but rather postpone it for an extended period of time.

Overall, our findings show that inexperienced consumers - prospective and recent adopters - strongly react to ongoing spot prices, which is a sign of present bias. Furthermore, we find evidence that consumers forgo adoption or abandon RTP and do not return. We hypothesize that the combination of present bias and spot price volatility jams the unraveling process: when spot prices spike attrition increases - particularly for recent adopters - and adoption drops but only so many consumers have the opportunity to adopt RTP when prices are low. We discuss potential mechanisms behind the effect of time spent on the tariff such as learning, investments, and search costs, among others.

Regarding the policy implications, our findings suggest that retailers or policymakers willing to foster the adoption of real-time pricing need to be "lucky" and hope that no unexpected period of high price spikes arises until many consumers have adopted the tariff and experienced it long enough. We derive three sets of recommendations to address this issue. First, strategically timing when consumers adopt (in an opt-in set-up) or are defaulted to (in an opt-out set-up) real-time pricing can increase the chances that consumers remain on real-time pricing and limit the risks that a crisis interrupts the unraveling process. Second, providing information to consumers, both before adoption (Ito et al., 2021) and after (Jessoe and Rapson, 2014), can accelerate the learning process and help consumers forecast their long-term payoffs. Third, insuring consumers against price spikes (see, eg. Borenstein (2007)) may help prevent consumers from abandoning real-time pricing when losses are salient.

Related literature. Our paper relates to two strands of the literature. First, it relates to the literature on time-varying electricity pricing. On the theory side, Joskow and Tirole (2006) show that in an economy with rational consumers and without agency costs, real-time pricing implements the Ramsey optimum. Their result is satisfied even if consumers are imperfectly reactive to spot prices because paying attention is costly and they (rationally) choose their degrees of awareness. A direct implication of this result is that, in the absence of frictions, the retail market unravels until all consumers have adopted RTP in the steady state, with no need for intervention. The low take-up of RTP in New Zealand contradicts this prediction. Because electricity is an essential commodity and time-varying tariffs could lead to large wealth redistribution, some authors have argued that the main barrier to their widespread implementation is political (Joskow and Wolfram, 2012; Wolak, 2013) and some papers study how to implement them equitably (Borenstein, 2012, 2013). Cahana et al. (2022) study the distributional impacts of RTP in Spain. Yet, the case of New Zealand shows that take-up can fail even before questions of redistribution arise. These puzzles justify our approach to identifying frictions and departures from the rational consumer theory as barriers to real-time pricing. The closest empirical papers to ours are Fowlie et al. (2021) and Ito et al. (2021) because they study consumer choices of time-varying tariffs. Both run randomized experiments and study adoption as well as consumption. Ito et al. (2021) document selection on price-elasticity and consumption profiles and show that providing consumers with information about expected financial payoffs from switching can significantly increase adoption rates. Fowlie et al. (2021) compare the adoption rates and aggregate demand response under opt-in and opt-out set-ups. They find that demand response decreases over time among always-takers and increases over time among complacents. However, both papers consider time-varying tariffs where rates are set ex-ante and therefore cannot address issues related to spot price uncertainty, which is a key element in the case of real-time pricing. In their set-ups, the only uncertainty consumers face relates to their preferences and in particular how costly it is to change their consumption habits. While they identify consumer learning, they find low rates of attrition. On the contrary, in the case of real-time pricing in New Zealand, we show that unexpected price spikes lasting several weeks - and therefore too long for consumption arbitrage - can lead to important attrition rates.

Second, our paper relates to the literature studying behavior that departs from the benchmark of rational and fully informed agents. Consumers may be present biased and rely on simple heuristics to make decisions with long-term consequences. For instance, the weather can affect investments in solar panels (Lamp, 2018) or car purchases (Busse et al., 2015). Relatedly, Anderson et al. (2013) show that individuals often make "no-change" forecasts about gasoline prices. In the case of the adoption of real-time pricing of electricity, we show that recent or current spot prices significantly affect consumer decisions. Furthermore, a growing literature shows that personal experience affects individuals' decisions. In macroeconomics, Malmendier and Shen (2019) shows that experiencing periods of unemployment has long-term effects on consumption decisions. In finance, Hirshleifer et al. (2020) finds that analysts are biased by their first impressions of a market. In industrial organization, Miravete (2003) shows that consumers learn about their preferences after they have chosen a phone plan and make new choices accordingly. In the case of real-time electricity pricing, we show that consumers with bad first impressions are more likely to abandon the tariff and less likely to return to it but that, with time, consumers focus less on immediate outcomes.

The rest of the paper proceeds as follows. Section 2 describes our data and the context of our analysis. In Section 3 we study the behavior of consume on real-time pricing and, in particular, attrition and demand response. In Section 4 we study the decision-making process of prospective adopters of real-time electricity pricing. Section 6 discusses policy implications and Section 7 concludes.

2 Context and Data

2.1 The retail electricity market in New Zealand

New Zealand initiated the liberalization of electricity markets in the late 1980s, establishing competition in generation and retailing, while transport and distribution became regulated monopolies. The entry of new retailers remained limited for some time but eventually grew. While there were 15 retail companies at the end of 2013, 32 retailers at the beginning of 2018 offered contracts under 48 brands. Yet, the retail market remains dominated by historical incumbents, known as the 'Big 5', with a collective market share of around 90% between 2013 and 2018. Electricity is traded on a wholesale electricity market since the end of the 1990s. Some retailers - such as the 'Big 5' - are vertically integrated while others, generally the entrants, purchase electricity directly on the wholesale market.

Public initiatives encouraging consumers to switch have partly facilitated entry. An online price comparison tool, Powerswitch, was created by a consumer advocacy group with the government's support. Furthermore, in 2011 the regulator (Electricity Authority) started a campaign called "What's My Number" to inform and educate consumers about retail market opportunities. Daglish (2016) reports that this campaign increased switching rates significantly. The switching rate was about 20% on average annually between 2013 and 2018, which is greater than that of any European country.[2]

New Zealand has been a world leader in the deployment of smart electricity meters. By 2016 more than 50% of old meters were replaced by smart meters. Because old meters measure aggregate consumption and are only read a few times a year, only simple tariffs could be implemented. Traditionally, the most common electricity tariffs were flat tariffs: two-part tariffs with known fixed and variable components.[3] Smart meters, on the other hand, can measure electricity consumption in real-time and thus their roll-out has allowed new electricity tariffs to emerge. For instance, Electric Kiwi offers two-part tariffs but also allows consumers to choose one hour of free consumption per day. Other retailers such as Paua to the People and Flick Electric offer real-time pricing tariffs, with rates varying half-hourly.

2.2 Real-time pricing in New Zealand

In New Zealand, real-time pricing contracts were introduced by private retailers, with no public intervention.[4] To the best of our knowledge, only two retailers offered real-time pricing in the

[2] See Oxford Institute for Energy Studies (2019).

[3] Special electricity meters allowed time-of-use tariffs with, for instance, different day and night rates, but flat tariffs were and still are dominant.

[4] In comparison, in Spain, real-time pricing became the default tariff for all residential consumers in 2015. It is regulated, and consumers can opt out if they prefer another tariff.

period covered in our dataset, Flick Electric Co. and Paua to the People. However, most consumers adopting RTP contracted with Flick Electric Co.[5] Furthermore, during the period time covered in our dataset, Flick Electric offered exclusively real-time pricing while Paua to the People also offered flat rates contracts[6] and we cannot identify which tariffs consumers chose in our dataset. Therefore, in the rest of the paper, we focus exclusively on Flick Electric Co. for real-time pricing tariffs and know that a consumer joining it adopts real-time pricing.

Flick Electric Co. entered the retail electricity market for the first time at the end of 2013 in Wellington and then gradually entered other cities. Figure 1 shows that its market share initially grew quickly, stalled in June 2017 - the start of what we refer to as the winter 2017 crisis - and then remained slightly above 1%. At the end of May 2017, before the start of the crisis, Flick Electric Co.'s market share in New Zealand was 1.28% - or 23,057 households - with large heterogeneity across cities: less than 1% in Auckland, 3.88% in Wellington, and 4.46% in Christchurch.

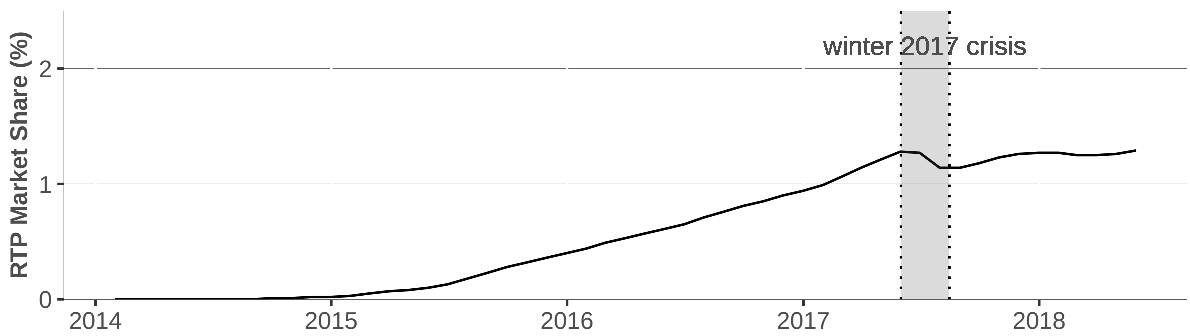

Figure 1: History of the share of households on real-time electricity pricing in New Zealand.

2.3 Tariffs comparison.

Electricity tariffs are often two-part tariffs and thus consist of a fixed daily fee independent of consumption and a variable fee to pay per unit of electricity consumed. The real-time pricing tariff offered by Flick Electric Co. is also a two-part tariff, with the variable part being the sum of a pre-determined amount (to cover transportation and distribution plus a margin) and the spot price at the time of consumption, which varies half-hourly. In Figure 2 we plot the fixed and variable parts of real-time pricing offered by Flick Electric Co. and of a flat tariff offered by Genesis Energy, the retailer with the largest market share in Wellington.

[5] In June 2017, Paua to the People had less than 1,000 customers, while Flick Electric had more than 23,000.

[6] See `https://www.rnz.co.nz/national/programmes/thiswayup/audio/201837850/power-to-the-people`

First, spot prices vary substantially over time, and therefore consumers on real-time pricing face varying variable fees. To give an order of magnitude, we find that in 2016, the average household on RTP in Wellington with an average consumption profile would pay an annual bill of NZ$1880, 29.8% of which comes from the variable part attributable to spot prices.[7]

Second, it is striking that both the fixed and variable fees of the flat tariff always exceed that of real-time pricing, except during the winter 2017 crisis and at the beginning of 2018. It suggests that many consumers would have a financial incentive to adopt RTP which is at odds with Flick's low market share. The average consumer in Wellington would pay NZ$2397 under the flat tariff offered by Genesis Energy in 2016. That is, she would save NZ$518, or 21.6%, under RTP[8].

Tariff competition. While we lack the data to study the supply side in detail, we provide here a brief discussion of tariff competition. Figure 2 shows that both Flick Electric Co. and Genesis Energy adjusted their tariffs only about once a year. In particular, there is no evidence suggesting that Genesis Energy increased its rates as a response to consumers adopting RTP, as suggested by the unraveling theory. Note, however, that RTP market share was very low and perhaps did not yet justify adjusting rates. Keeping rates low could also be a strategy to deter entry by limiting switches (Farrell and Klemperer, 2007).

Relatedly, it is noteworthy that most retailers did not adjust their tariffs during the winter 2017 crisis while wholesale prices were passed through in RTP rates. This gap created an incentive for RTP consumers to switch to another tariff. As suggested in Electricity Authority (2018), one reason might be that retailers hedged themselves in advance and therefore did not need to adjust their rates. It could also be a strategic decision by a deep-pocketed incumbent to attract RTP consumers.

Termination fees. Flick Electric Co.'s contracts imposed no commitment periods nor termination fees. Intuitively, this incentivizes consumers to experiment with RTP because they can switch easily. It can also allow consumers to arbitrage between tariffs, for instance by choosing RTP when spot prices are low and flat tariffs when they are high. Indeed, we find evidence that some consumers adopted this strategy during the winter 2017 crisis, although we lack the data to measure their gains.

Other retailers offer a wide variety of tariffs and under different terms which we do not observe. Informal discussions suggest that flat tariffs with one and two years commitment periods are the most common ones, although most retailers also offer short-term contracts.

[7] We consider the average annual electricity consumption in 2016, equal to 8884kWh, with a consumption profile uniformly distributed between 7:00 am to 10:00 am and 5:30 pm to 9:30 pm

[8] This figure is slightly larger than the one reported by Flick Electric Co. who advertised annual savings of 479NZ$ between June 2016 and June 2017.

