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

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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

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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. 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 2014 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. Absent agency costs, RTP implements the Ramsey optimum (Joskow and Tirole, 2007) and hence the first welfare theorem predicts that, in a friction-less decentralized economy, all consumers adopt this tariff in equilibrium. In practice, theory predicts that 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 spiral that continues until a significant share of consumers has switched to RTP. 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 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, if any, 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 on 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. Our dataset of consumer switching decisions allows us to study how consumers react to spot price variations and in particular to large price spikes. We focus most of our attention on a particular event, referred to as the winter 2017 crisis. We use this event to study how consumers on RTP and prospective adopters react to large and unanticipated price spikes and quantify the effect of the crisis on attrition and adoption. We address the following questions. Which consumers discard real-time pricing and does experience with the tariff affect their decisions? How do spot prices affect adoption decisions and, in particular, 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. The fact that the New Zealand retail electricity market did not unravel and that RTP pricing was introduced in different places at different times generates a unique setting to study real-time pricing. It allows us to compare the profiles of the early and late adopters and the behavior of consumers who have been exposed to RTP during different lengths of time, and to distinguish between the effects of selection and experience on their decisions. Furthermore, real-time pricing competed with more traditional tariffs over a long period with important spot price variations relative to the rates of other tariffs, including a sustained period of high spot prices that sparked more than three years after RTP was first introduced.

Following the adoption of RTP, nearly no consumers left RTP until the spark of a crisis

[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`

on the electricity spot market during the winter of 2017 (hereafter referred to as the crisis). We find that during this crisis, the share of consumers switching to another tariff decreased with their time spent on RTP before the crisis. Furthermore, among consumers who discarded RTP during the crisis, the share of those switching back after the crisis increases with the time spent on RTP before the crisis. Exploiting temporal variations in the roll-out of real-time pricing across different cities, we rule out that this correlation is due to selection effects. The setting in New Zealand also allows us to study consumer choices between real-time pricing and other tariffs over a long period with important spot price variations. 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). Focusing on adoption decisions around the crisis, we also find evidence that most consumers choose to forego adoption rather than postpone it.

Overall, we find that inexperienced consumers - prospective and recent adopters - strongly react to unanticipated price spikes, but that consumers with longer experience react less. These findings may be a sign that inexperienced consumers are present biased. While we cannot rule out that consumers with longer experience with RTP are simply inert or inattentive, the fact that those among them who had switched tariff during the crisis disproportionately come back to in the aftermath may be a sign that experience with RTP changed their preferences for or their perception of the tariff. Moreover, our results suggest that households who experience a spot market crisis shortly after adopting RTP get scarred and never return to real-time pricing. In a nutshell, when spot prices spike unexpectedly attrition increases - particularly for recent adopters - and adoption drops and remains low afterward. Therefore, we posit that the combination of high spot price volatility starting with the Winter 2017 crisis with present biased inexperienced consumers could have led to a jamming of the unraveling process.

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. Due to a larger share of intermittent electricity generation sources and more prevalent extreme weather events due to climate change, spot market crises may become more common in the future. We derive two 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 and after adoption, can accelerate the learning process that they go through with experience. It is essential that consumers understand how spot prices form and that long-run gains can compensate for immediate losses. Relatedly, easing the access to consumption profiles recorded by smart meters can help consumers estimate whether it is beneficial for them to adopt real-time pricing.

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). Yet, the case of New Zealand shows that take-up can fail even before questions of redistribution arise. These two arguments justify our approach to identify 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 macro-economics, 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) show 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 discard the tariff and less likely to return to it but that, with experience, consumers focus less on immediate outcomes. The behavioral biases that we document are not only interesting in themselves, but they also affect the equilibrium of the retail electricity market, since they impeded the unraveling towards real-time pricing. These biases thus have profound implications regarding the implementation of real-time pricing.

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. The roll-out was based on private initiatives with no public intervention. While old meters measured the aggregate consumption and were read a few times a year, smart meters can measure and record electricity consumption in real-time. As a consequence, the roll-out of smart meters has allowed new electricity tariffs to emerge. Traditionally, consumers could only have flat tariffs - two-part tariffs with known fixed and variable components. Special electricity meters allowed time-of-use tariffs with, for instance, different day and night rates, but flat tariffs were and still are dominant. With smart meters, electricity tariffs can be more sophisticated. For instance, Electric Kiwi offers two-part tariffs and 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 under which consumers face the spot price of electricity which clears every half-hour.

2.2 Real-time pricing in New Zealand

In New Zealand, real-time pricing contracts were introduced by private retailers, with no public intervention.[3] To the best of our knowledge, only two retailers offered real-time pricing in the period covered in our dataset, Flick Electric Co. and Paua to the People. However, most consumers adopting RTP contracted with Flick Electric Co.[4] Furthermore, Flick Electric offered exclusively real-time pricing while Paua to the People also offered flat rates contracts[5] and, as a result, we cannot identify whether consumers contracting with this retailer chose RTP or another tariff. Therefore, in the rest of the paper, we focus exclusively on Flick Electric for real-time pricing tariffs and we know that a consumer joining Flick Electric adopts real-time pricing.

Flick Electric 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's market share in New Zealand was 1.28% - or 23,057 households - with large heterogeneity across cities: while in Auckland, less than 1% of households were on real-time pricing, they were 3.88% in Wellington and 4.46% in Christchurch.

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

[3] 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.

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

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

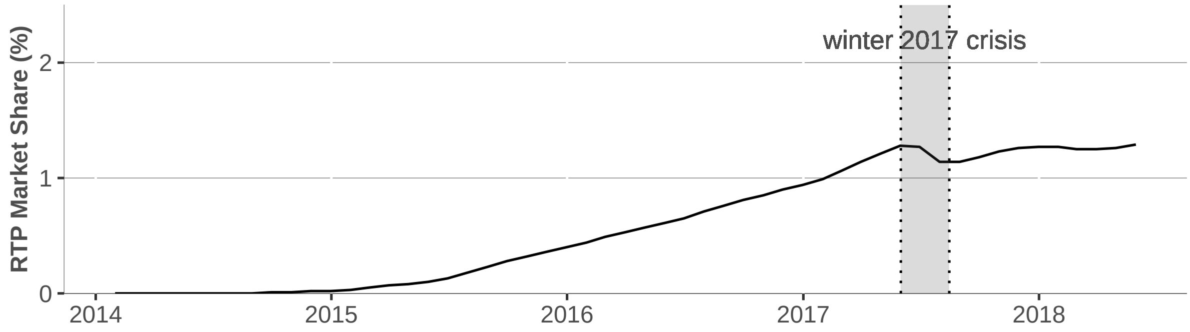

Figure 1: History of the share of households on real-time electricity pricing in New Zealand.

Tariff 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 is 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. Thus, contrary to a flat tariff with a fixed variable part, the variable part under real-time pricing is uncertain and varies every half-hour. To give an order of magnitude, we find that a household on RTP in Wellington, with an average consumption profile[6] would pay, in 2016, an annual bill of NZ$1880, 29.8% of which comes from the variable part attributable to spot prices.

In Figure 2 we plot the fixed and variable parts of real-time pricing offered by Flick Electric and of a flat tariff offered by Genesis Energy, the retailer with the largest market share in Wellington. Both Flick Electric and Genesis Energy adjusted their tariffs only about once a year but, given that spot prices vary substantially over time, consumers on real-time pricing faced varying variable fees. It is striking that both the flat and the variable rates of the flat tariff always exceed that of real-time pricing, except during the winter 2017 crisis and at the beginning of the year 2018. It appears from these figures that many consumers would have a financial incentive to adopt RTP which is at odds with Flick's low market share.

