An evaluation of TOU-tariffs: a literature review and an open-source simulation tool

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Abstract

Time-of-Use (ToU) tariffs is currently on many policy-makers agenda. Two of the most fundamental challenges in the implementation these tariffs are what price levels to use and at what times the prices should shift up and down. Recently a number of dynamic tariffs have been evaluated by using randomized control trials, which has increased the confidence in what effect these tariff structures have on demand. Many of the recent, most rigorously conducted projects have found that the short run price elasticity is close to zero. Policy-makers should therefore continue to explore new tariff designs, possibly in combination with other policies, such as information and education campaigns. In the simulations performed using data from Queensland, it is found that relatively large price increases are needed to shift a sufficiently amount of consumption to off- and mid-peak periods. With high peak prices (+50%) and lower mid-peak prices (e.g. -100%), network investments might decrease, but even if they do, such aggressive ToU schemes will exert pressure on network owners' budget, causing them to significantly reduce their cost and find alternative revenue streams. It is also likely to be unpopular with customers. More detailed scenario planning should be performed, which will require software support. A simple, open-source ToU simulator is provided as a supplementary file to this paper. The main conclusion is that ToU tariffs can be used to reduce the economic burden on customers but, unless network owners are willing to consider extreme peak price increases (and/or mid-peak price decreases), it does not seem that ToU is a suitable intervention to reduce network investments.

Keywords: Time-of-use tariff, electricity, demand response, elasticity

1. Introduction

The number of electricity customers on dynamic tariffs are increasing in Australia.^{[1](#page-1-0)} The purpose of this document is to review how electricity customers react to intra-day price variations, a tariff structure often referred to as time-of-use (TOU). An open-access simulation tool is developed that allows the analytical curious reader to explore how the network load vary as a function of different flat-rate- and TOU-tariff structures.

2. Literature Review

The literature on how residential (and other) customers respond to electricity price variations is huge. The traditional literature has often found that the electricity price elasticity is around -0.3, see for example Deryugina et al. (2020) for a recent example. Because consumers' opportunities to react in the short term are more limited than in the long term, the literature has attempted to identify different elasticities depending on how much time consumers have to respond to a price change (e.g. Björnerstedt and Söderberg, 2011). As a rule of thumb, short term reactions have been defined as what consumers do between one month and up to one year following a price change, and long-term reactions as what they do if they are given an infinite amount of time to react – in reality at least a couple of years. In this literature, the short-term elasticity has been found to be around -0.2, whereas the long-term elasticity has been found to be between -0.25 och -1.5 (e.g. Vaage, 2000; Reiss and White, 2005; Maddala et al., 1997). These studies are almost always based on revealed data sets and they therefore suffer from several methodological challenges, some of which have been pointed out by Ryan and Plourde (2009).

The literature above is generally not useful when evaluating ToU tariff since the responses to such tariff structure occur in the 'super-short' term. Given the short time households have to adjust their behaviours, we expect those elasticities to be lower than those reported above. An example of an early study that evaluates a real-time (hourly) pricing scheme (non-Randomized Control Trial) is Allcott (2011). He finds an elasticity between -0.06 and -0.08. Faruqui et al. (2017) conduct a metaanalysis of several real-world ToU trials that were implemented over 20 years. They present consumer reaction as a function of the peak-to-off-peak price ratio and find that a 2:1 (4:1) ratio decreases peak demand by approximately 5 percent (10 percent). However, this assumes that a price increase during the peak period and a price decrease during off-peak period trigger the same behavioural reaction from consumers. Given what is reported in Table 1, that seems like an unrealistic assumption. Whether households' response is primarily determined by a price ratio, i.e. $D = f\left(\frac{P^{Peak}}{P^{Off-peak}}\right)$ or two independent price levels, i.e. $D = f\left(P^{Peak}, P^{Off-peak}\right)$, is an empirical question. Also, it seems these trials suffer from selection bias since care has not been taken to control for the selection into the trials. With a closer look at the individual trial effects (e.g. Faruqui, 2022), the heterogeneity is substantial, and that casts doubts on these simple rules of thumb.

In fact, substantial heterogeneity is also observed in energy conservation programs more generally. A recent meta-analysis published in Nature Energy (Khanna et al., 2021) shows that the correlation between interventions and effects is as low as 0.1 to 0.15. The implication of that is that the results from one study can hardly be transferred to another setting. Effects are likely to be influenced by

 1 For example, statistics for Australia was reported by ABC News on the 20 Apr 2024. Source: [https://www.abc.net.au/news/2024-04-20/aer-admits-to-serious-concerns-over-time-of-use-power](https://www.abc.net.au/news/2024-04-20/aer-admits-to-serious-concerns-over-time-of-use-power-tariffs/103737008)[tariffs/103737008,](https://www.abc.net.au/news/2024-04-20/aer-admits-to-serious-concerns-over-time-of-use-power-tariffs/103737008) visited on the 15 June 2024.

site-specific factors incl. socio-economic, geographical, climate, and culture characteristics. Thus, policy makers are advised to run trials, preferably using a RCT approach, in areas where they intend to roll out large scale tariff innovations.

In the Table below, we summarize some of the most recent and trustworthy trials and their corresponding elasticities that we have evaluated during this review. Two key conclusions are:

- The elasticities are generally very low, in some cases indistinctive from zero.
- The own-price elasticity is about three times as large as the cross-price elasticity.

Table 1. Summary of dynamic tariff schemes applied to electricity, using RCTs.

^a The length of the notice period influences the elasticity (behavioural response), see Jessoe and Rapson (2014).