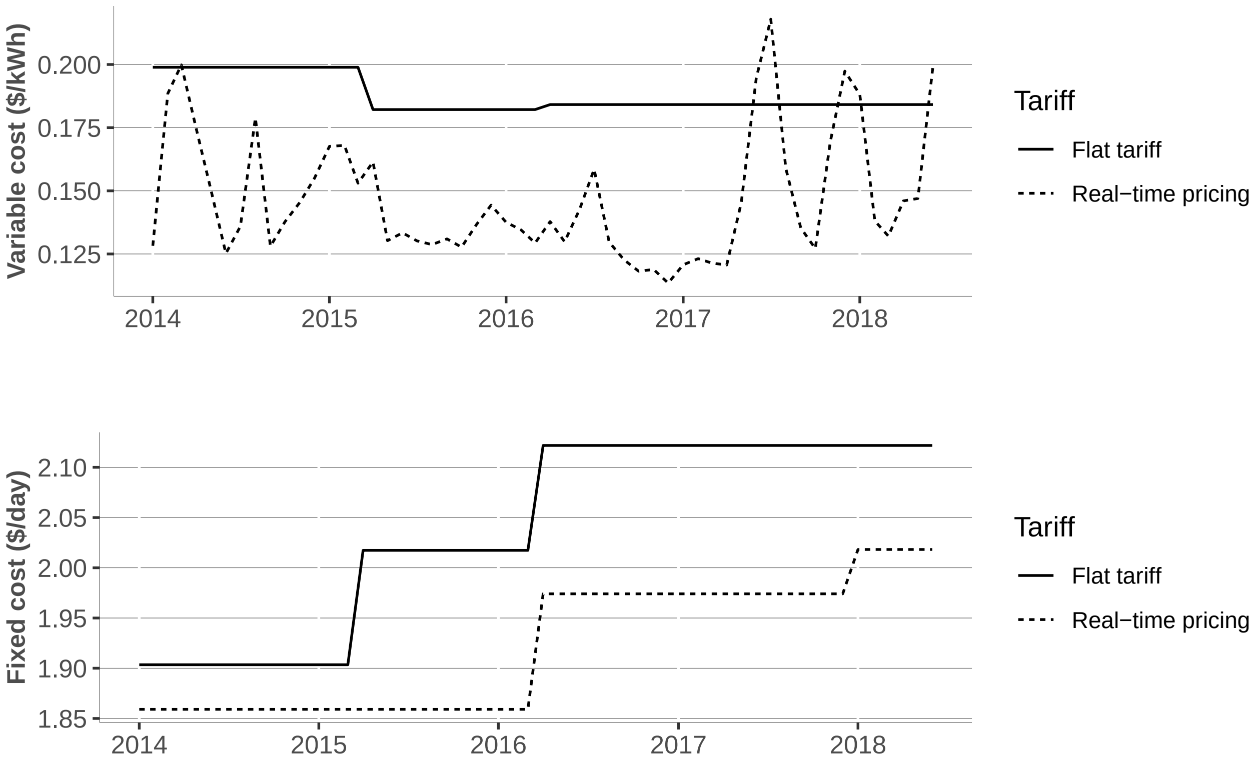

Figure 2: Tariff comparison in Wellington.

Note: For the flat tariff, we use the tariff 'Household Composite (Standard user)' offered by Genesis Energy, the retailer with the largest market share in Wellington. For the real-time pricing plan, we use the 'Standard plan, All Inclusive' offered by Flick Electric. To compute the variable part of RTP tariff, we take the sum of the consumption weighted average monthly spot price of electricity (assuming an extreme case with consumption concentrated during peak hours from 7:00am to 10:00am and from 5:30pm to 9:30pm) and the variable part of the 'Standard plan, All Inclusive' of 2019 (we do not have data about the variable part for the other years). All tariffs include discounts for prompt payment and electronic payment.

These tariffs typically come with early termination fees, typically of NZ$150 which roughly amounts to an average monthly bill. Early termination fees protect the retailers who purchase electricity in advance but also create inertia because consumers generally wait until the end of their contracts before switching.

2.4 The winter 2017 crisis

A distinctive feature of RTP compared with flat tariffs is that consumers bear the risk that spot prices spike. Such events happened several times in the period covered in our dataset. Our analysis will focus on the first one, which we refer to as the winter 2017 crisis.

Studying a crisis on the wholesale market is interesting in itself because crises are likely.

Therefore, practitioners and policymakers need to understand how they affect consumers on real-time pricing. To the best of our knowledge, our paper is the first to document a crisis on the electricity wholesale market with consumers on real-time pricing.

It is also an interesting event from an empirical strategy perspective because it simultaneously affects everyone and is hardly predictable, in particular for residential consumers. Therefore, it reveals the state of mind of all consumers at the same time. Specifically, during a crisis on the wholesale market, the trade-off between short-term losses and potential long-term benefits is particularly salient to every consumer. It affects both the consumers who consider adopting real-time pricing and those who have already adopted it.

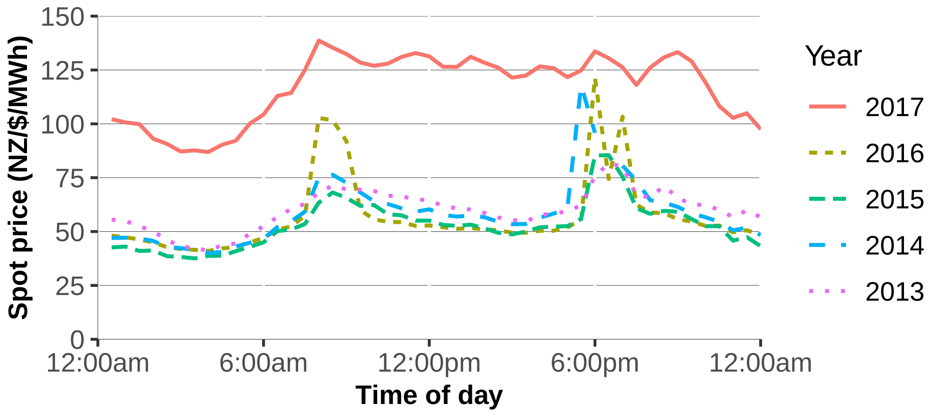

Figure 3: Average half-hourly spot price in winter (June 1st - August 31st) - from 2013 to 2017.

The winter 2017 crisis refers to a sustained period of high spot prices that occurred between June and August 2017. It was the first significant event on the electricity wholesale market since Flick Electric Co. entered the residential retail electricity market. This crisis was due to low hydro levels coupled with high electricity demand driven by electric heating in winter.[9] Because about 60% of electricity comes from hydro generation in New Zealand, low water levels made electricity scarce, leading to high spot prices. As illustrated in Figure 3, spot prices increased two- to three-fold compared to previous winters.

Such crises are rare - the previous dry winter had occurred in 2008 - and its duration was hard to predict because it largely depends on rainfalls. While flat tariffs hedged consumers against the risk of a crisis, those on a real-time pricing tariff directly faced these high spot prices. Furthermore, spot prices during the winter 2017 crisis did not vary much throughout the day and only lowered during the night when consumers are asleep. Therefore, there was little room for consumers to adjust their consumption to avoid high prices. While we do not have information about consumer losses, Flick Electric Co. reported that their consumers made a loss of 80NZ$ on average from mid-June to mid-July compared with their previous tariff.

[9] See Electricity Authority (2018), a report by the Electricity Authority.

As we will document in length in the rest of the paper, the winter 2017 crisis had a great impact on adoption and attrition. In particular, during the crisis, about 16.2% of consumers on real-time pricing switched to another tariff. Among those who switched to another tariff, 26% switched back to real-time pricing after the crisis. Furthermore, while on average 939 new households adopted RTP every month in the six months preceding the crisis, only 68 adopted this tariff in July 2017, when the crisis was reaching its peak.

2.5 Data and summary statistics

We use a unique data set containing all occurrences of consumers switching retailers between January 2013 and June 2018. These switches are recorded at the installation control point (ICP)-level, a unique electricity meter identifier. We observe the previous retailer, the new retailer that the consumer is switching to, and the switching date. However, we do not observe which tariff the consumer chooses, only the retailer he contracts with. Furthermore, we observe whether the switch was related to the household moving into the accommodation or if it occurred while he was already living there.[10] Because we cannot trace where consumers move to nor which retailer a new tenant was with before moving in, we focus exclusively on switches unrelated to changing accommodation. Given that consumers often sign long-term contracts with their retailers that bind them even when they change accommodations, it is likely that our restriction is not too severe.

At the individual level (i.e. at the ICP level), we also have yearly and monthly electricity consumption data. However, we do not observe consumers' half-hourly consumption used for billing them if they adopt real-time pricing. Furthermore, we observe the census tract in which an ICP is located, which allows us to merge the switching data to census data from 2013. We use median data by census tract and use information on income, age, education, and work levels.[11] A census tract usually contains between 50 and 80 households. We have missing observations for both the consumption and census data. Removing observations where information on consumption or one of the socio-demographic characteristics are missing leads us to lose 19.18% of our data.

We also collect publicly available data from the Electricity Authority's website for the period covered by our dataset on switches (January 2013 to June 2018). First, we collect aggregate data about each retailer's market share and the number of consumers each retailer gains and loses each month.[12] Second, we collect spot price data for each network reporting region

[10]We only observe those switches occurring due to moving where the retailer chosen by the new occupant is not the same as the retailer of the previous occupant.

[11]The variable for education is the percentage of households in the census tract (called a 'meshblock') with a bachelor's degree or above. The variable for work is the percentage of households in the census tract who work as 'managers' or 'professionals'.

[12]Source from the electricity authority's website: `https://www.emi.ea.govt.nz/Retail/Reports`

at the half-hourly level.[13] We use these half-hourly price data to compute the price faced by consumers on real-time pricing and compute average spot prices over different time horizons and locations.

Finally, we have information about the history of a subset of tariffs offered by each retailer in each network reporting region and their changes over time. In the dataset, the tariffs are two-part tariffs. For each tariff, we observe the fixed and variable parts, the prompt payment discount, and electronic payment discounts, as well as the start and end dates at which these tariffs are available. However, we do not know whether a tariff is part of a long- or short-term contract. Regarding the rates of real-time pricing offered by Flick, we only have an estimate of the variable rate in this dataset. Therefore, we only use the variable rate in 2019 advertised online.

Summary statistics. In Table 1, we provide summary statistics about different groups of households. We compare the average electricity consumption and the average socioeconomic characteristics of all households, households who switch retailers at least once during the sample period, households who switch to a retailer which is not one of the large incumbents, and households who adopt real-time pricing contracts at least once during the sample period.

We can see that all groups share the same average age. Furthermore, households who switch retailers have average electricity consumption and average socio-economic characteristics. Households adopting real-time pricing are those who, on average, have the highest electricity consumption and income, and are more likely to have high educational attainments and work in high positions. On all these characteristics, they are followed by households who switch to a non-incumbent retailer.

In Table 2, we compare the socio-economic characteristics of households adopting RTP at different times. Over time, adopters of RTP become somewhat younger on average, earn less, are less educated, and are less likely to work in white-collar jobs. Average consumption also declines over time. However, average consumption seems to stabilize towards the end of the sample period.

3 Attrition of consumers on real-time pricing

In this section, we investigate the behavior of consumers who have adopted real-time pricing. In particular, we are interested in their response to variations in spot prices. We first investigate what drives the decisions of consumers who abandon the tariff before investigating what drives

[13] The electricity network in New Zealand is split into different network reporting regions (NRRs). The three largest cities, Auckland, Wellington, and Christchurch, belong to three distinct network reporting regions. We will focus our analysis on these three network reporting regions and refer to them by the name of the cities.

Table 1: Comparison of household characteristics

	All ICPs	Switchers		Switchers to non big 5		RTP adopters	
	2	3	4	5	6	7	8
Consumption (kWh/yr)	7,231.1	7,700.1	21	7,974.5	5.5	8,311.6	4.3
	(3,847)	(3,794.6)	(0.000)	(3,856.8)	(0.000)	(3,816.8)	(0.000)
Income (x1,000 NZ$/yr)	86.7	87.1	1.9	90.4	8.4	93.6	5.3
	(31.3)	(30.7)	(0.053)	(29.8)	(0.000)	(29.7)	(0.000)
Age	37.1	36.7	-9.1	36.6	-1.3	36.5	-1
	(8)	(7.3)	(0.000)	(7.3)	(0.188)	(7.2)	(0.305)
Education (%)	29.2	28.9	-3.3	31.8	14.4	33.6	5.9
	(15.8)	(15.5)	(0.001)	(15.4)	(0.000)	(15.4)	(0.000)
Work (%)	48.7	48.3	-4.3	50.9	13.1	52.5	5.3
	(16.6)	(15.7)	(0.000)	(15.4)	(0.000)	(14.7)	(0.000)
Number of households	138,195	36,866		6,989		3,735	

Note:
Data for Wellington, from January 2014 to June 2017. The columns 2, 3, 5 and 7 hold mean values with standard deviations in parentheses. Columns 4, 6 and 8 report t-test of means of the previous two mean columns, with p-values in parentheses.