2.3 The winter 2017 crisis

The tariff comparison above suggests that RTP is cheaper than other flat tariffs. However, it also shows that price variability and uncertainty are important features of real-time pricing. On top of these frequent price fluctuations, there is the risk that spot prices increase considerably.

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

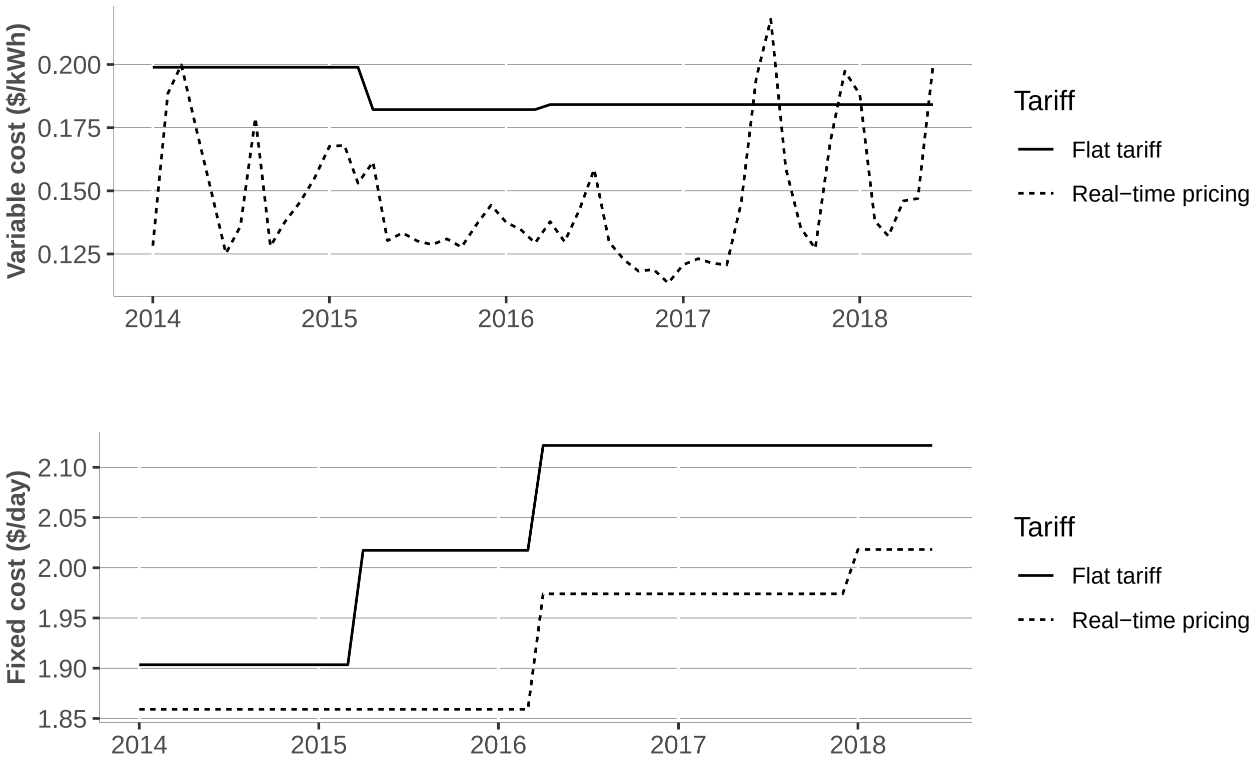

Figure 2: Tariff comparison in Wellington.

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).

Such events happened several times in the period covered in our dataset. Our analysis will focus on the first price spike which we refer to as the winter 2017 crisis. Studying a crisis on the wholesale market is interesting in itself because crises are inevitable. In consequence, practitioners and policy-makers need to understand how they affect consumers on real-time pricing and, 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 affects everyone and is hardly predictable and thus reveals the state of mind of 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 because there are no fees associated with switching to another tariff.

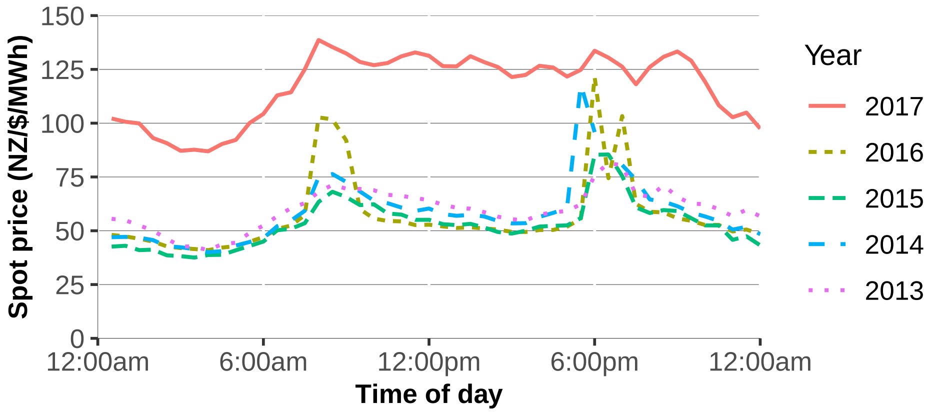

Figure 3: Average half-hourly spot price in winter - from 2013 to 2017.

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 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.[7] 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 reported that consumers made a loss of 80NZ$ from mid-June to mid-July compared with their previous tariff.

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 and 26% of them 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.

[7] See Electricity Authority (2018)

2.4 Data and summary statistics

We use a unique dataset 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.[8] 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 retailer that binds them even when they change accommodation, 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 the information on income, age, education, and work levels.[9] 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 losing 19.18% of our data.

We also collect publicly available data for the period covered by our dataset on switches (January 2013 to June 2018). First, aggregate data about each retailer's market share and the number of consumers each retailer gains and loses each month.[10] Second, spot price data[11] for each network reporting region at the half-hourly level.[12] 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

[8]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.

[9]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'.

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

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

[12]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.

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 or whether consumers have negotiated a discount. 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.

Table 1: Comparison of household characteristics

	All ICPs	Switchers	Switchers to non big 5	RTP Adopters
Consumption (kWh/yr)	7.2 (3.8)	7.7 (3.8)	8 (3.9)	8.3 (3.9)
Income (x1,000 NZ$/yr)	85.6 (33.4)	86.9 (30.9)	90.8 (30.2)	94.1 (29.8)
Age	36.6 (9)	36.7 (7.4)	36.7 (7.4)	36.6 (7.2)
Education (%)	28.5 (16.3)	28.8 (15.5)	31.7 (15.4)	33.7 (15.3)
Work (%)	55.7 (37.9)	48.2 (15.8)	51 (15.6)	52.8 (14.8)

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

In Table 2, we compare the socio-economic 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

Table 2: Change in mean household characteristics of RTP adopters

	2014	2015	2016	2017 - sem 1
Consumption (kWh/yr)	8.9 (3.9)	8.4 (3.9)	8.2 (3.8)	8.2 (3.6)
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)

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

what drives the decisions of consumers who discard the tariff before investigating what drives 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 discarding 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 discarded it.[13]

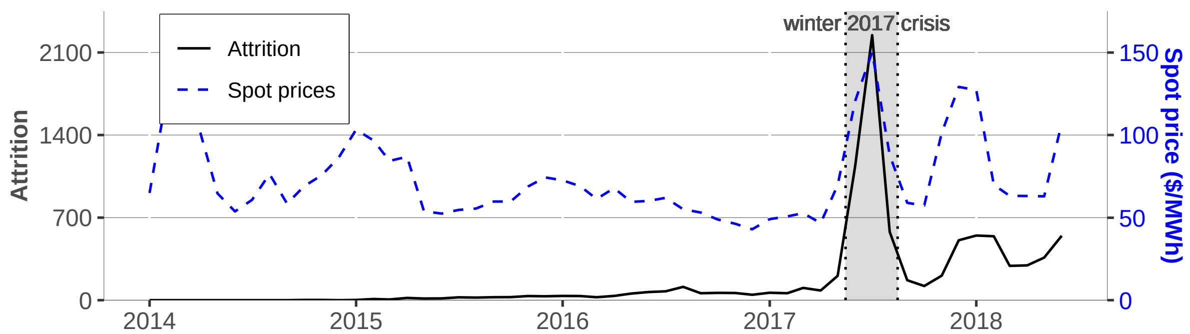

Figure 4: History of monthly attrition from real-time pricing and average electricity spot prices.

A natural follow-on 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

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

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.

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 for 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 discard real-time pricing and, by a reveal preference argument, we can infer their preferences by studying their choices.

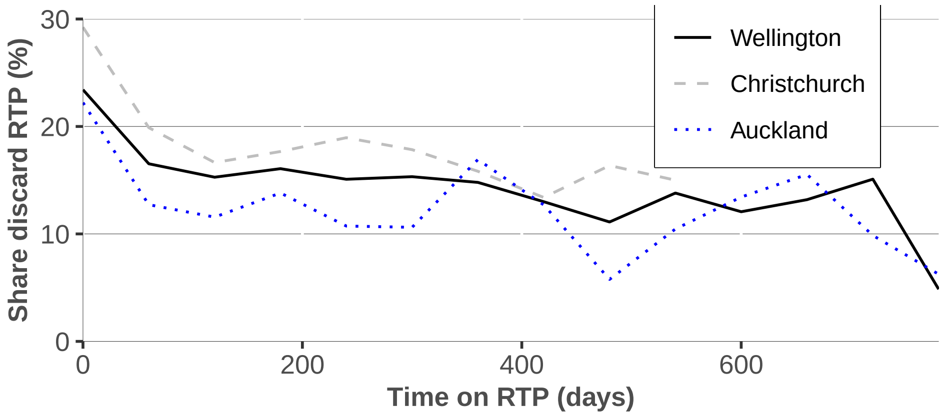

Figure 5: Share of consumers on RTP who discard the tariff during the winter 2017 crisis as a function of the time they have spent on the tariff before June 1st 2017.

In Figure 5, we plot the share of consumers discarding real-time pricing during the winter 2017 crisis as a function of the time they have 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 discarding real-time pricing during the winter 2017 crisis decreases with the time spent on the tariff.

To investigate the effect of time spent on RTP, we regress the decision to discard real-time pricing during the crisis on the time spent on RTP, the winter electricity consumption, and control variables. More specifically, we estimate the following equation:

$$\text{Discard RTP}_i = \alpha \text{Time on RTP}_i + \gamma \text{Winter Consumption}_i + X_i'\beta + \varepsilon_i, \tag{1}$$

where Discard $\text{RTP}_i \in \{0, 1\}$ is an indicator equal to 1 if consumer i decides to discard 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, Winter Consumption is the electricity consumption from June to August 2016, 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 consumer's 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 $log(\text{Time on RTP}_i)$. The effect of Winter Consumption is similar across all specifications and statistically significant at the 5% level. Interestingly, the coefficient for time spent on the tariff is statistically and economically significant, both in the linear and the 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 discard real-time pricing by 2.21 percentage points (the average probability to discard RTP is 19.43%).

We can also see that the coefficient on *Winter Consumption* is statistically significant and positive. However, the economic effect is negligible. Using the results from column 2, at average value of the covariates, increasing Winter Consumption by 20% (or 209.63MWh), increases the probability to discard real-time pricing by 0.14 percentage points - which is low compared to 19.43%,the unconditional probability to discard it.[14]

The effects of consumer demographics are similar in all specifications and none are economically significant. In particular, $log(Income)$, $Education$, and $Work$ are not statistically significant. The fact that the effect of income is small and not significant suggests that consumer decision to discard 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 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 discard 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 a final robustness check, we control for arbitrage behavior. The fact that 25.96% of

[14]For robustness, we use two more specifications for electricity consumption - Annual Consumption (measured in 2015) and Seasonal Difference (measured as the difference between winter and summer consumption in 2016). The latter specification may be relevant if consumers react to bill shocks. In both cases, we also conclude that the effect of consumption is not statistically significant. The results are in Table 10, in the Appendix.

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

	Dependent variable:					
	Discard RTP					
	(1)	(2)	(3)	(4)	(5)	(6)
Time on RTP(month)	-0.038^{***}	-0.036^{***}	-0.022^{***}			
	(0.005)	(0.005)	(0.005)			
log(Time on RTP)				-0.226^{***}	-0.224^{***}	-0.128^{***}
				(0.025)	(0.025)	(0.040)
Joined Last			0.488^{***}			0.370^{***}
			(0.087)			(0.120)
Winter Consumption (MWh)		0.062	0.062		0.058	0.058
		(0.059)	(0.060)		(0.060)	(0.060)
log(Income) (k$/yr)		0.065	0.091		0.081	0.092
		(0.103)	(0.104)		(0.104)	(0.104)
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 (%)		-0.004	-0.004		-0.004	-0.004
		(0.004)	(0.004)		(0.004)	(0.004)
Location-on-Previous retailer FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,674	7,674	7,674	7,674	7,674	7,674
Note:				*p<0.1; **p<0.05; ***p<0.01		

consumers who discarded RTP eventually switched back to it after the crisis, suggests that arbitrage may have been an important motive for discarding 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.

3.2 Selection versus experience

We now 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 discard 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, or learning about their price-elasticity. Also, consumers accumulate electricity bills that may matter for projecting future electricity bills.

To shed light on which mechanism can explain the effect of time spent on real-time pricing, we take advantage of the fact that the tariff became available at different times in different cities. We reason by contradiction: Assume that some innate unobservable characteristics matter in consumer switching decisions during the crisis and that there was selection at adoption on these unobservable characteristics. 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. 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 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 relevant set-up to test whether selection at adoption explains the correlation between time spent on real-time pricing and the decision to discard real-time pricing during the crisis.

Formally, we regress consumer decisions to discard RTP during the crisis (Discard RTP$_i \in \{0, 1\}$) on time spent on real-time pricing, a location dummy for Christchurch, an interaction

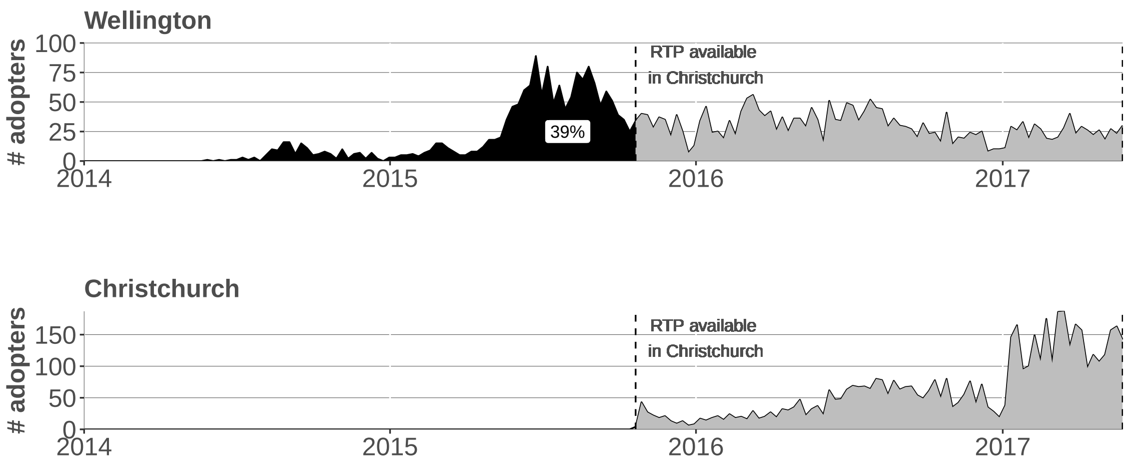

Figure 6: Number of consumers adopting real-time electricity pricing every week in Wellington (top) and Christchurch (bottom) between November 2013 and June 2017.

between the location dummy and control variables:

$$\begin{aligned}\text{Discard RTP}_i = &\alpha_{exp}\text{Time on RTP}_i + \alpha_{loc}\text{Christchurch}_i + \gamma\text{Time on RTP}_i \times \text{Christchurch}_i\\ &+ X_i'\beta + \varepsilon_i,\end{aligned}$$

where Discard RTP$_i$ and Time on RTP are defined as in 1, 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 12 in Appendix B.3.