Table 2: Change in mean household characteristics of RTP adopters

	2014	2015	2016	2017 - sem 1
Consumption (kWh/yr)	8,942.2 (3,904.6)	8,439.6 (3,888.7)	8,159.2 (3,803)	8,174.9 (3,559.4)
Income (x1,000 NZ$/yr)	101.3 (28.6)	94.2 (29.5)	93.4 (30.1)	89.7 (29)
Age	37.1 (6.7)	36.5 (7.1)	36.6 (7.3)	35.7 (6.8)
Education (%)	37.1 (16.2)	33.7 (15.2)	33.3 (15.3)	33 (15.6)
Work (%)	55.7 (14.8)	52.8 (15)	52.4 (14.6)	50.9 (14.3)
Number of households	152	1,579	1,528	476

Note: Data for Wellington, from January 2014 to June 2017. Standard deviations in parentheses

consumer decisions to return to real-time pricing after having left.

3.1 The role of time spent on real-time pricing

In Figure 4, we jointly plot the average spot price and then the number of consumers on real-time pricing abandoning the tariff each month. By and large, there is very little attrition unless spot prices spike, such as during the winter 2017 crisis. Between November 2013 and June 2017, only about 6.2% of all the consumers who had adopted real-time pricing eventually abandoned it.[14]

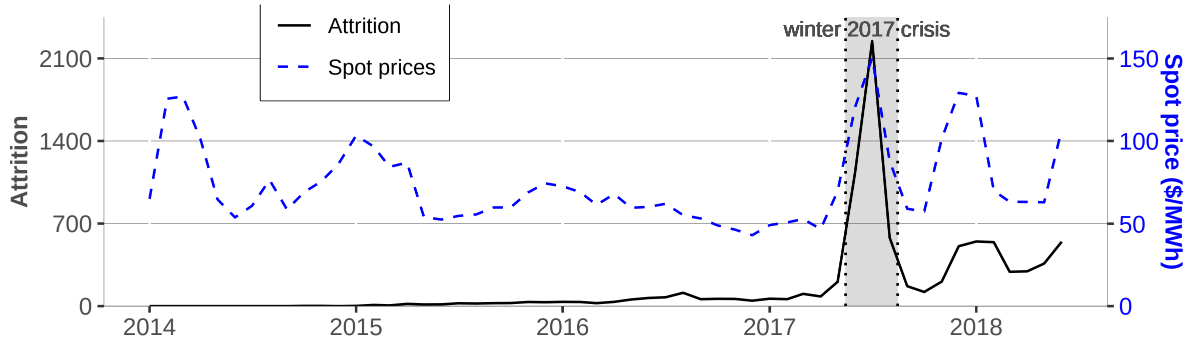

Figure 4: History of monthly attrition from real-time pricing and average electricity spot prices.

A natural follow-up question is to understand why, when these price spikes occur, some consumers remain on real-time pricing while others switch to another tariff. While consumers with the largest electricity consumption incur more considerable losses when prices are high, they also obtain larger benefits from real-time pricing when prices are low relative to other tariffs. Also, because real-time pricing is a new form of tariff and the formation of spot prices is a complex process, switching decisions may depend on how sophisticated consumers are - measured by socioeconomic characteristics such as education - or how sophisticated they have become with experience. Regarding the incentives consumers faced, note that Flick Electric did not impose any early termination fees and consumers could leave the real-time pricing contract to switch to another retailer at any time. Hence, the decision of whether or not to abandon real-time pricing did not involve a trade-off between increased spot prices and paying a hefty early termination fee.

To examine these different effects, we focus on the winter 2017 crisis during which 19.4% of consumers on real-time pricing switched to another tariff. This event is relevant to our analysis for multiple reasons. It was a large and unexpected shock, and it affected all consumers on real-time pricing. Furthermore, while it was hard to anticipate, we argue that consumers were likely aware of the crisis once it occurred. Indeed, consumers are billed weekly, they receive notifications on their mobile app when prices spike, and their retailer, Flick Electric, regularly provided information about the crisis. Also, the event received media coverage. Therefore, all consumers on real-time pricing had to make a conscious decision to stay on or abandon real-time pricing, and, by a revealed preference argument, we can infer their preferences by studying their choices.

[14]To compute this number, we take the ratio between the number of consumers who abandon real-time pricing for reasons unrelated to moving into a new accommodation over the total net number of consumers who adopted real-time pricing.

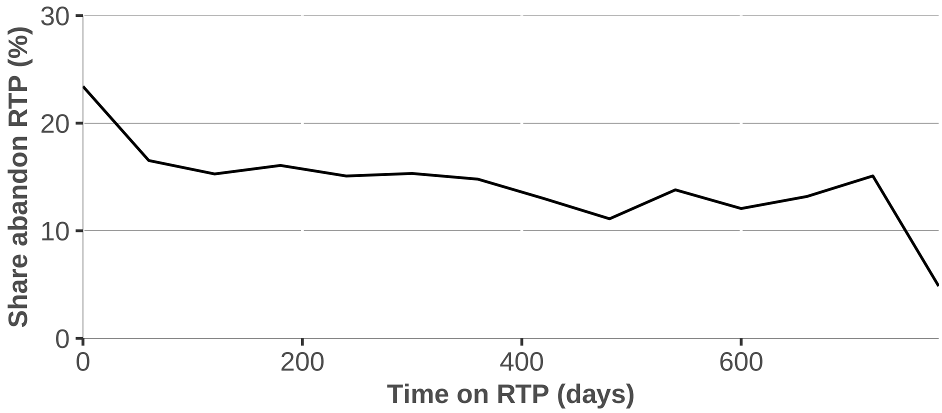

Figure 5: Share of consumers on RTP who abandon the tariff during the winter 2017 crisis as a function of the time they had spent on the tariff before the start of the crisis. Data for Wellington.

In Figure 5, we plot the share of consumers who abandoned real-time pricing during the winter 2017 crisis as a function of the time they spent on the tariff before it started and compare consumers residing in the regions of Wellington, Christchurch, and Auckland. The attrition rates are highest in Christchurch and lowest in Auckland, but the pattern is very similar in all three regions. The share of consumers abandoning real-time pricing during the winter 2017 crisis decreased with the time spent on the tariff.

In the first step, we investigate what drove consumers to leave real-time pricing in the crisis. To do so, we build an indicator that is equal to one if a consumer decided to abandon real-time pricing at some point during the crisis. We then regress this indicator on the time the consumer had spent on RTP by the time the crisis began, the yearly electricity consumption, the difference between winter and summer consumption, and control variables:

$$\begin{aligned}\text{Abandon RTP}_{im} =& \alpha \text{Time on RTP}_{im} + \gamma_1 \text{Yearly Consumption}_{im} + \gamma_2 \text{Seasonal Difference}_{im} \\ &+ X'_{im}\beta + \varepsilon_{im},\end{aligned}$$

where Abandon $\text{RTP}_i \in \{0, 1\}$ is an indicator equal to 1 if consumer i decides to abandon RTP during the winter 2017 crisis, Time on RTP_i is the number of months that consumer i spent on RTP prior to June 1st, 2017, Yearly Consumption is the electricity consumption from 2015, X_i contains control variables, and ε_i is assumed to follow a logistic distribution. In X_i, we control for census-level logged median household income, age, and work and education indexes, and consumers' previous retailer by location.

The results are summarized in Table 3. The specifications in the first three columns assume a linear effect of Time on RTP_i. In the last three columns, we use $log(\text{Time on RTP}_i)$. Interestingly, the coefficient for time spent on the tariff is statistically and economically significant, both in the linear and log specifications. Using the results from column 2, at average value of the covariates, spending 4 more months on real-time pricing decreases the probability to abandon real-time pricing by 2.06 percentage points (the average probability to abandon RTP is 19.42%).

We can also see that the coefficient on *Yearly Consumption* is negative and statistically significant. However, the economic effect is negligible. Using the results from column 2, at average value of the covariates, increasing Yearly Consumption by 20% (or 1894.96 kWh), increases the probability to abandon real-time pricing by -1.04 percentage points - which is low compared to 19.42%, the unconditional probability to abandon it.

The effects of consumer demographics are similar in all specifications and none are economically significant. In particular, $Income$, $Education$, and $Work$ are not statistically significant. The fact that the effect of income is small and not significant suggests that a consumer's decision to abandon real-time pricing was not driven by wealth effects - which is consistent with the fact that households who adopt RTP generally have a high income. Also, the fact that education and work are not significant indicates that consumer sophistication did not play a role either.

In addition, we run the same regressions and control for a "first impression" effect for consumers who joined last with a dummy ('Joined Last') equal to one if the consumer adopted RTP with the last cohort. The goal is to ensure that the effect of time spent on RTP is not solely driven by the last adopters. The results are displayed in columns (3) and (6). In both cases, the coefficient for 'Joined Last' is positive and significant, which means that the last consumers to join are significantly more likely to abandon RTP. The effect of time spent on RTP diminishes by about one-third but it remains statistically significant, both when measured in levels and in log terms.

As an additional robustness check, we control for arbitrage behavior. The fact that 25.96% of consumers who abandoned RTP eventually switched back to it after the crisis, suggests that arbitrage may have been an important motive for abandoning real-time pricing, which may bias our results. We first use the same specification as in columns (3) and (6) of Table 3 except that we treat consumers who leave and come back as if they didn't leave at all. The underlying assumption is that these consumers had anticipated that they would switch back to RTP after the crisis. We also use the same specification as in columns (3) and (6) of Table 3 except that we remove consumers who leave and come back from the dataset and test what affects the decision to leave. The results are summarized in Table 11, in the Appendix. In all cases, the effect of Time on RTP is greater than in the baseline regressions, which suggests that our results are robust.

Table 3: Abandoning real-time pricing during the winter 2017 crisis.

	Dependent variable:					
	Abandon RTP					
	(1)	(2)	(3)	(4)	(5)	(6)
Time on RTP(month)	−0.038***	−0.037***	−0.022***			
	(0.005)	(0.005)	(0.005)			
log(Time on RTP)				−0.226***	−0.222***	−0.131***
				(0.025)	(0.025)	(0.040)
Joined Last			0.475***			0.354***
			(0.087)			(0.121)
Yearly Consumption (MWh)		−0.038***	−0.037***		−0.038***	−0.037***
		(0.010)	(0.010)		(0.010)	(0.010)
Seasonal Difference (MWh)		0.429***	0.413***		0.415***	0.409***
		(0.092)	(0.092)		(0.092)	(0.092)
Income (k$/yr)		0.001	0.002		0.002	0.002
		(0.001)	(0.001)		(0.001)	(0.001)
Age		−0.010**	−0.010**		−0.010**	−0.011**
		(0.004)	(0.004)		(0.004)	(0.004)
Work (%)		−0.005	−0.005		−0.005	−0.005
		(0.003)	(0.003)		(0.003)	(0.003)
Education (%)		−0.005	−0.005		−0.005	−0.006
		(0.004)	(0.004)		(0.004)	(0.004)
Location-on-Previous retailer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,674	7,653	7,653	7,674	7,653	7,653
Note:						*p<0.1; **p<0.05; ***p<0.01

3.2 Selection versus experience

In this subsection, we investigate what the coefficient of *Time on RTP* captures. Three different mechanisms can explain why consumers who have spent more time on real-time pricing are more likely to remain on the tariff during the crisis.

The first mechanism is selection through attrition. After adopting, consumers gradually learn about their preferences and the specificities of RTP, and only those who value it the most remain on it. As a result, when the crisis happens, the attrition process has just started for the last cohort of adopters but is more advanced for the older cohorts. However, we can rule out this mechanism because we have shown that there was nearly no attrition before the winter 2017 crisis.

The second possible mechanism is selection at the time of adoption that plays a role in the attrition process. Note that the results in Table 3 provide evidence that selection on observable characteristics did not play a role. Even when controlling for demographics and electricity consumption, time spent on RTP remains statistically and economically significant and of close magnitude - see columns (1)-(2) and (4)-(5) of Table 3. However, there may be unobservable characteristics uncorrelated with observable ones that explain the correlation between time spent on RTP and the decision to abandon RTP during the crisis.

Finally, time spent on real-time pricing may reflect the experience that consumers on real-time pricing acquire after they have adopted the tariff, such as a better understanding of the spot price formation process, adjusting their consumption habits, investing in smart appliances, or learning about their price-elasticity.

To identify the mechanism at play, we exploit the fact that the tariff became available at different times in different cities. Our identification strategy rests on reasoning by contradiction: Assume that there was selection at adoption on some unobservable characteristics at the time of RTP adoption and that these unobservable characteristics matter in the decision to abandon RTP during the crisis. Then, because the tariff was available in Christchurch about 22 months after its introduction in Wellington, we would expect that two similar consumers adopting real-time pricing at the same time in Wellington and Christchurch make two different switching decisions. This is because the consumer in Wellington will be a late adopter whereas the one in Christchurch is an early adopter. If, on the other hand, we find no significant difference in their switching decisions then we can rule out that selection on unobservable characteristics plays a role.