These results suggest that consumers' perception of real-time electricity tariffs changes experience with the tariff and that, in the case studied in this paper, consumers became more optimistic about real-time pricing.

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

	Dependent variable:					
	Discard RTP					
	(1)	(2)	(3)	(4)	(5)	(6)
Time on RTP (month)	−0.049***	−0.045***	−0.049***			
	(0.012)	(0.013)	(0.013)			
log(Time on RTP)				−0.238***	−0.216***	−0.234***
				(0.059)	(0.063)	(0.070)
Christchurch	0.111	0.075	0.188	−0.019	−0.062	−0.046
	(0.147)	(0.148)	(0.348)	(0.351)	(0.352)	(0.566)
Time on RTP x Christchurch	0.002	0.010	0.018			
	(0.016)	(0.016)	(0.018)			
log(Time on RTP) x Christchurch				0.035	0.046	0.085
				(0.067)	(0.068)	(0.087)
Yearly Consumption (MWh)	−0.028***	−0.028***	−0.028***	−0.028***	−0.028***	−0.028***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Seasonal Difference (MWh)	0.379***	0.375***	0.376***	0.379***	0.377***	0.378***
	(0.092)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)
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*	−0.006	−0.007*	−0.007*	−0.007*	−0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Education (%)	−0.003	−0.004	−0.003	−0.003	−0.004	−0.003
	(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	5,525	5,525	5,525	5,525	5,525	5,525
Log Likelihood	−2,774.711	−2,763.210	−2,760.000	−2,769.748	−2,763.909	−2,760.598
Akaike Inf. Crit.	5,569.422	5,568.419	5,584.000	5,559.496	5,569.817	5,585.196
Note:						*p<0.1; **p<0.05; ***p<0.01

3.3 Switching back to RTP

Overall, 25.96% of consumers who discarded 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 have 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 regressing (logit) consumers decision de return to real-time pricing on the time spent on RTP and control variables, see Table 6 in Appendix A.

We find that time spent on RTP affects the decision to return to real-time pricing significantly, 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 4.8 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 discard the tariff forever. This suggests that spot market crises leading to price spikes may permanently drive consumers away from choosing real-time pricing.

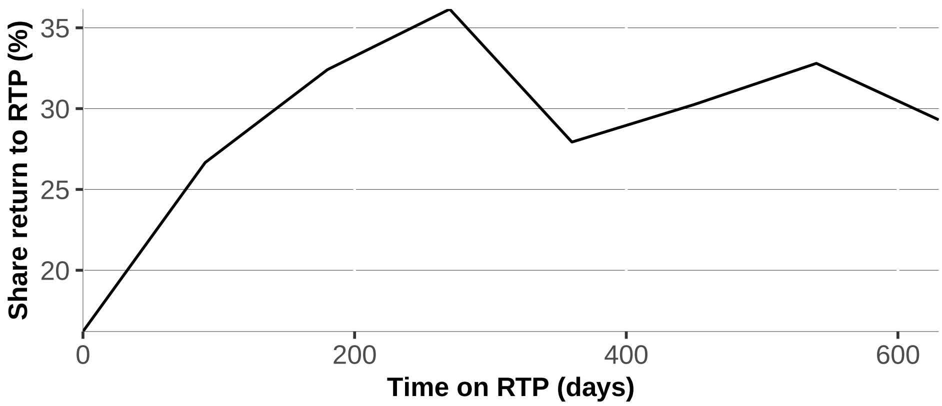

Figure 7: Share of households switching back to RTP after opting-out during the winter 2017 crisis within three months after the end of the crisis as a function of the number of days spent on RTP prior to the crisis.

4 Adoption of real-time electricity pricing

In this section, we examine how consumers decide whether to adopt real-time pricing. The purpose is to better understand the decision-making process of prospective adopters and what affects it. In particular, we ask which prices do consumers refer to when deciding whether to adopt RTP and whether they strategically time adoption.

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: when spot prices are high, adoption is low, and vice-versa. This relationship is particularly evident when the spot prices increase or decrease significantly, such as in 2017, when adoption is high both before and after the winter 2017 crisis 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.

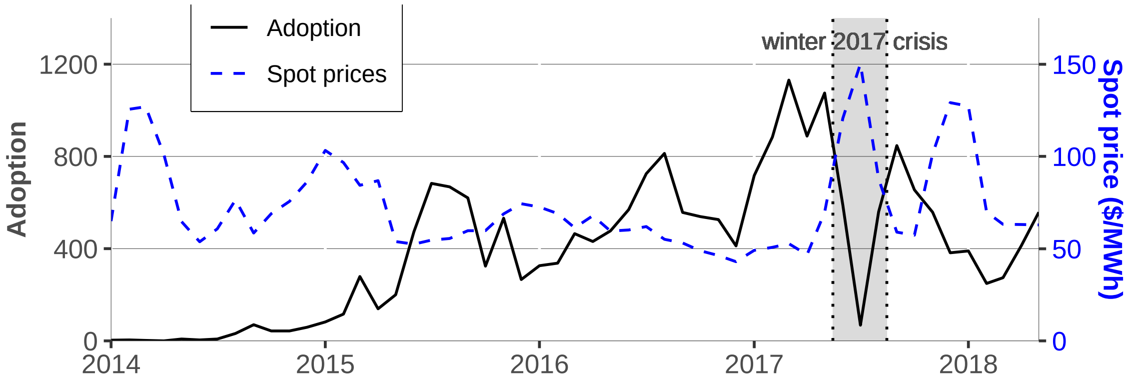

Figure 8: History of monthly RTP adoption and average spot prices in New Zealand.

Next, we investigate the effect of contemporaneous spot prices on the probability to adopt real-time pricing.[15]

Ideally, we would like to investigate this question by analyzing the decision-making process of all consumers. However, due to data limitations, we cannot capture some of the important features of the retail electricity market such as inertia. [16] To circumvent this issue, we restrict our analysis to the subset of consumers who decided to switch retailers.

Given that RTP is a new form of tariff, many consumers switching tariff 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. Therefore, by considering all switchers we risk underestimating the effect of price on adoption decisions or even missing it. We define the relevant market as the set of retailers who are not among the five incumbents and restrict our attention to the subset of consumers who switch to one of those retailers.[17]

Note that, whether our estimates may be biased, and the direction of the bias, is ambiguous. On the one hand, by focusing on a small set of consumers we risk overestimating the effect of price on adoption because any effect mechanically appears larger when it is compared to a group of smaller size. On the other hand, because we do not allow for the option not to switch, we may underestimate the effect of prices on adoption. However, we are not directly interested in estimating price-elasticity but rather in identifying which price consumers look at.

[15]Note that we do not examine the relationship between the number of adopters with contemporaneous spot prices, otherwise we risk only capturing the fact that some prices happen with higher probability.

[16]There is a large literature documenting consumer inertia in the retail electricity market (see Hortaçsu et al., 2017; Dressler and Weiergraber, 2019). Inertia is generally attributed to high switching costs, behavioral or contractual. Because we do not observe which contracts consumers choose, but only which retailer they contract with, we cannot control for inertia, which may bias our results.

[17]Real-time pricing was introduced in New Zealand at the same time as other retailers entered the market and offered, among others, various non-traditional tariffs. For instance, Electric Kiwi offered a flat two-part tariff and the customer could choose one hour per day when electricity is free. Note that, in the period covered by our sample, the five incumbents had collectively a market share of the residential electricity market that dropped from 93% to 88% .

Therefore, as long as the source of the bias doesn't affect our different estimates differently, obtaining biased results is not an issue.

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. 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.

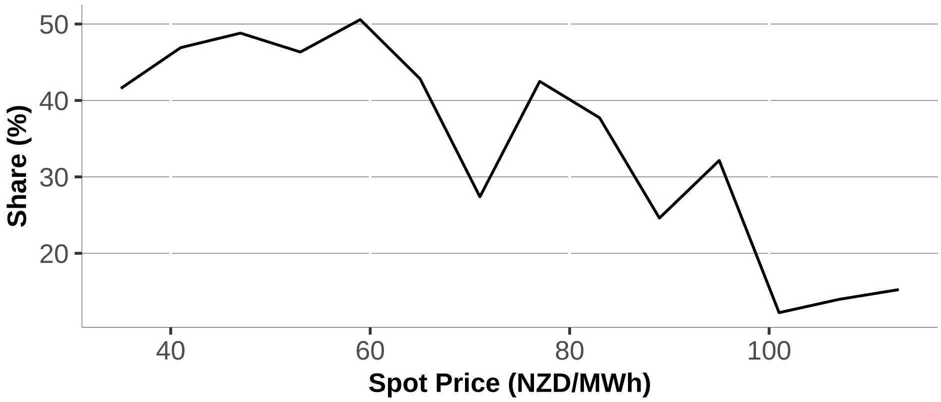

Figure 9: Share of consumers switching to a non-Big-5 retailer who adopt RTP as a function of the average spot prices in the 4 weeks preceeding the switch - in Wellington.

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. In Table 7 in Appendix , we present 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

We now investigate more formally whether consumers react to recent spot prices rather than different proxies of future payoffs. We build several definitions of future prices that consumers may consider and examine whether these future prices affect adoption decisions more than recent spot prices.

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.[18] We build

[18]Because the rates of fixed tariffs and those charged by Flick stay virtually unchanged throughout the sample

several definitions of future prices that consumers may consider and examine whether, controlling for recent spot prices, future prices affect their adoption decisions. 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.[19] We consider three proxies for *Future Price*: realized spot price, last year's price, and future price predicted 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, we assume that the relevant benchmark for rational forward-looking consumers is to consider a one-year period. However, forecasting spot prices over one year is a complicated exercise and forecasts are less reliable the further away in time they are. Therefore, it could be that consumers, while being forward-looking, do not trust their long-run forecasts and chose shorter a time horizon. Therefore, we compute for robustness future prices over 1-month ("short-run") and 6-month ("medium-run") horizons as well, next to the 12-month ("long-run") horizon.

Formally, our specification writes

$$Y_{it} = \alpha_1 P_{mt,\text{Recent}} + \alpha_2 P_{mt,\text{Future}_f} + X_{it}\beta + \gamma_m + \lambda_t + \varepsilon_{it}, \tag{2}$$

where Y_{it} is equal to one if consumer i in market m at date t decides to adopt RTP (conditional on switching to a non-traditional retailer), $P_{mt,\text{Recent}}$ 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_{it} 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, the winter 2017 crisis, the time after the 2017 winter crisis, and census-level median household income, age, and work- and education status.

The results are in Table 5. We can see that across definitions of future prices and across the time horizon over which we compute these 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 8.94 percentage points. For reference, at the average value of covariates, the probability of 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 prices rather

period (see Figure 2), the only variations come from the spot prices. Therefore we only consider those rather than the difference between real-time and fixed prices.

[19] We use this time horizon because consumers consume the bulk of their electricity during these hours.

Table 5: Logit regression of switchers to non-traditional tariffs. 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	−0.171***	−0.152***	−0.149***	−0.135***	−0.151***	−0.149***	−0.132***	−0.182***	−0.149***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Future Price (realized)	0.040***			0.091***			0.381***		
	(0.009)			(0.016)			(0.023)		
Future Price (last year)		0.013			−0.080***			−0.135***	
		(0.029)			(0.010)			(0.011)	
Future Price (AR (1))			0.021***			0.066***			0.131***
			(0.007)			(0.024)			(0.047)
Consumption (MWh)	0.037***	0.037***	0.037***	0.036***	0.037***	0.037***	0.036***	0.036***	0.037***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Seasonal Difference (MWh)	0.015	0.015	0.013	0.017	0.014	0.013	0.016	0.012	0.013
	(0.052)	(0.052)	(0.052)	(0.053)	(0.053)	(0.052)	(0.053)	(0.053)	(0.052)
Income	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***	0.003***	0.004***
	(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***	0.007***	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	0.621***	0.619***	0.618***	0.623***	0.618***	0.619***	0.573***	0.609***	0.619***
	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)
Education	1.344***	1.342***	1.343***	1.345***	1.331***	1.341***	1.397***	1.343***	1.341***
	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.162)	(0.161)	(0.161)
Winter Crisis	−1.407***	−1.302***	−1.365***	−1.553***	−0.871***	−1.355***	−1.100***	−0.661***	−1.355***
	(0.111)	(0.108)	(0.110)	(0.117)	(0.121)	(0.110)	(0.109)	(0.121)	(0.110)
Post Crisis	−0.761***	−0.691***	−0.721***	−0.799***	−0.186*	−0.718***	−0.733***	−0.242***	−0.718***
	(0.084)	(0.082)	(0.083)	(0.084)	(0.104)	(0.083)	(0.083)	(0.091)	(0.083)
Location FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year 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

than trying to predict long-run prices and hence the existence of present bias. We can also see that the *Post Crisis* dummy is negative and significant, suggesting that even after controlling for prices and other factors, adoption was lower after the winter 2017 crisis.

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 (2). The results are in Table 8 in Appendix A. We see that price volatility is not significant, leading us to conclude it does not play an important role in adoption decisions. As additional robustness checks, we re-run the specification (2) but make two changes: In the first robustness check, 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.

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 when spot prices surged and remained high for several weeks. Because spot prices more than doubled, 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 Wellington.[20] While the number of new adopters is relatively constant before the crisis, adoption drops during the crisis with only about 40.6 new households per week joining. 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 54.3157895 new households per week. This surge may suggest 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 which we predict how many households would have adopted RTP 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 train a predictive model in which we linearly regress the number of households adopting RTP each week on the average spot price in the previous week with year, month, and week fixed effects. We train the model on data spanning from January 2014 to the start of the crisis defined on June 1st, 2017, and use it to predict the number of households who would have adopted RTP during the crisis defined by the period June 1st, 2017 to August 15th, 2017. The heteroskedasticity-adjusted $R^2 = 0.79$. We plot the results on Fig. 10 where the red shaded area under the full red line represents the number of households who would have adopted during the

[20]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.

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 on Fig. 10.