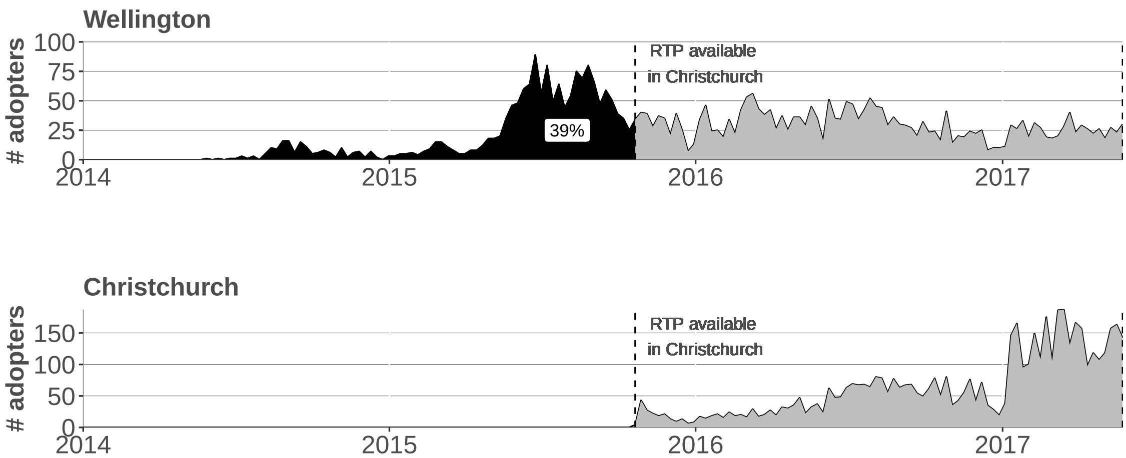

Figure 6: Number of consumers adopting real-time electricity pricing every week in Wellington (top) and Christchurch (bottom) between November 2013 and June 2017.

Figure 6 shows that when real-time pricing became available in Christchurch, 39% of all consumers in Wellington who adopted RTP before the crisis had already adopted it. Then, under the (untestable) assumption that the selection of unobservable characteristics was similar in Christchurch and Wellington, we can conclude that consumers who adopt real-time pricing in Wellington and Christchurch at the same time are significantly different. Therefore, we have a set-up allowing us to test whether selection at adoption explains the correlation between time spent on real-time pricing and the decision to abandon real-time pricing during the crisis.

Formally, we regress consumer decisions to abandon RTP during the crisis (Abandon RTP$_i \in \{0, 1\}$) on time spent on real-time pricing by the time the crisis started, a location dummy for Christchurch, an interaction between the location dummy and time spent on real-time pricing by the time the crisis started, and control variables:

$$\text{Abandon RTP}_i = \alpha_{exp}\text{Time on RTP}_i + \alpha_{loc}\text{Christchurch}_i + \gamma\text{Time on RTP}_i \times \text{Christchurch}_i \\ + X_i'\beta + \varepsilon_i,$$

where Abandon RTP$_i$ and Time on RTP are defined as previously, Christchurch is a dummy equal to one if the consumer in question lives in Christchurch, X holds consumer characteristics, and ε_i is a logistic error term. Our sample is the set of consumers who adopted real-time pricing in Wellington and Christchurch only after the tariff was available in Christchurch in September 2015. Therefore, the Wellington sample is truncated - we have removed the initial adopters - while the Christchurch sample is not. Our main variable of interest is γ. If selection at adoption were an important driver, the interaction variable γ between the location dummy and experience would be statistically significant.

The results are in Table 4. We see that across all specifications, γ is statistically - and economically - insignificant. This suggests that selection at adoption does not explain the correlation between time spent on the tariff and the decision to stay or opt out during the winter 2017 crisis. For robustness, we repeat the same exercise between Auckland and Christchurch and find that the interaction term is insignificant as well. The results are in Table 14 in Appendix B.2.

These results suggest that adoption on unobservable characteristics cannot explain the fact that consumers who had spent more time on RTP by the time the crisis started were less likely to leave during the crisis.

3.3 Switching back to RTP

Overall, 25.96% of consumers who abandoned RTP during the winter 2017 crisis switched back to RTP after the crisis. In Figure 7 we plot the share of consumers who switched back to RTP as a function of the time they spent with the tariff before the crisis. The probability to switch back to RTP increases from 15% for consumers who spent less than 100 days on RTP before the crisis to more than 30% for those who spent more than 500 days. We confirm this graphical evidence by using a logit model in which we regress consumer decisions to return to real-time pricing on the time spent on RTP and control variables, see Table 12 in Appendix B.

We find that time spent on RTP affects the decision to return to real-time pricing signifi-

Table 4: Comparison of the probability to abandon RTP in Wellington and Christchurch.

	Dependent variable:					
	Abandon RTP					
	(1)	(2)	(3)	(4)	(5)	(6)
Time on RTP (month)	−0.051***	−0.047***	−0.051***			
	(0.012)	(0.013)	(0.013)			
log(Time on RTP)				−0.241***	−0.224***	−0.242***
				(0.059)	(0.063)	(0.070)
Christchurch	0.104	0.071	0.176	−0.047	−0.081	−0.079
	(0.147)	(0.149)	(0.348)	(0.351)	(0.353)	(0.568)
Time on RTP x Christchurch	0.003	0.010	0.018			
	(0.016)	(0.016)	(0.018)			
log(Time on RTP) x Christchurch				0.042	0.050	0.090
				(0.067)	(0.068)	(0.087)
Yearly Consumption (MWh)	−0.048***	−0.047***	−0.047***	−0.047***	−0.047***	−0.047***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Seasonal Difference (MWh)	0.486***	0.472***	0.471***	0.467***	0.466***	0.466***
	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.101)
Income (k$/yr)	0.002	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	−0.009*	−0.009*	−0.009*	−0.009*	−0.009*	−0.009*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Work (%)	−0.007*	−0.007*	−0.007*	−0.007*	−0.007*	−0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Education (%)	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Month FE	No	Yes	No	No	Yes	No
Month-on-NRR FE	No	No	Yes	No	No	Yes
Observations	5,520	5,520	5,520	5,520	5,520	5,520
Log Likelihood	−2,766.751	−2,756.131	−2,753.137	−2,762.985	−2,757.243	−2,754.125
Akaike Inf. Crit.	5,553.502	5,554.262	5,570.274	5,545.970	5,556.486	5,572.249

Note: *p<0.1; **p<0.05; ***p<0.01

cantly, both statistically and economically. At the average of the covariates, increasing experience by 4 months increases the probability to return to RTP after the crisis by 4.01% percentage points. A revealed preference argument would suggest that only consumers with a good perception of the tariff would return, reinforcing the previous finding that consumer perception of real-time pricing improved with experience. And, reciprocally, consumers who adopted shortly before the crisis started got scarred by a bad first impression and, thus, were more likely to abandon the tariff for good. This suggests that spot market crises leading to price spikes may permanently drive consumers away from choosing real-time pricing.

In Appendix B.1, we also compare the characteristics of consumers who abandoned RTP and returned after the winter 2017 crisis to the characteristics of all RTP adopters. We can see that those who left and returned consume more electricity but have somewhat lower incomes, and also have somewhat lower educational attainment. These factors could suggest that those returners are particularly sensitive to prices because of their high consumption. However, we also see that there are less than 200 of those consumers, resulting in most t-tests that compare the mean characteristics of all RTP adopters to those leaving and returning being not statistically significant or only marginally so. Also, once controlling for other factors, we can see in Table 12 in Appendix B.1 that consumption is no longer statistically significant in the decision to leave and return.

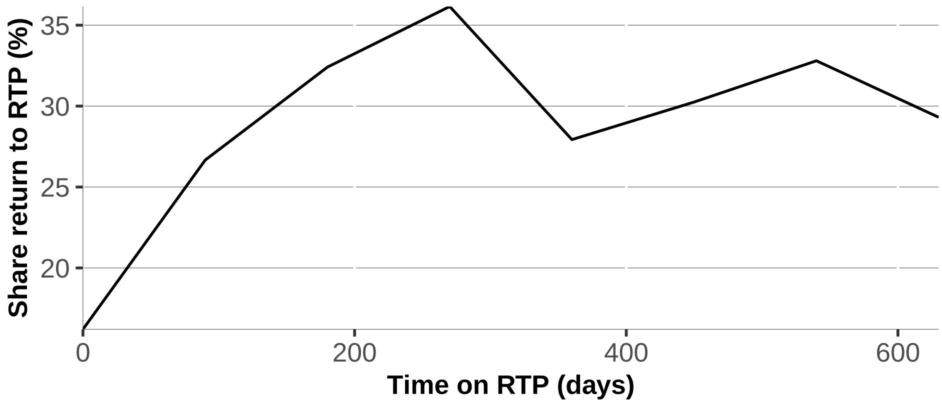

Figure 7: Share of households switching back to RTP after abandoning RTP during the winter 2017 crisis within three months after the end of the crisis as a function of the number of days spent on RTP prior to the crisis.

4 Adoption of real-time electricity pricing

In this section, we examine what affects consumers' decisions to adopt real-time pricing. In particular, we investigate which prices consumers refer to when deciding whether to adopt RTP and whether they strategically time adoption. The purpose is to better understand the decision-making process of prospective adopters and what affects it. Doing so is also helpful to validate the results found in the previous section. The fact that less experienced consumers are more likely to abandon RTP permanently or for a long time during spot price spikes suggests consumers overreact to contemporaneous spot prices. Studying adoption decisions gives us an opportunity to study whether inexperienced consumers also react strongly to ongoing spot prices at the adoption stage.

4.1 Descriptive evidence

In Figure 8, we plot jointly the history of monthly spot prices and the number of consumers adopting real-time pricing in New Zealand. Adoption numbers correlate negatively with contemporaneous spot prices. This relationship is particularly evident around the winter 2017 crisis: adoption is high both before and after but low during the crisis. The link between adoption and spot prices is also apparent for more minor variations, such as the period between late 2015 to early 2016.

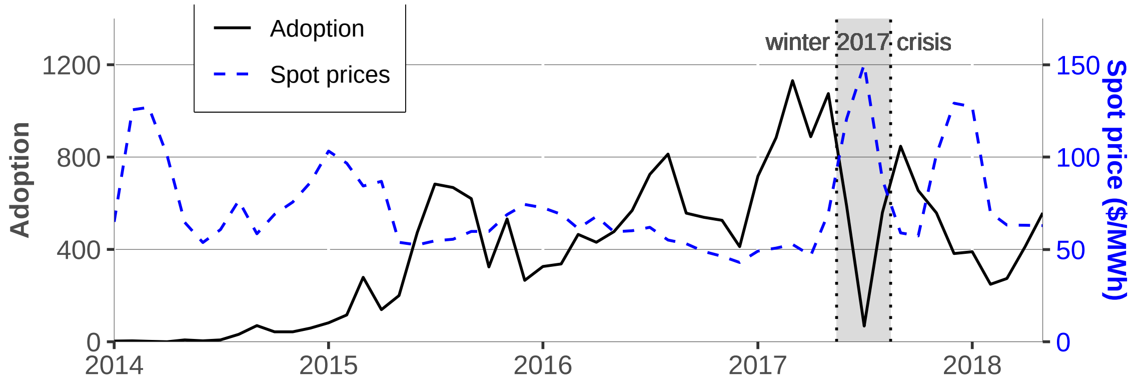

Figure 8: Number of monthly RTP adopters and average spot prices in New Zealand.

Next, we investigate the effect of contemporaneous spot prices on the probability to adopt real-time pricing. In Figure 9 we plot the share of consumers switching to a non-incumbent retailer who adopt real-time pricing as a function of the average spot prices in the four weeks preceding the switch.[15] The plot suggests that consumers are sensitive to prices contemporaneous to their switching decisions. The share of switchers adopting real-time pricing drops nearly 50% when spot prices are in the range 40-60 $/MWh to less than 20% when prices exceed 100 $/MWh.

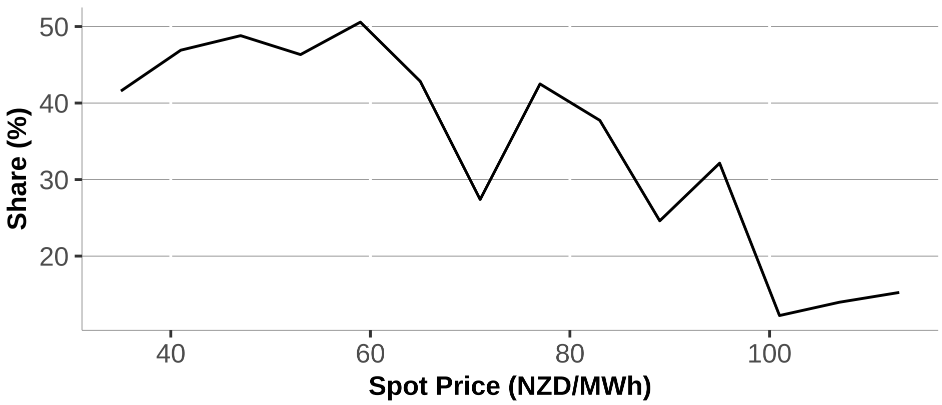

Figure 9: Share of consumers switching to a non-Big-5 retailer who adopt RTP, as a function of the average spot prices in the 4 weeks preceeding the switch - in Wellington.

[15]Examining the share rather than the number of consumers adopting RTP circumvents issues of seasonality or other shocks affecting switching decisions.

The fact that prospective adopters react to spot prices contemporaneous to their switching decisions does not necessarily mean that they are not forward-looking, because it could be that spot prices are persistent and can thus serve as a relevant proxy for future ones. Table 8 in Appendix A presents the correlation between recent and future spot prices over several time horizons (one, three, six, and twelve months). We find that future prices do not correlate strongly with different definitions of recent prices. This finding, together with the graphical evidence, suggests that consumers rely mostly on contemporaneous spot prices to decide whether to adopt real-time pricing.

4.2 Empirical strategy

In this subsection we investigate more formally whether consumers react to recent spot prices rather than different proxies of future payoffs.

Consumer incentives. We assume that a consumer's main incentives for choosing a tariff are financial: a consumer adopts RTP if she expects to pay lower bills. [16]

As discussed in Section 2, on average, about 30% of the bill of a consumer on RTP comes from spot prices. Thus spot prices are an important information for prospective adopters. Furthermore, Figure 12 in Appendix C.1 shows that Flick Electric Co's fixed rates are close to those of other entrants and that spot prices vary substantially over time while entrants rarely adjust their tariffs. When deciding whether or not to adopt real-time pricing, consumers make a choice involving frequently varying spot prices against an almost constant baseline of alternatives. Hence, when deciding whether or not to adopt real-time pricing, consumers mainly need to compare flat tariff's variable rates to the spot prices.

These observations motivate our choice to only include spot prices in our analysis of adoption decisions rather than the (expected) bill difference between real-time pricing and other tariffs. We build several definitions of future spot prices that consumers may consider and examine whether they affect adoption decisions more than recent spot prices.

Sample selection. Ideally, we would like to study RTP adoption by estimating a structural model of individual decisions. However, we only observe which retailer consumers contract

[16] Consumers may have preferences for other attributes, such as consumer service, reliability, trustworthiness, brand name, etc. See, for instance, Ndebele et al. (2019). We do not have data about those characteristics and thus cannot control for them in the analysis. Note, however, that Flick Electric Co. won multiple awards, such as the Consumer NZ Retailer of the Year award, in 2016, when it was recognized as "the only 'Consumer Trusted' electricity retailer, which means its consumer information, contracts, and customer management practices have been fully scrutinized by Consumer NZ and certified to be of a standard that is beyond what is required by law." (see www.energyawards.co.nz), and the Energy Retailer of the Year at the Deloitte Energy Excellence Awards in 2017 its "rapid-growth, innovation and award-winning customer service" (see www.scoop.co.nz). Furthermore, there is a limited risk of bankruptcy since Flick Electric Co. passes through the spot prices directly to consumers.

with and do not observe which contract they select, the menu of contracts they choose from, or the tariffs they know of. As a consequence, we restrict analysis in two ways.

First, our outcome is a consumer's decision to adopt RTP upon switching retailers. This circumvents the question of inertia (see Hortaçsu et al., 2017; Dressler and Weiergraber, 2019) which we cannot rigorously control for and is not the subject of our study. Inertia is generally attributed to behavioral biases or contractual restrictions, such as early termination fees. Failing to account for it would bias price coefficients towards zero, as we would falsely attribute inertia and/or early termination fees to low price sensitivity.

Second, we restrict attention to the subset of consumers who switch to an entrant; that is, a retailer which is not one of the five incumbents. The reason is that, because RTP is a new form of tariff, many consumers switching tariffs would not consider adopting it, either because it is too different from what they know or look for, or even because they have never heard of it. Focusing on this subset of consumers makes it more likely that we capture consumers who had the RTP option in their consideration set. Note that the underlying assumption for the validity of this approach is that the number of people switching to non-incumbent retailers is independent of spot prices, at least in a first-order approximation.

Model Specification. We employ a logit model, where we regress the individual decision to adopt RTP upon switching retailers on the different price definitions, controls, and fixed effects. For each day, we define *Recent Price* as the average spot prices over the past four weeks ending that day, between 7 am and 10 pm. We consider three proxies for *Future Price*: realized spot price, last year's price, and future predicted price based on an AR(1) process. Essentially, our three price definitions assume, respectively, perfect foresight, backward-looking behavior, and consumers acting as "econometricians" using a prediction model to make forecasts. Because spot prices are seasonal, a relevant benchmark for rational forward-looking consumers is to consider a one-year period when comparing tariffs. However, forecasting spot prices over one year is a complicated exercise and forecasts are less reliable the further away in time they are. Therefore, we compute future prices over 1-month ("short-run"), 6-month ("medium-run"), and 12-month ("long-run") horizons.

Formally, our specification writes

$$Y_{imt} = \alpha_1 P_{mt,\text{Recent}} + \alpha_2 P_{mt,\text{Future}_f} + X_{it}\beta + \text{NRR-Month-Year FE} + \varepsilon_{imt}, \tag{1}$$

where Y_{it} is equal to one if consumer i in market m at date t decides to adopt RTP, $P_{mt,\text{Recent}}$ is the recent spot price, P_{mt,Future_f} is the future price, where $\text{Future}_f \in \{\text{realized, last year, AR(1)}\}$, X_{it} holds control variables and ε_{imt} is assumed to follow a logistic distribution. In X_{it}, we control for yearly household consumption as well as consumption differences between winter and summer, the origin retailer, and census-level median household income, age, and work and education status. We also include NRR-on-Month-of-Year fixed effects. We do so in order to control for possible unobserved, time- and location-specific factors affecting the adoption of real-time pricing, such as local advertising campaigns. We use data from June 2014 to June 2018.

Table 5: Logit regression of switchers to entrants. Recent price always computed over 4 weeks. We use data from 2014-06-01 to 2018-06-01

	Dependent variable:								
	Individual decision to adopt RTP								
	1 Month	1 Month	1 Month	6 Months	6 Months	6 Months	12 Months	12 Months	12 Months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Recent Price	−0.225***	−0.226***	−0.235***	−0.235***	−0.248***	−0.235***	−0.232***	−0.247***	−0.235***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Future Price (realized)	−0.037*			0.046			0.171*		
	(0.020)			(0.052)			(0.089)		
Future Price (last year)		−0.079*			−0.088***			−0.083**	
		(0.040)			(0.030)			(0.034)	
Future Price (AR (1))			0.012			0.025			0.049
			(0.013)			(0.045)			(0.089)
Yearly Consumption (MWh)	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Seasonal Difference (MWh)	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.018	0.017
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Income	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
White collar worker	0.599***	0.602***	0.600***	0.600***	0.600***	0.600***	0.599***	0.599***	0.600***
	(0.155)	(0.156)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)
Education	1.407***	1.408***	1.411***	1.411***	1.413***	1.410***	1.416***	1.413***	1.410***
	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)
Location-Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,000	34,000	34,000	34,000	34,000	34,000	34,000	34,000	34,000
Note:									*p<0.1; **p<0.05; ***p<0.01

The results are in Table 5. Across definitions of future prices, *Recent Price* is always statistically and economically significant and keeps the same magnitude. In fact, the coefficient on *Recent Price* in column 1 of Table 5 means that at average values of the covariates, an increase in the recent spot price by one standard deviation decreases the probability of adopting real-time pricing by around 11.13 percentage points. For reference, at the average value of covariates, the probability of RTP adoption is around 32.82%. Moreover, we see that the different definitions of future prices are either not statistically significant, have an unintuitive sign, or both. The only exceptions are *Future Price (last year)* computed from the previous year's spot prices over 6 and 12 months.

These results suggest that consumers focus on contemporaneous spot prices rather than trying to predict long-run prices and hence the existence of present bias. These results are also in line with findings by Anderson et al. (2013) who find that average consumer beliefs about future gasoline prices cannot be distinguished from "no-change" forecasts.

We also check whether the volatility of spot prices may play a role in adoption decisions. We compute the standard deviation of peak-hour spot prices and take averages over the last 1, 2, and 4 weeks. We then regress the individual switching decisions on both *Recent Price* and our measure of volatility, including all controls we use in (1). The results are in Table 9 in Appendix A. We see that price volatility is not significant or has an unintuitive sign, leading us to conclude it does not play an important role in adoption decisions.

As additional robustness checks, we re-run the specification (1) but make two changes: first, we change the time horizon over which we compute *Recent Price* to two weeks. In the second check, we keep the time horizon for computing *Recent Price* at 4 weeks but include the log of prices (both recent and future) in the regressions. Our findings are robust to these changes. Detailed results for the robustness checks are in Appendix C.1.

4.2.1 Do households postpone or forego adoption?

The results from the previous subsection suggest that prospective adopters react to spot prices that are contemporaneous to their switching decision. A natural follow-up question is whether households postpone or forgo adoption when spot prices are high. To answer this question, we focus on the winter 2017 crisis. Because spot prices surged and remained high for several weeks, consumers who were willing to adopt RTP and were able to postpone adoption had an interest in doing so.

In Figure 10 we plot the weekly number of households switching to real-time pricing for the first time in New Zealand.[17] While the number of new adopters is relatively constant before the crisis, about 115.2 per week, adoption drops during the crisis with only about 6.7 new households per week in July. Interestingly, there is a surge in adoption between mid-August and early September when spot prices returned to normal levels. After this surge, the number of households adopting real-time pricing for the first time reduces and remains fairly constant, below the pre-crisis level, with about 42.5 new households per week. This surge suggests that some consumers who would have adopted during the crisis waited until spot prices decreased. The goal is to quantify whether waiting for the right price is a widespread strategy among prospective adopters or if only a few of them do. To do so, we run a counterfactual analysis in

[17] As we saw in the previous section, some consumers who were on real-time pricing switched to another tariff during the crisis and then switched back to real-time pricing. We do not consider them in this analysis as we are only interested in the decision of consumers who were considering adopting real-time pricing for the first time.

which we predict how many households would have adopted RTP in Winter 2017 had there not been a crisis and compare it to the number of households who actually adopted the tariff and to those who (allegedly) postponed adoption.

To predict how many households would have adopted real-time pricing during the crisis, we estimate a model similar to the one in the previous subsection. We consider the set of households who switch to an entrant[18] and regress individual adoption decisions on the average spot price of the past four weeks, household consumption, consumer demographics, location-on-year and location-on-month fixed effects, see the specification in Equation 2 below 2.

$$Y_{imt} = \alpha P_{mt,\text{Recent}} + X_{it}\beta + \text{Location FEs} + \text{Month FEs} + \text{Year FEs} + \varepsilon_{imt}, \quad (2)$$

where $P_{mt,\text{Recent}}$ is the average spot price of the previous four weeks, X_{it} holds demographic variables, and ε_{imt} is assumed to follow a logistic distribution.

To test the predictive performance of our model, we first estimate the model with data from June 1st, 2014 to March 31st, 2017, and predict adoption during April and May of 2017. See the regression Table 17 in Appendix C.1. Our model predicts that 1101 consumers would have adopted RTP during that period. This number is quite close to the actual number of adopters (1169), suggesting our model does a good job predicting RTP adoption. The accuracy rate[19] of our model is 71.94, meaning we correctly predict 71.94 of all decisions during April and May of 2017.

We then re-estimate the model using the full data from June 2014 to May 2017 and use the fitted model to predict the number of households who would have adopted RTP during the crisis defined by the period from June 1st, 2017 to August 15th, 2017. For counterfactual wholesale prices, we use the average previous month's prices from 2014-2016. We plot the results in Fig. 10 where the red shaded area under the full red line represents the number of households who would have adopted during the crisis, and the red-dotted lines represent the 95% confidence interval.

To compute the number of consumers who postponed adoption because of the crisis, we assume that these consumers waited until prices decrease and not longer and consider that all consumers who adopt RTP in the two weeks following the crisis are those who have postponed adoption, which is an upper bound (under the first assumption). This period is marked as post-crisis in Fig. 10.

[18]We use this subset for the consistency of our methodology throughout the paper. In this exercise, restricting attention to households who switch retailers provides conservative estimates because it does not account for consumers who choose not to switch rather than adopting RTP. Accounting for these consumers would strengthen our results and conclusions.

[19]Accuracy measures the share of correctly predicted outcomes. Assuming that a household adopts RTP if and only if her predicted probability of adoption is greater than 0.5, accuracy is the ratio of the number of true positives and true negatives over the number of observations.

The model predicts that absent the crisis, 1523 consumers would have adopted real-time pricing during the period it occurred (the 95% confidence interval is [1284, 1763]). Of those, 411 (or 27%) adopted despite the crisis and at most 257 (or 16.9%) postponed adoption. The remaining 855 (or 56.2%) chose to forego adoption altogether.

These results thus suggest that few consumers strategically time adoption. Rather, our results suggest that consumers make one-shot decisions on whether to adopt real-time pricing and forego adoption when spot prices have been high before switching contracts.