The model predicts that absent the crisis, 2447 consumers would have adopted real-time pricing during the period it occurred (the 95% confidence interval is [2003, 2891]). Of those, 507 (or 20.7%) adopted despite the crisis and at most 388 (or 15.9%) postponed adoption. The remaining 1552 (or 63.4%) 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.

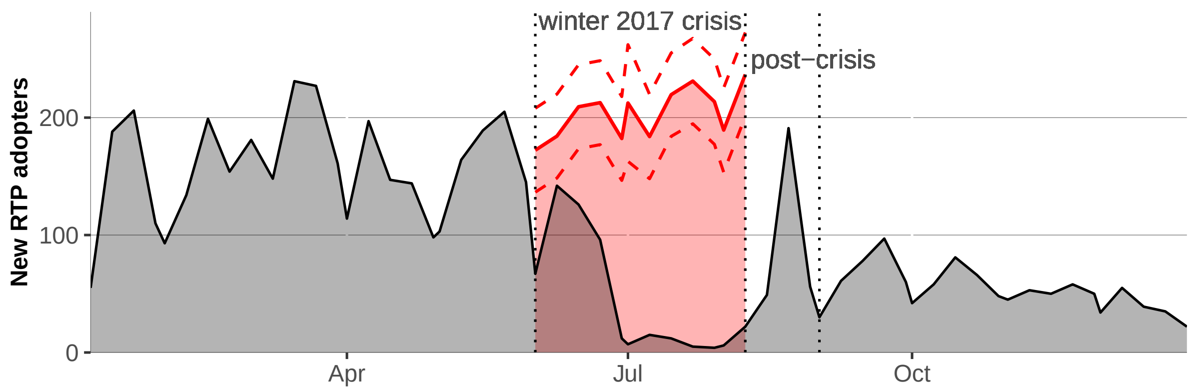

Figure 10: Actual and predicted number of new consumers adopting RTP during the winter 2017 crisis in New Zealand (with 95% confidence interval).

4.2.2 External validity

Note that the previous results come from a distinct subset of consumers. As we saw in section 2, consumers who adopt RTP are, on average, more educated, have higher income, are more likely to work in white-collar jobs, and are therefore likely to be more sophisticated than the rest of the population. Thus, the finding that these consumers rely on simple strategies likely extends to the other consumers as well.

In Table 9 in Appendix A, we provide some evidence of how different demographic characteristics interact with price sensitivity. We use both *Recent Price* and *Future Price*, computed as last year's price and over 12 months, and interact both with income and education. In the first column, we see that consumers with higher income 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, a bit 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 directions.

5 Discussion

In Sections 3 and 4 we have examined how variations in spot prices affect adoption and attrition but we have been silent about the underlying mechanisms driving our results. In this section, we discuss plausible explanations - focusing on the consumer's decision-making process and what affects it.

Present bias. The findings in Section 4 suggest that consumers who consider adopting real-time pricing make "now-or-never" decisions rather than strategically time adoption. This behavior is consistent with the fact that consumers often sign long-term contracts with their electricity retailer and, therefore, only have rare switching opportunities. However, we also find that consumers strongly react to recent or ongoing spot prices, even outside the crisis. But because spot prices are seasonal and volatile, ongoing spot prices are a poor predictor for long-term payoffs. This observation, therefore, suggests that prospective adopters are present biased. Present bias is also consistent with our finding in Section 3 that recent adopters disproportionately discarded real-time pricing during the winter 2017 crisis. The fact that decision-making processes do not change much before and slightly after adoption would not be surprising.

Present bias means that consumers rely excessively on recent or ongoing spot prices to make decisions. But when prices drop, there are only so many consumers with a switching opportunity while when prices spike, all consumers on RTP have the possibility to discard the tariff. In New Zealand, we have shown that the period of stable spot prices prior to the crisis is concomitant to that of high adoption rates and that, after the winter 2017 crisis when spot prices vary greatly adoption rates are low. We have only presented suggestive evidence, but the idea that present bias may have jammed the unraveling process towards widespread adoption of real-time pricing is worth exploring.

The role of experience. Our results from Section 3 suggest that experience with RTP affected consumer decisions during the winter 2017 crisis and, in particular, that attrition was highest among inexperienced consumers. Irrespective of whether consumers are rational or not, by a revealed preference argument we can say that consumers who decided to stay on RTP during the crisis had higher expectations regarding the payoffs that they derive from real-time pricing.[21] However, we are not able to identify whether inexperienced consumers were excessively pessimistic or if experienced ones were excessively optimistic. A welfare analysis would require a better understanding of the channels through which experience affected consumers and could help identify how to help consumers make rational and informed decisions.

Because spot prices are seasonal and volatile, it takes time to experience different situations and how to adjust consumption to the price variations. Therefore, even if all consumers used the entire history of spot prices, those who experienced RTP gained superior knowledge about their own preferences and price-elasticities and therefore about their payoffs with RTP. We argue that 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). As the comparison of tariffs on Figure 2 suggests, many consumers would likely have benefited financially from real-time pricing relative to other tariffs before the winter 2017 crisis started. Therefore, consumers who have experienced RTP for longer may have grown more optimistic about the long-run payoffs of RTP. Furthermore, the winter 2017 crisis sent a negative signal about RTP and all consumers had to update their beliefs. However, if consumers with longer experience had more entrenched beliefs then their beliefs changed less.

To understand how experience affects beliefs one needs to identify how consumers form their expectations and what information they use. Interestingly, consumers on real-time pricing could check their weekly and their accumulated savings on their mobile app and their online personal accounts. The retailer 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$ savings. The consumer from the right panel had adopted RTP just as the crisis started, and after three weeks, had made losses every week. Providing such information can help consumers compute their expected payoffs but can also mislead them if they put too much emphasis on the past.

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,

[21]This assumes that consumers were aware of the crisis. This assumption seems credible since consumers on RTP are billed weekly, they receive notifications on their mobile app when prices spike and their retailer regularly provided information about the crisis. Also, the event received media coverage.

with experience, consumers are less sensitive to them. Spot price volatility may increase due to the increasing production of electricity from intermittent energy sources and because extreme weather events - such as in Texas in early 2021 - may become more prevalent with climate change. Because countries plan to produce large amounts of electricity from intermittent renewable electricity, spot price volatility may increase. Similarly, spot price surges due to extreme weather events, such as in Texas in early 2021, may also become more common due to climate change, making the issues outlined in this paper even more salient. Therefore, it is relevant to anticipate how it can affect the adoption of real-time pricing and to think of remedies.

Essentially, present bias and lack of experience generate a setting where retailers or policymakers introducing real-time pricing need to be "lucky" and hope that no unexpected period of high price spikes arises until sufficiently many consumers have adopted real-time pricing and experienced it long enough. We derive two sets of recommendations: timing of adoption and information provision.

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 are defaulted to RTP is a choice variable. Note that timing matters even in this case because of the risk of early attrition. 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 subsidies. Note, however, that strategic timing does not guarantee widespread adoption, as suggests the case of New Zealand where spot prices were low and stable for more than three years after the introduction of real-time pricing.

Second, providing information to consumers, both before and after adoption, can accelerate the learning process that they go through with experience and help them make rational and informed decisions. It is essential that consumers understand how spot prices form and that long-run gains can compensate for immediate losses. In addition, consumers 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. Ito et al. (2021) show that providing this information ex-ante to consumers significantly affects their choices by helping the structural winners self-select to time-varying tariffs.[22]

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

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. It is all the more puzzling that adoption appears financially beneficial. We find that consumers inexperienced with real-time pricing - prospective and recent adopters - are highly sensitive to ongoing spot prices. The combination of present bias and lack of experience and unexpected periods of high spot prices may explain the puzzle: price spikes lead to low adoption and large attrition if they were not expected. However, with experience, consumers on real-time pricing focus less on ongoing events. Based on these findings, we make recommendations to help overcome these barriers to real-time pricing. We have derived two types of recommendations: timing of adoption - to increase adoption and limit attrition - and information provision - to help consumers make informed and rational decisions.