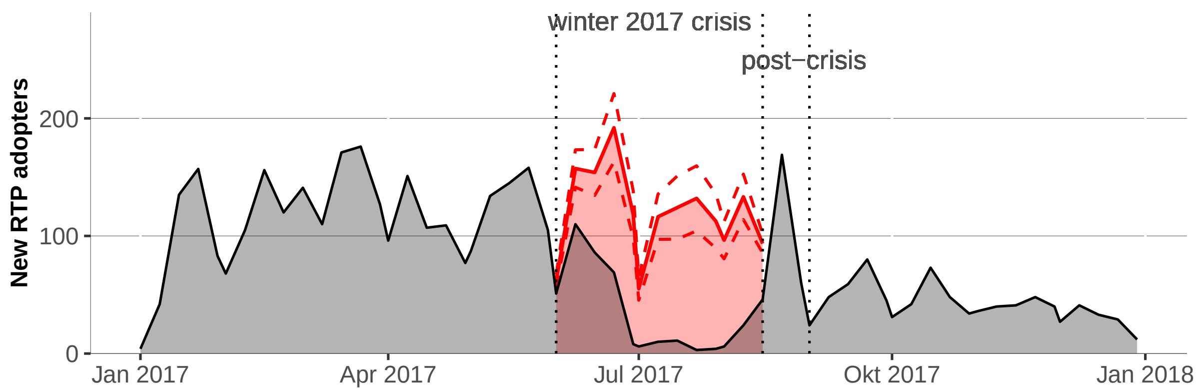

Figure 10: Actual and predicted weekly number of new consumers adopting RTP during the winter 2017 crisis in New Zealand (with 95% confidence interval).

5 Discussion

In this section, we review our results and discuss their external validity, we propose a hypothesis for why the New Zealand retail electricity market did not unravel as theory predicts, and discuss potential underlying mechanisms explaining our results.

5.1 Review of the results

The analysis of attrition during the winter 2017 crisis in Section 3 reveals that consumers who adopted RTP shortly before the crisis are significantly more likely to abandon this tariff than consumers who have spent more time on the tariff. They are more likely to switch to another tariff during the crisis and, conditional on switching tariffs, are less likely to return to RTP after the crisis. By exploiting the lag in the roll-out of RTP in different locations, we have rejected the hypothesis that this difference is explained by differences in observed or unobserved characteristics of consumers who adopt RTP at different times. As a consequence, we attribute this finding to a difference in experience with the tariff.

The study of adoption in Section 4 shows that consumers who consider adopting RTP strongly react to recent or ongoing spot prices and the counterfactual exercise for adoption during and after the winter 2017 crisis suggests that a majority of them make ”now-or-never” decisions rather than strategically time adoption.

Taken together, these findings indicate that many inexperienced consumers - prospective and recent adopters - rely on short-term signals and make definitive decisions such as foregoing adoption or abandoning the tariff. Furthermore, time spent on RTP under favorable conditions increases retention. The challenge for widespread adoption of RTP is thus not only to attract consumers but also to retain them long enough to win their loyalty. This observation seems specific to RTP as other tariffs are less complex to apprehend.

External validity. The fact that our results come from a distinct subset of consumers begs the question of their external validity. In the following, we present arguments suggesting that our findings are informative even for a broader set of consumers.

First, we run a heterogeneity analysis of price sensitivity at adoption. We use both *Recent Price* and *Future Price*, computed as last year’s price and over 12 months, and interact them with income and education. The results are summarized in Table 10 in Appendix A. In the first column, we see that consumers with higher incomes respond more to future prices, all else equal. In the second column, we see that consumers with more education react both less strongly to current prices and more to future prices. When combining all interaction terms into one regression in the third column, we see that, surprisingly, higher-income individuals tend to put relatively more weight on current spot prices. However, this effect is dominated by the effect of education, which goes in the expected direction. Second, regarding attrition, we have shown in Section 3 that decisions were not explained by observed and unobserved attributes of early adopters but rather by time spent on real-time pricing.

Finally, and more generally, we argue that if the consumers we observe are present biased, in the sense that they strongly rely on contemporaneous spot prices, then the others would be as well. Indeed, the 1% of consumers who have adopted RTP can be considered early adopters, who are more likely to be interested in RTP, enjoy following spot price variations, and optimize their consumption. Furthermore, as we saw in Section 2, consumers who adopt RTP are, on average, more educated, have a higher income, and are more likely to work in white-collar jobs. They are therefore likely to be savvier and less budget constrained than the rest of the population, and therefore less present biased.

5.2 Interpretation of the results

We build on our results to propose a hypothesis explaining why the unraveling process predicted by economic theory did not go through in New Zealand.

On the demand side, we argue that the combination of present bias among inexperienced consumers - prospective and recent adopters - and repeated spot price spikes created the conditions to jam the unraveling process. Indeed, compared with a flat tariff, losses are concentrated - and thus salient - during crises while gains are spread out over time. Therefore, the incentives to abandon the tariff or forego adoption when prices are high are stronger than the incentives to adopt when prices are low, especially for present-biased consumers. This hypothesis is consistent with what happened in New Zealand where RTP adoption was high before the winter 2017 crisis when spot prices were low and stable, and low afterward when spot prices spiked repeatedly. Furthermore, there was high attrition, especially among recent adopters, during the crisis.

This may have been exacerbated by supply-side conditions and behavior. First, while consumers often sign long-term contracts with termination fees, Flick Electric Co. did not charge termination fees. Therefore, only so many consumers have an opportunity to adopt RTP when spot prices are low, but when prices spike all consumers on RTP can abandon the tariff. Second, as discussed earlier, other retailers rarely adjust their tariffs and, in particular, did not increase them during or shortly after the winter 2017 crisis. While we do not know whether this was a strategic decision or not, keeping flat rates constant makes losses from RTP even more salient and thus increases the incentives to abandon RTP or forego adoption.

5.3 Potential underlying mechanisms

While the identification of the underlying mechanisms behind our results is beyond the scope of this paper, in this subsection, we review a set of potential mechanisms on the demand side and discuss their strengths and weaknesses. The mechanisms need to explain the change in the dynamics of adoption and attrition, why inexperienced consumers are present biased, and the role of time spent on real-time pricing. We first discuss those that we believe are the most novel and promising and then review existing ones in the literature.

Learning through experience. Because spot prices are seasonal and volatile, it takes time to experience different situations and learn how to adjust consumption to the price variations. Therefore, consumers who experienced RTP longer gained superior knowledge about their own preferences and price-elasticities and therefore about their payoffs with RTP. Experience could have shifted the mean and/or the variance of consumer beliefs: consumers became more optimistic (higher mean) about RTP or their beliefs became more entrenched (lower variance).

Both cases are consistent with our results. As the comparison of tariffs on Figure 2 suggests, many consumers would likely have benefited financially from RTP before the winter 2017 crisis started. Therefore, consumers who have experienced RTP for longer may have grown more optimistic. Furthermore, while the winter 2017 crisis sent a negative signal about RTP to all consumers, those with more entrenched beliefs may have still believed that RTP was beneficial in the long run.

Learning through the app. Consumers on real-time pricing could check their weekly and their accumulated savings on their mobile app and their online personal accounts. Flick Electric Co. computed savings by comparing realized bills with the hypothetical bill consumers would have had to pay with their previous tariff if they had consumed electricity identically. Figure 11 in Appendix A provides two examples of how the app displayed this information to consumers during the winter 2017 crisis. The consumer from the left panel had adopted RTP several months before the crisis and, by the beginning of June 2017, had accumulated more than 1500$ in savings. The consumer from the right panel had adopted RTP just as the crisis started, and after three weeks, had made losses every week. If consumers used the savings displayed on the app to decide whether to stay on or abandon RTP then it would generate outcomes consistent with our results.

Sunk investments. Consumers can make investments that increase the long-run benefits of being on RTP, for instance in smart appliances and in changing their habits. If making those investments takes time, then consumers who have spent more time on RTP would be more likely to have made them and would thus have more incentive to remain on RTP during the crisis, which would explain our findings. It could also be that consumers who have made those investments follow sunk cost fallacy and decide to stay on RTP despite their losses.

We have highlighted novel mechanisms that might play as barriers to a large take-up of RTP in the residential electricity market. Next, we discuss other mechanisms affecting consumer switching decisions in retail electricity markets analyzed in the literature that might have played a role in New Zealand as well. While we do not dismiss their importance, we highlight why we have not considered them as primary explanations of the patterns of adoption and attrition that we have uncovered. In particular, we argue that while these barriers can explain low levels of adoption or high levels of attrition, they cannot explain the (change of) dynamics that we have documented or the relationship between consumer behavior and time spent on the tariff.

Risk aversion. The concomitance between the significant spot price volatility starting with the winter 2017 crisis and the drop in adoption and increase in attrition suggests that consumers are risk averse. Yet, some arguments show that the role of risk aversion in the stalling of the unraveling process is not as straightforward as it might seem.

Consumers who have not adopted RTP could be risk averse, which would explain the drop in adoption following the winter 2017 crisis. However, RTP's market share did not increase after Flick Electric Co. started guaranteeing positive savings (relative to the previous tariff) for the first 12 months to all new customers. [20] Furthermore, in our dataset, consumers on RTP are generally wealthier than the rest of the population, which suggests that they could absorb the financial shock during the crisis.[21]

Inertia. A large literature documents consumer inertia in the retail electricity market (see Hortaçsu et al., 2017; Dressler and Weiergraber, 2019) and its consequences on the market share of entrants. For inertia to explain the relationship between attrition and time spent on RTP, one needs a theory explaining why over time consumers on RTP become more inert. We discuss inattention and search costs.

Consumers who have spent the most time on RTP might be less likely to be aware of the crisis, for instance, because they have stopped paying attention to spot prices. However, the winter 2017 crisis was salient: consumers on RTP are billed weekly, receive notifications on their mobile app when prices spike, their retailer regularly provided information about the crisis, and the crisis received media coverage.

Furthermore, consumers who adopted RTP shortly before the crisis may still have in mind the set of tariffs available while consumers who have been on RTP for a longer time would have to search again. If search costs are high then consumers might decide not to incur them, which could explain the relationship between attrition and time spent on the tariff. Yet, the availability of tariff comparison websites suggests that search costs are not that high.

Non-price attributes. Ndebele et al. (2019) study switching determinants in New Zealand and find that non-price attributes - such as call waiting time, length of fixed-rate contract, renewable energy, loyalty rewards, supplier ownership, and supplier type - are important. Relatedly, since Flick Electric Co. was a new retailer, consumers might not trust this new company or might fear it goes bankrupt because of the crisis. Unfortunately, we do not observe these attributes nor the quality of customer service during the crisis. Note, however, that Flick Electric Co. won multiple awards for its customer service[22] and that there is limited risk of bankruptcy since

[20]In September 2018, one year after the end of the winter 2017 crisis, Flick Electric Co. guaranteed all new consumers they would make positive savings relative to their previous tariff or would pay back the difference.

[21]Flick Electric Co. reports that, on average, consumers on RTP saved NZ$479 in the year preceding the crisis and lost NZ$81 during the first month of the crisis compared with their earlier tariff.

[22]See footnote 16 for examples

Flick Electric Co. passes through the spot prices directly to consumers.

6 Policy implications

We have presented evidence that consumers who are inexperienced with real-time pricing - both prospective and recent adopters - strongly react to recent or ongoing spot prices but that, after spending time on the tariff, consumers are less sensitive to them. A corollary is that the challenge for widespread adoption of RTP is not only to attract consumers but also to retain them long enough.

Essentially, present bias and spot price volatility generate a setting where retailers or policymakers introducing real-time pricing need to be "lucky" and hope that no unexpected crisis in the wholesale electricity market arises before sufficiently many consumers have adopted real-time pricing and experienced it long enough. We propose a set of recommendations to better the odds of widespread adoption of RTP: timing of adoption, information provision, and insurance.

First, strategically timing when consumers adopt (in an opt-in set-up) or are defaulted to (in an opt-out set-up) real-time pricing can increase the chances that consumers remain on real-time pricing and limit the risks that a crisis interrupts the unraveling process. In an opt-out set-up, the date when consumers defaulted to RTP is a choice variable. In an opt-in set-up, consumers decide whether or not to switch but one can time when to encourage switching, for instance through advertising campaigns or with time-contingent subsidies.

Second, providing information to consumers, both before and after adoption, can accelerate the learning process and help them make rational and informed decisions. Consumers need to understand how spot prices form and that long-run gains can compensate for immediate losses. Consumers also need to be aware of whether, in the long run, they would benefit or not from real-time pricing. For that purpose, a simple policy would be to facilitate access to records of household consumption profiles and use them on tariff comparison websites. For instance, Ito et al. (2021) show that providing this information ex-ante to consumers allows structural winners to self-select to time-varying tariffs.[23]

Third, insuring consumers against price spikes and bill volatility could prevent or reduce attrition. For instance, Borenstein (2007) show that simple forward purchase contracts can eliminate most bill volatility. Alternatively, a year after the winter 2017 crisis, Flick Electric Co. guaranteed that new customers would not pay more than under their previous tariff during their first year by covering eventual differences. Flick Electric Co. also offered to smooth bill payments over time. However, this scheme did not attract many new adopters, as evidenced by

[23] Structural winners are consumers who benefit from adopting real-time pricing even without adjusting their electricity consumption

the flat market share curve in Figure 1.

7 Conclusion

In this paper, we document the adoption of a new electricity tariff, real-time pricing, by residential consumers in New Zealand. Contrary to theoretical predictions, the retail market did not unravel and, more than seven years after the introduction of real-time pricing, less than 1.25% of consumers switched to this tariff.

We find that consumers inexperienced with real-time pricing - prospective and recent adopters - are highly sensitive to ongoing spot prices. Specifically, adoption decreases with current spot prices, and consumers forego adoption rather than postpone it when spot prices spike. During a crisis in the electricity spot market, consumers who have spent the most time on RTP are less likely to switch to another tariff and, when they do, are more likely to return to RTP afterward. We show that this result is not explained by selection on observed or unobserved characteristics.

We discuss several mechanisms that can explain how time spent on the tariff can affect consumer decisions and their reliance on short-term payoffs such as learning, investments, and search costs, among others. We hypothesize that the combination of present bias and spot price volatility may explain why the market did not unravel: price spikes lead to low adoption and large attrition while only so many consumers have the opportunity to adopt RTP when prices are low. Based on these findings, we make recommendations to help overcome these barriers to the widespread adoption of real-time pricing. We have derived three types of recommendations: timing of adoption to increase adoption and limit attrition, information provision to help consumers forecast their long-term payoffs, and insurance to reduce losses when prices spike.

This paper opens several promising alleys for future research. First, eliciting which mechanisms explain that time spent on RTP affects consumer decisions is an important goal to identify relevant policies. Second, while our analysis has focused on the demand side, the role of the supply side remains unexplored. Finally, the design of optimal policies to incentivize not only adoption but also retention is an open research question.

References

Ambec, S. and C. Crampes (2021). Real-time electricity pricing to balance green energy intermittency. *Energy Economics 94*, 105074.

Anderson, S. T., R. Kellogg, and J. M. Sallee (2013). What do consumers believe about future gasoline prices? *Journal of Environmental Economics and Management 66*(3), 383–403.

Borenstein, S. (2005a). The long-run efficiency of real-time electricity pricing. *The Energy Journal 26*(3).

Borenstein, S. (2005b). Time-varying retail electricity prices: Theory and practice. *Electricity deregulation: choices and challenges 4*, 317–356.

Borenstein, S. (2007). Customer risk from real-time retail electricity pricing: Bill volatility and hedgability. *The Energy Journal 28*(2).

Borenstein, S. (2012). The redistributional impact of nonlinear electricity pricing. *American Economic Journal: Economic Policy 4*(3), 56–90.

Borenstein, S. (2013). Effective and equitable adoption of opt-in residential dynamic electricity pricing. *Review of Industrial Organization 42*(2), 127–160.

Busse, M. R., D. G. Pope, J. C. Pope, and J. Silva-Risso (2015). The psychological effect of weather on car purchases. *The Quarterly Journal of Economics 130*(1), 371–414.

Cahana, M., N. Fabra, M. Reguant, and J. Wang (2022). The distributional impacts of real-time pricing.

Daglish, T. (2016). Consumer governance in electricity markets. *Energy Economics 56*, 326–337.

Dressler, L. and S. Weiergraber (2019). Alert the Inert! Switching Costs and Limited Awareness in Retail Electricity Markets. *Working Paper*.

Electricity Authority (2018). 2017 Winter Review - Final report.

Fabra, N., D. Rapson, M. Reguant, and J. Wang (2021). Estimating the Elasticity to Real Time Pricing: Evidence from the Spanish Electricity Market. *American Economic Association Papers and Proceedings forthcoming*.

Farrell, J. and P. Klemperer (2007). Coordination and lock-in: Competition with switching costs and network effects. *Handbook of industrial organization 3*, 1967–2072.

Fowlie, M., C. Wolfram, P. Baylis, C. A. Spurlock, A. Todd-Blick, and P. Cappers (2021). Default effects and follow-on behaviour: Evidence from an electricity pricing program. *The Review of Economic Studies 88*(6), 2886–2934.

Hirshleifer, D., B. Lourie, T. G. Ruchti, and P. Truong (2020). First impression bias: Evidence from analyst forecasts. *Review of Finance*.

Hortaçsu, A., S. A. Madanizadeh, and S. L. Puller (2017). Power to choose? an analysis of consumer inertia in the residential electricity market. *American Economic Journal: Economic Policy 9*(4), 192–226.

Ito, K., T. Ida, and M. Tanaka (2021). Selection on welfare gains: Experimental evidence from electricity plan choice. NBER Working Papers 28413, National Bureau of Economic Research.

Jessoe, K. and D. Rapson (2014). Knowledge is (less) power: Experimental evidence from residential energy use. *American Economic Review 104*(4), 1417–38.

Joskow, P. and J. Tirole (2006). Retail electricity competition. *The RAND Journal of Economics 37*(4), 799–815.

Joskow, P. L. and C. D. Wolfram (2012). Dynamic pricing of electricity. *American Economic Review 102*(3), 381–85.

Lamp, S. (2018). Sunspots that matter. Working Paper.

Malmendier, U. and L. S. Shen (2019). Scarred consumption. NBER Working Papers 24696, National Bureau of Economic Research.

Miravete, E. J. (2003). Choosing the wrong calling plan? Ignorance and learning. *American Economic Review 93*(1), 297–310.

Ndebele, T., D. Marsh, and R. Scarpa (2019). Consumer switching in retail electricity markets: Is price all that matters? *Energy Economics 83*, 88–103.

Oxford Institute for Energy Studies (2019). Liberalized retail electricity markets: What we have learned after two decades of experience?

Poletti, S. and J. Wright (2020). Real-time pricing and imperfect competition in electricity markets. *The Journal of Industrial Economics 68*(1), 93–135.

Reguant, M. (2019). The Efficiency and Sectoral Distributional Impacts of Large-Scale Renewable Energy Policies. *Journal of the Association of Environmental and Resource Economists 6*(S1), 129–168.

Wolak, F. A. (2013). Economic and political constraints on the demand-side of electricity industry re-structuring processes. *Review of Economics and Institutions 4*(1), 42.

Appendix

For Online Publication

A Additional tables and figures

Table 6: Comparison of household characteristics

	All ICPs	Switchers		Switchers to non big 5		RTP adopters	
	2	3	4	5	6	7	8
Consumption (kWh/yr)	6,903.4	7,194.3	17	7,172.5	-0.5	8,024.4	7.9
	(3,852.6)	(3,691.5)	(0.000)	(3,708.3)	(0.629)	(3,789)	(0.000)
Income (x1,000 NZ$/yr)	82.8	80.4	-17.8	78.9	-4.1	89.7	12.7
	(30.8)	(29.2)	(0.000)	(29.7)	(0.000)	(29.8)	(0.000)
Age	35.7	34.6	-32	34.5	-0.9	36.2	8
	(8.4)	(7.4)	(0.000)	(7.7)	(0.391)	(7.2)	(0.000)
Education (%)	25.9	24.1	-28.5	25.1	5.8	30.5	15.2
	(13.5)	(13.1)	(0.000)	(13.3)	(0.000)	(12.4)	(0.000)
Work (%)	45.5	42.5	-37.5	43.6	5.3	50.3	15.2
	(18.6)	(16.9)	(0.000)	(17.4)	(0.000)	(14.8)	(0.000)
Number of households	261,996	57,338		7,583		1,450	

Note:
Data for Auckland, from January 2014 to June 2017. The columns 2, 3, 5 and 7 hold mean values with standard deviations in parentheses. Columns 4, 6 and 8 report t-test of means of the previous two mean columns, with p-values in parentheses.

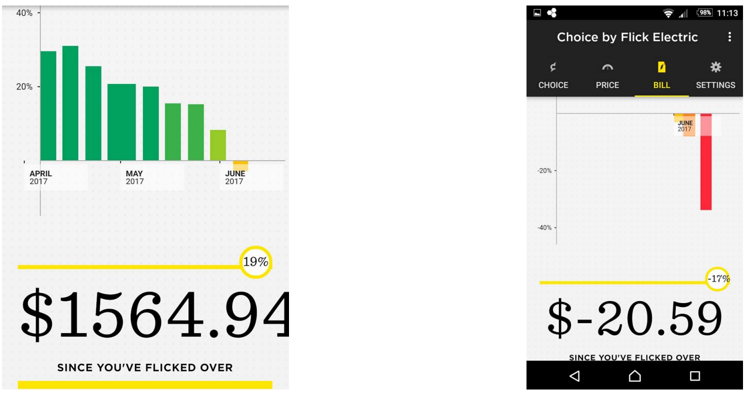

Figure 11: Screenshots of the display of two customers' cumulative savings on their mobile application - obtained on search engine.

Table 7: Comparison of household characteristics

	All ICPs	Switchers		Switchers to non big 5		RTP adopters	
	2	3	4	5	6	7	8
Consumption (kWh/yr)	8,708.5	9,545.9	30.9	9,762.8	4.3	10,458.2	8.6
	(4,421.9)	(4,370.4)	(0.000)	(4,373.3)	(0.000)	(4,478.7)	(0.000)
Income (x1,000 NZ$/yr)	70	71	6.4	71.7	2.7	76.4	10.3
	(24.6)	(24.9)	(0.000)	(24.3)	(0.008)	(25.2)	(0.000)
Age	39.2	38.8	-8.4	38.3	-4.5	38.5	0.9
	(8.5)	(8.2)	(0.000)	(7.6)	(0.000)	(7.5)	(0.349)
Education (%)	19.1	18.8	-4	18.5	-2.7	19.5	5.4
	(10)	(9.8)	(0.000)	(9.4)	(0.007)	(9.5)	(0.000)
Work (%)	38.2	37.8	-4.3	37.6	-1.4	39.2	6.3
	(14.3)	(13.9)	(0.000)	(13.7)	(0.152)	(13.5)	(0.000)
Number of households	147,492	31,824		9,768		4,336	

Note:
Data for Christchurch, from January 2014 to June 2017. The columns 2, 3, 5 and 7 hold mean values with standard deviations in parentheses. Columns 4, 6 and 8 report t-test of means of the previous two mean columns, with p-values in parentheses.

Table 8: Correlation between recent price and future expected price.

		Future price			
		1 month	3 months	6 months	12 months
Recent price	2 weeks	0.71	0.40	0.31	0.08
	1 month	0.66	0.32	0.28	0.02

Note: On a given day d, the recent price is computed as the average spot price in the period preceeding and ending at day d. The future price is computed as the average spot price in the period following and starting at day d+1.

Table 9: Logit regression of switchers to entrants. We use data from 2014-06-01 to 2018-06-01

	Dependent variable:		
	Individual decision to adopt RTP		
	1 Week	2 Weeks	4 Weeks
	(1)	(2)	(3)
Recent Price	−0.106***	−0.150***	−0.250***
	(0.013)	(0.016)	(0.022)
Volatilty	0.022***	0.026**	0.036
	(0.008)	(0.012)	(0.024)
Yearly Consumption (MWh)	0.034***	0.034***	0.034***
	(0.005)	(0.005)	(0.005)
Seasonal Difference (MWh)	0.019	0.019	0.017
	(0.055)	(0.055)	(0.055)
Income	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Age	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)
White collar worker	0.602***	0.598***	0.599***
	(0.155)	(0.155)	(0.155)
Education	1.406***	1.397***	1.412***
	(0.169)	(0.169)	(0.170)
Location-Year-Month FE	Yes	Yes	Yes
Observations	34,000	34,000	34,000
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10: Logit regression of switchers to entrants with interaction effects between Recent/Future prices and demographics. We use data from 2014-06-01 to 2018-06-01

	Dependent variable:		
	Individual decision to adopt RTP		
	12 Month	12 Month	12 Month
	(1)	(2)	(3)
Recent Price	−0.201***	−0.293***	−0.222***
	(0.028)	(0.024)	(0.028)
Future Price (Last Year)	−0.067*	−0.071**	−0.064*
	(0.037)	(0.035)	(0.037)
Recent Price x Income	−0.001**		−0.001***
	(0.0002)		(0.0003)
Future Price (Last Year) x Income	−0.0002		−0.0001
	(0.0002)		(0.0002)
Recent Price x Education		0.002***	0.003***
		(0.001)	(0.001)
Future Price (Last Year) x Education		−0.0004	−0.0002
		(0.0003)	(0.0004)
Yearly Consumption (MWh)	0.034***	0.034***	0.034***
	(0.005)	(0.005)	(0.005)
Seasonal Difference (MWh)	0.018	0.017	0.017
	(0.055)	(0.055)	(0.055)
Income	0.009***	0.003***	0.013***
	(0.002)	(0.001)	(0.002)
Age	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)
White collar worker	0.611***	0.594***	0.604***
	(0.155)	(0.156)	(0.155)
Education	1.400***	0.565	−0.471
	(0.170)	(0.463)	(0.529)
Location-Year-Month FE	Yes	Yes	Yes
Observations	34,000	34,000	34,000
Note:			*p<0.1; **p<0.05; ***p<0.01

B Attrition - robustness checks

B.1 Consumers who leave and come back

Table 11: Abandon real-time pricing during the winter 2017 crisis. Sample without consumers who leave RTP during the crisis and come back afterwards.