This paper opens several promising alleys for future research. First, as discussed in Section 6, because consumers are present biased, eliciting the optimal timing for advertising campaigns to encourage adoption in an opt-in set-up and for defaulting consumers to real-time pricing in an opt-out set-up is an open question. Second, because consumer learning about real-time pricing is important and there may be market failures associated with it, it may be efficient to subsidize the adoption of real-time pricing (in an opt-in set-up). Typically, if there are agency costs such as risk aversion (e.g., liquidity constraints) or externalities (e.g., social learning), then adoption rates will be inefficiency low. Then, for instance, consumers could receive a transfer after they have remained on real-time pricing for a certain amount of time. The transfer should not depend on the consumption while on the tariff to avoid creating distortions.[23] A retailer incurring the costs of experimentation may not be able to recover them ex-post if, once the consumer has learned her valuation, she can switch to a competitor offering a low price. Thus, public subsidies may be required, and finding the optimal scheme is an open research question.

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[23]In the case of New Zealand, the retailer Flick Electric guarantees its new customers that after 12-month they will have positive savings. This guarantee risks creating perverse incentives to over-consume during a crisis on the wholesale market.

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Appendix

For Online Publication

A Additional tables and figures

Table 6: 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***	0.048***	0.026***	0.026***	0.018**
	(0.008)	(0.008)	(0.010)	(0.007)	(0.007)	(0.008)
Joined Last			−0.928***			−0.315**
			(0.166)			(0.159)
Winter consumption (MWh)		−0.032	−0.019		0.183**	0.185**
		(0.102)	(0.103)		(0.090)	(0.090)
log(Income) (k$/yr)		0.228	0.198		0.356**	0.347**
		(0.180)	(0.181)		(0.167)	(0.167)
Age		0.007	0.008		0.00001	0.0004
		(0.007)	(0.007)		(0.007)	(0.007)
Work (%)		0.002	0.001		−0.003	−0.003
		(0.006)	(0.006)		(0.005)	(0.005)
Education (%)		−0.0001	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	2,126	2,126	11,023	11,023	11,023
Log Likelihood	−1,135.616	−1,133.215	−1,116.470	−1,910.404	−1,904.931	−1,902.879
Akaike Inf. Crit.	2,351.233	2,356.430	2,324.939	3,914.808	3,913.861	3,911.757

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

Table 7: 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.

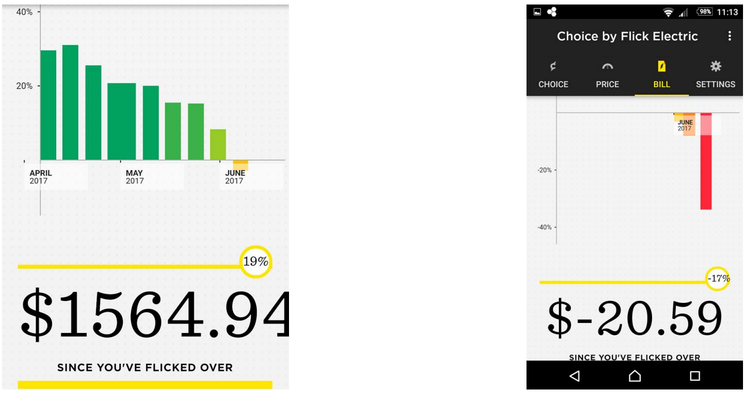

Figure 11: Screenshots of the display of two customers' cumulative savings on their mobile application - obtained on search engine.

Table 8: Logit regression of switchers to non-traditional tariffs. 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	−0.084***	−0.109***	−0.155***
	(0.008)	(0.010)	(0.011)
Volatilty	0.005	−0.006	0.011
	(0.007)	(0.011)	(0.017)
Consumption (MWh)	0.036***	0.037***	0.037***
	(0.005)	(0.005)	(0.005)
Seasonal Difference (MWh)	0.015	0.015	0.015
	(0.052)	(0.052)	(0.052)
Income	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Age	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)
White collar worker	0.619***	0.617***	0.619***
	(0.147)	(0.147)	(0.148)
Education	1.350***	1.335***	1.342***
	(0.161)	(0.161)	(0.161)
Winter Crisis	−1.880***	−1.676***	−1.275***
	(0.099)	(0.105)	(0.115)
Post Crisis	−0.979***	−0.872***	−0.679***
	(0.079)	(0.080)	(0.084)
Location FE?	Yes	Yes	Yes
Month FE?	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes
Observations	34,000	34,000	34,000
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: Logit regression of switchers to non-traditional tariffs 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	−0.159	−0.235	−0.169
	(0.020)	(0.015)	(0.020)
Future Price (Last Year)	−0.046	−0.058	−0.038
	(0.017)	(0.014)	(0.017)
Recent Price x Income	−0.0003		−0.001
	(0.0002)		(0.0003)
Future Price (Last Year) x Income	−0.001		−0.0004
	(0.0001)		(0.0002)
Recent Price x Education		0.002	0.004
		(0.0004)	(0.001)
Future Price (Last Year) x Education		−0.003	−0.003
		(0.0003)	(0.0004)
Consumption (MWh)	0.036	0.036	0.036
	(0.005)	(0.005)	(0.005)
Seasonal Difference (MWh)	0.014	0.017	0.018
	(0.053)	(0.053)	(0.053)
Income	0.016	0.003	0.015
	(0.002)	(0.001)	(0.002)
Age	0.006	0.006	0.006
	(0.002)	(0.002)	(0.002)
White collar worker	0.639	0.646	0.658
	(0.148)	(0.149)	(0.148)
Education	1.302	2.897	1.496
	(0.162)	(0.408)	(0.483)
Winter Crisis	−0.654	−0.673	−0.670
	(0.121)	(0.121)	(0.121)
Post Crisis	−0.267	−0.292	−0.291
	(0.091)	(0.091)	(0.091)
Location FE?	Yes	Yes	Yes
Month FE?	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes
Observations	34,000	34,000	34,000
Note:			*p<0; **p<0; ***p<0

B Attrition - robustness checks

B.1 Alternative measures of electricity consumption

Table 10: Discarding real-time pricing during the winter 2017 crisis.

	Dependent variable:					
	Discard RTP					
	(1)	(2)	(3)	(4)	(5)	(6)
Time on RTP(month)	−0.021***	−0.022***	−0.022***			
	(0.005)	(0.005)	(0.005)			
log(Time on RTP)				−0.127***	−0.128***	−0.128***
				(0.040)	(0.040)	(0.040)
Joined Last	0.490***	0.488***	0.485***	0.372***	0.370***	0.371***
	(0.087)	(0.087)	(0.087)	(0.120)	(0.120)	(0.120)
Annual Consumption (MWh)	−0.008			−0.008		
	(0.007)			(0.007)		
Winter Consumption (MWh)		0.062			0.058	
		(0.060)			(0.060)	
Seasonal Difference (MWh)			0.265***			0.260***
			(0.075)			(0.075)
log(Income) (k$/yr)	0.120	0.091	0.090	0.122	0.092	0.091
	(0.104)	(0.104)	(0.103)	(0.105)	(0.104)	(0.103)
Age	−0.010**	−0.010**	−0.011**	−0.010**	−0.011**	−0.011**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Work (%)	−0.004	−0.005	−0.005	−0.005	−0.005	−0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education (%)	−0.004	−0.004	−0.004	−0.005	−0.004	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Location-on-Previous retailer FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,666	7,674	7,655	7,666	7,674	7,655
Log Likelihood	−3,610.450	−3,614.827	−3,600.506	−3,613.534	−3,618.016	−3,604.034
Akaike Inf. Crit.	7,318.899	7,327.654	7,299.011	7,325.067	7,334.033	7,306.067

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

B.2 Consumers who leave and come back

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

	Dependent variable:			
	Discard RTP			
	(1)	(2)	(3)	(4)
Time on RTP(month)	-0.039^{***}		-0.038^{***}	
	(0.006)		(0.006)	
log(Time on RTP)		-0.242^{***}		-0.229^{***}
		(0.044)		(0.044)
Joined Last	0.626^{***}	0.384^{***}	0.624^{***}	0.401^{***}
	(0.095)	(0.132)	(0.096)	(0.133)
Winter Consumption (MWh)	0.083	0.076	0.082	0.075
	(0.068)	(0.068)	(0.069)	(0.069)
log(Income) (k$/yr)	0.003	0.006	0.021	0.023
	(0.118)	(0.118)	(0.118)	(0.119)
Age	-0.012^{**}	-0.013^{**}	-0.012^{**}	-0.013^{**}
	(0.005)	(0.005)	(0.005)	(0.005)
Work (%)	−0.005	−0.006	−0.006	−0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Education (%)	−0.003	−0.004	−0.003	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Location-on-Previous retailer FE?	Yes	Yes	Yes	Yes
Observations	7,674	7,674	7,261	7,261
Log Likelihood	−2,950.054	−2,955.272	−2,881.953	−2,887.628
Akaike Inf. Crit.	5,998.107	6,008.545	5,861.906	5,873.257

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

B.3 Comparing Wellington and Auckland

Table 12: Robustness check: Probability of discarding RTP (Location refers to Christchurch in columns 1-3 and Auckland in columns 4-6)

	Dependent variable:					
	Discard RTP					
	Wel-Chr	Wel-Chr	Wel-Chr	Auc-Chr	Auc-Chr	Auc-Chr
	(1)	(2)	(3)	(4)	(5)	(6)
Time on RTP (month)	−0.05***	−0.05***	−0.05***	−0.05**	−0.04*	−0.03
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Location	0.11	0.07	0.19	0.11	0.08	0.36
	(0.15)	(0.15)	(0.35)	(0.21)	(0.21)	(0.55)
Time on RTP x Location	0.002	0.01	0.02	0.002	0.01	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Annual elec cons (MWh)	−0.03***	−0.03***	−0.03***	−0.03***	−0.03***	−0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Win/Sum cons diff (MWh)	0.38***	0.37***	0.38***	0.45***	0.45***	0.45***
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)
Income (k$/yr)	0.002	0.002	0.002	−0.0003	0.0003	0.0003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	−0.01*	−0.01*	−0.01*	−0.005	−0.01	−0.01
	(0.005)	(0.005)	(0.005)	(0.01)	(0.01)	(0.01)
Work (%)	−0.01*	−0.01	−0.01*	−0.004	−0.004	−0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Education (%)	−0.003	−0.004	−0.003	−0.01	−0.01	−0.01
	(0.004)	(0.004)	(0.004)	(0.01)	(0.01)	(0.01)
Month FE?	No	Yes	No	No	Yes	No
Month-on-NRR FE?	No	No	Yes	No	No	Yes
Observations	5,525	5,525	5,525	4,397	4,397	4,397
Log Likelihood	−2,774.71	−2,763.21	−2,760.00	−2,279.59	−2,267.47	−2,261.16
Akaike Inf. Crit.	5,569.42	5,568.42	5,584.00	4,579.19	4,576.94	4,586.32
Note:						*p<0.1; **p<0.05; ***p<0.01

C Adoption - robustness checks

Table 13: Logit regression of switchers to non-traditional tariffs. 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	−0.141***	−0.112***	−0.108***	−0.098***	−0.118***	−0.109***	−0.114***	−0.153***	−0.109***
	(0.010)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Future Price (realized)	0.052***			0.115***			0.422***		
	(0.009)			(0.016)			(0.023)		
Future Price (last year)		0.030			−0.092***			−0.152***	
		(0.029)			(0.010)			(0.012)	
Future Price (AR (1))			0.016**			0.047**			0.093**
			(0.007)			(0.024)			(0.047)
Consumption (MWh)	0.037***	0.037***	0.037***	0.036***	0.037***	0.037***	0.036***	0.037***	0.037***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Seasonal Difference (MWh)	0.015	0.015	0.014	0.018	0.013	0.014	0.016	0.012	0.014
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.053)	(0.053)	(0.052)
Income	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***	0.003***	0.004***
	(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***	0.007***	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	0.618***	0.615***	0.615***	0.621***	0.616***	0.616***	0.568***	0.605***	0.616***
	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.148)	(0.147)	(0.147)
Education	1.336***	1.340***	1.338***	1.341***	1.322***	1.337***	1.395***	1.333***	1.337***
	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.162)	(0.161)	(0.161)
Winter Crisis	−1.777***	−1.658***	−1.714***	−1.911***	−1.107***	−1.705***	−1.243***	−0.889***	−1.705***
	(0.102)	(0.099)	(0.102)	(0.105)	(0.116)	(0.102)	(0.102)	(0.115)	(0.101)
Post Crisis	−0.945***	−0.863***	−0.892***	−0.967***	−0.256**	−0.888***	−0.813***	−0.334***	−0.888***
	(0.081)	(0.079)	(0.080)	(0.081)	(0.103)	(0.080)	(0.080)	(0.089)	(0.080)
Location FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year 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 14: Logit regression of switchers to non-traditional tariffs. 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)	−1.286***	−1.110***	−1.103***	−0.988***	−1.039***	−1.090***	−0.937***	−1.332***	−1.088***
	(0.090)	(0.078)	(0.079)	(0.081)	(0.079)	(0.079)	(0.079)	(0.081)	(0.079)
log(Future Price (realized))	0.298***			0.840***			2.689***		
	(0.075)			(0.134)			(0.182)		
log(Future Price (last year))		0.130			−0.696***			−1.733***	
		(0.201)			(0.114)			(0.140)	
log(Future Price (AR (1)))			0.037			0.372**			0.791**
			(0.060)			(0.176)			(0.328)
Consumption (MWh)	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***	0.036***
	(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	0.016	0.020	0.016	0.016	0.017	0.014	0.015
	(0.052)	(0.052)	(0.052)	(0.053)	(0.052)	(0.052)	(0.053)	(0.053)	(0.052)
Income	0.004***	0.004***	0.004***	0.004***	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***	0.007***	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	0.621***	0.616***	0.616***	0.626***	0.620***	0.616***	0.568***	0.601***	0.616***
	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)
Education	1.347***	1.348***	1.346***	1.344***	1.336***	1.345***	1.406***	1.360***	1.345***
	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.162)	(0.162)	(0.161)
Winter Crisis	−1.406***	−1.344***	−1.359***	−1.633***	−1.068***	−1.390***	−1.155***	−0.729***	−1.396***
	(0.113)	(0.112)	(0.114)	(0.121)	(0.120)	(0.114)	(0.113)	(0.122)	(0.114)
Post Crisis	−0.687***	−0.637***	−0.649***	−0.781***	−0.291***	−0.667***	−0.542***	−0.347***	−0.668***
	(0.087)	(0.086)	(0.088)	(0.089)	(0.103)	(0.087)	(0.087)	(0.089)	(0.087)
Location FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year 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