	Dependent variable:			
	Abandon RTP			
	(1)	(2)	(3)	(4)
Time on RTP(month)	-0.040^{***}		-0.039^{***}	
	(0.006)		(0.006)	
log(Time on RTP)		-0.245^{***}		-0.231^{***}
		(0.044)		(0.044)
Joined Last	0.610^{***}	0.366^{***}	0.611^{***}	0.387^{***}
	(0.096)	(0.133)	(0.097)	(0.134)
Yearly Consumption (MWh)	-0.045^{***}	-0.046^{***}	-0.047^{***}	-0.048^{***}
	(0.012)	(0.012)	(0.012)	(0.012)
Seasonal Difference (MWh)	0.515^{***}	0.505^{***}	0.533^{***}	0.523^{***}
	(0.106)	(0.107)	(0.107)	(0.108)
Income (k$/yr)	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.012^{**}	-0.013^{**}	-0.012^{**}	-0.013^{**}
	(0.005)	(0.005)	(0.005)	(0.005)
Work (%)	-0.006	-0.006	-0.006	-0.007
	(0.004)	(0.004)	(0.004)	(0.004)
Education (%)	-0.005	-0.005	-0.005	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Location-on-Previous retailer FE	Yes	Yes	Yes	Yes
Observations	7,653	7,653	7,241	7,241
Log Likelihood	$-2,926.862$	$-2,932.589$	$-2,858.285$	$-2,864.460$
Akaike Inf. Crit.	5,953.725	5,965.178	5,816.570	5,828.920
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 12: Switching back to RTP after the winter 2017 crisis.

	Dependent variable:					
	Return to RTP (vs. Not)			Leave and Return (vs. Stay)		
	(1)	(2)	(3)	(4)	(5)	(6)
Time on RTP (month)	0.075***	0.074***	0.049***	0.026***	0.026***	0.019**
	(0.008)	(0.008)	(0.010)	(0.007)	(0.007)	(0.008)
Joined Last			−0.907***			−0.302*
			(0.166)			(0.159)
Yearly Consumption (MWh)		0.027	0.024		0.016	0.015
		(0.018)	(0.018)		(0.015)	(0.015)
Seasonal Difference (MWh)		−0.316*	−0.286*		−0.053	−0.048
		(0.161)	(0.163)		(0.139)	(0.139)
Income (k$/yr)		0.002	0.002		0.004*	0.004*
		(0.002)	(0.002)		(0.002)	(0.002)
Age		0.007	0.008		0.0002	0.001
		(0.007)	(0.007)		(0.007)	(0.007)
Work (%)		0.003	0.002		−0.002	−0.002
		(0.006)	(0.006)		(0.005)	(0.005)
Education (%)		0.0003	0.001		−0.006	−0.006
		(0.007)	(0.007)		(0.006)	(0.006)
Location-on-Previous retailer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,126	2,111	2,111	11,023	10,951	10,951
Log Likelihood	−1,135.616	−1,123.769	−1,107.905	−1,910.404	−1,898.532	−1,896.659
Akaike Inf. Crit.	2,351.233	2,339.537	2,309.810	3,914.808	3,903.064	3,901.317

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: Comparison of household characteristics: RTP adopters vs those who leave during the crisis and come back

	All ICPs	RTP adopters		RTP adopters: leave + return		
Consumption (kWh/yr)	7,473	9,245.4	-8.3	9,851		0.4
	(4,085.1)	(4,274.6)	(0.000)	(4,013.2)		(0.656)
Income (x1,000 NZ$/yr)	80.3	85.2	35	83.3		8.8
	(30.1)	(28.9)	(0.000)	(26.9)		(0.000)
Age	37	37.3	-9.4	37.6		-2.1
	(8.5)	(7.4)	(0.000)	(7)		(0.039)
Education (%)	24.9	26.7	46.9	23.7		8.5
	(13.8)	(14.2)	(0.000)	(12.5)		(0.000)
Work (%)	44.3	46.1	40.2	43.3		8
	(17.5)	(15.6)	(0.000)	(14.5)		(0.000)
Number of households	547,980	9,521		432		

Note:
Data for Wellington, Auckland, and Christchurch. From January 2014 to June 2017. The columns 2, 3, 5 and 7 hold mean values with standard deviations in parentheses. Columns 4, 6 and 8 report t-test of means of the previous two mean columns, with p-values in parentheses.

B.2 Comparing Auckland and Christchurch

Table 14: Robustness check: Comparison of the probability to abandon RTP in Auckland and Christchurch.

	Dependent variable:					
	Abandon RTP					
	(1)	(2)	(3)	(4)	(5)	(6)
Time on RTP (month)	−0.047**	−0.036*	−0.023			
	(0.021)	(0.021)	(0.023)			
log(Time on RTP)				−0.192**	−0.133	−0.027
				(0.093)	(0.097)	(0.115)
Christchurch	0.135	0.097	0.262	0.174	0.138	0.915
	(0.208)	(0.207)	(0.523)	(0.507)	(0.506)	(0.834)
Time on RTP x Christchurch	−0.001	0.006	−0.009			
	(0.023)	(0.023)	(0.026)			
log(Time on RTP) x Christchurch				−0.005	0.004	−0.124
				(0.098)	(0.098)	(0.126)
Yearly Consumption (MWh)	−0.038***	−0.037***	−0.037***	−0.037***	−0.036***	−0.036***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Seasonal Difference (MWh)	0.398***	0.382***	0.384***	0.378***	0.377***	0.379***
	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)	(0.106)
Income (k$/yr)	0.0002	0.001	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Work (%)	−0.004	−0.004	−0.004	−0.005	−0.004	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Education (%)	−0.007	−0.008	−0.008	−0.007	−0.008	−0.008
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
Month FE	No	Yes	No	No	Yes	No
Month-on-NRR FE	No	No	Yes	No	No	Yes
Observations	4,361	4,361	4,361	4,361	4,361	4,361
Log Likelihood	−2,260.545	−2,249.281	−2,243.026	−2,256.663	−2,250.045	−2,243.132
Akaike Inf. Crit.	4,541.090	4,540.563	4,550.051	4,533.325	4,542.090	4,550.265
Note:						*p<0.1; **p<0.05; ***p<0.01

C Adoption

C.1 Robustness checks

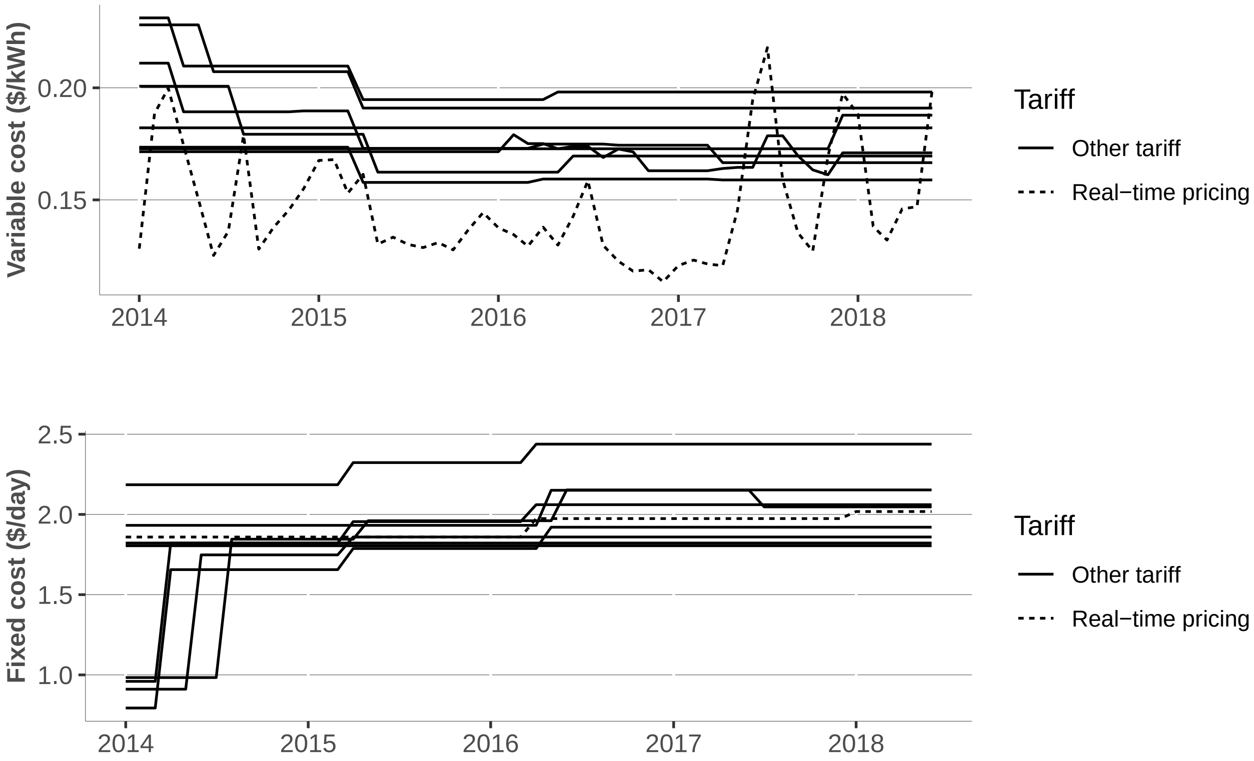

Figure 12: Comparison of tariffs offered by entrants in Wellington.

Note: The solid lines show the tariffs offered by entrants other than Flick, which offers RTP. The dashed line shows Flick Electric's real-time pricing plan. For the real-time pricing plan, we use the 'Standard plan, All Inclusive' offered by Flick Electric. To compute the variable part of RTP tariff, we take the sum of the consumption weighted average monthly spot price of electricity (assuming an extreme case with consumption concentrated during peak hours from 7:00am to 10:00am and from 5:30pm to 9:30pm) and the variable part of the 'Standard plan, All Inclusive' of 2019 (we do not have data about the variable part for the other years). All tariffs include discounts for prompt payment and electronic payment.

Table 15: Logit regression of switchers to entrants. Recent price always computed over 2 weeks. We use data from 2014-06-01 to 2018-06-01

	Dependent variable:								
	Individual decision to adopt RTP								
	1 Month	1 Month	1 Month	6 Months	6 Months	6 Months	12 Months	12 Months	12 Months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Recent Price	−0.124***	−0.123***	−0.134***	−0.134***	−0.141***	−0.134***	−0.133***	−0.139***	−0.134***
	(0.014)	(0.015)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.015)	(0.014)
Future Price (realized)	−0.074***			0.068			0.240***		
	(0.020)			(0.051)			(0.088)		
Future Price (last year)		−0.103**			−0.067**			−0.051	
		(0.041)			(0.030)			(0.034)	
Future Price (AR (1))			0.021*			0.054			0.105
			(0.012)			(0.044)			(0.088)
Yearly Consumption (MWh)	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Seasonal Difference (MWh)	0.018	0.017	0.017	0.018	0.018	0.018	0.018	0.018	0.018
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Income	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
White collar worker	0.598***	0.601***	0.598***	0.598***	0.599***	0.599***	0.598***	0.598***	0.599***
	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)
Education	1.390***	1.392***	1.396***	1.396***	1.395***	1.395***	1.402***	1.395***	1.394***
	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)
Location-Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,000	34,000	34,000	34,000	34,000	34,000	34,000	34,000	34,000
Note:									*p<0.1; **p<0.05; ***p<0.01

Table 16: Logit regression of switchers to entrants. Recent price always computed over 4 weeks. All prices in logs. We use data from 2014-06-01 to 2018-06-01

	Dependent variable:								
	Individual decision to adopt RTP								
	1 Month	1 Month	1 Month	6 Months	6 Months	6 Months	12 Months	12 Months	12 Months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(Recent Price)	−1.497***	−1.465***	−1.609***	−1.604***	−1.737***	−1.611***	−1.585***	−1.709***	−1.612***
	(0.172)	(0.174)	(0.167)	(0.166)	(0.169)	(0.167)	(0.167)	(0.170)	(0.167)
log(Future Price (realized))	−0.492***			0.910*			1.909**		
	(0.171)			(0.467)			(0.769)		
log(Future Price (last year))		−0.861***			−1.250***			−1.154**	
		(0.287)			(0.361)			(0.476)	
log(Future Price (AR (1)))			0.207*			0.444			0.729
			(0.111)			(0.349)			(0.640)
Yearly Consumption (MWh)	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Seasonal Difference (MWh)	0.019	0.018	0.018	0.020	0.019	0.019	0.019	0.019	0.019
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Income	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
White collar worker	0.598***	0.602***	0.598***	0.599***	0.599***	0.600***	0.598***	0.598***	0.600***
	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)
Education	1.406***	1.407***	1.413***	1.414***	1.414***	1.412***	1.418***	1.413***	1.411***
	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)
Location-Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,000	34,000	34,000	34,000	34,000	34,000	34,000	34,000	34,000

Note: *p<0.1; **p<0.05; ***p<0.01

C.2 Counterfactual analysis

Table 17: Regression results used to predict counterfactual adoption.

	Dependent variable:
	Individual decision to adopt RTP
Recent Price	-0.143^{***}
	(0.023)
Yearly Consumption (MWh)	0.046^{***}
	(0.006)
Seasonal Difference (MWh)	-0.003
	(0.064)
Income	0.006^{***}
	(0.001)
Age	0.005^{*}
	(0.002)
White collar worker	0.694^{***}
	(0.175)
Education	1.094^{***}
	(0.192)
Location FE	Yes
Month FE	Yes
Year FE	Yes
Observations	20,574
Note:	*p<0.1; **p<0.05; ***p<0.01