A few studies have also looked at more specific aspects of ToU tariffs. For example, a study conducted in Texas showed that three quarters of the response was due to changes in the use of air conditioners (Burkhardt et al., 2019).

There are plenty of studies in economics, and behavioural economics in particular, that look at how consumers respond to a 'zero-price'. Several of those studies find that there is an inflated demand effect, i.e. that demand increases unproportionally when the price goes from 'very low' to zero. Based on findings in other fields (e.g. Douven et al., 2020), it is plausible that a zero-price during the off-peak price period can increase the elasticities, maybe as much as double them.

In the next section, Jacobsen and Stewart's (2022) paper is reviewed in more detail. The reasons for why this paper is analysed in detail are that (i) it is recent, (ii) it uses RCTs and (iii) it includes several different ToU tariff structures, as well as a number of critical peak pricing structures.

3. Experiment conducted by Jacobsen & Stewart (2022)

The paper evaluates nine different dynamic tariff structures/levels: three Time-of-Use (ToU), three Critical Peak Price (CPP)^{[2](#page-3-0)} and three where these two structures are combined. The three combination structures are ignored since they do not add any extra value on top of what the individual structures do. ToU tariff levels were calculated so that if consumers did not change their consumption in response to the dynamic tariffs, they would pay the same as if they have had a standard blockrate/fixed price tariff. Table 1 describes the seven tariffs (the fixed, plus the six dynamic ones). It is worth noting that the three CPP tariffs are the fixed tariff with high price premiums that last for short periods of time (typically three hours) and happen at irregular intervals (i.e. they are not generally predictable for more than 1-2 days in advance).

Table 1. Tariff structure and levels.

Notes. ToU=Time-of-Use tariff; CPP=Critical Peak Price tariff. Critical events typically lasted 3 hours; no information about how many critical events customers experienced.

Consistent with much of the existing literature on ToU tariffs, the effects for those three tariffs turn out to be insignificant, i.e. they have no clear effect on consumers' behaviour. However, the CPP tariffs do lead to demand reductions during critical events (in the range 14-24%).

Table 2. Treatment effects.

² Another type of tariff scheme that is sometimes mentioned in the literature is Variable Peak Pricing. It is similar to Critical Peak Pricing, but the price can vary across critical events.

The fact that demand goes down during critical events when CPPs are used should not come as a surprise given how much the prices are increased during those hours (see the right-most column in Table 1). A more relevant way to evaluate these tariff increases is to calculate the price elasticity: $\varepsilon =$ % demand change⁄% price change. They are included in Table 3 and while they are statistically significant, the actual elasticities are very close to zero. Comparing those elasticity values to what the literature frequently suggests about longer-term electricity price elasticities (from a couple of months to a year) at around -0.3, we conclude that the behavioural change reported in Table 2 is not due to consumers being price responsive, but to the very large price increases. It is worth emphasising that the price elasticity reported here is based on a randomized controlled trial. If policy makers intend to make the ToU scheme voluntary, one can suspect that the most price sensitive customers will sign up and then the price elasticity will be higher than what is reported here.

Table 3. Elasticities.

4. Simulations based on QLD data

In the following section, a simulation is conducted using demand and pricing data from Queensland in Australia. The simulation identifies what different ToU-tariffs would imply in terms of network load, customer demand and customer cost. Simulations are performed using the Excel file "ToU simulations – $v1_0$. The analyses reported in this section are based on the aggregate demand – solar generated power is ignored.

Cells that can be set by the user has a yellow background. Given this load input, the Excel file is constructed so that the user can specify:

- Today's tariff (a fixed tariff). This is done in cell *F7*.
- The characteristics of an alternative ToU tariff (up to three different price levels and the time intervals that apply to each price level). The price levels are set in the following cells: *N7*, *N10* and *N13*. The time intervals that apply to each tariff level is set in column J. A "1" indicates that the period is off-peak, a "2" indicates that the period is mid-peak, and a "3" indicates that the period is peak.
- The elasticity. The default is set to -0.02, which is based on the result for CPP-1, as indicated in Table 3. The cross-price elasticity is set to 0.007 – remembering that the absolute ratio between these two was identified as 3:1 in section 2.
- Zero-price. When the off-peak price is zero, the cross-price elasticity increases to 0.014 (double the default). This reflects the higher response rate when something is free, as suggested by Douven et al. (2020).

The outputs include:

- The total electricity consumption (for an average customer).
- The consumption during each tariff level (off-peak, mid-peak and peak).
- The total daily cost for the customer.
- All results are presented in both absolute values and % change.

According to the assumption about price elasticity and ToU characteristics, we can simulate how demand changes for different hypothetical tariffs. Table 4 displays four different scenarios that have been suggested by different energy stakeholders.

Scenario 1: mid-peak reduced by 50%

The first scenario maintains the current price, except during the mid-peak period (10am – 2pm) where the price is reduced by 50%. Customers decrease their consumption during the peak period by 0.3% and increase their consumption during the middle of the day (mid-peak) by 0.9%. Total consumption is practically unaffected (-0.3%). Consumers' total cost drops by 10%.

Scenario 2: mid-peak reduced by 100%

It has also been suggested that the tariff should be reduced to \$0 during mid-peak. This is considered as the second scenario in Table 4. With this change (i.e. mid-peak reduced by 100%), the consumption during mid-peak increases by 1.8% and total daily consumption decreases by 1.1%. Consumers' total cost decreases by 20%.

Table 4. Simulation results when mid-peak is from 10am to 2pm.

Scenario 3: mid-peak reduced by 50% and peak price increased by 50%

The perhaps most important electricity system objective, which is also the primary purpose of ToU, is to reduce consumption during peak hours. It is pertinent, therefore, to also evaluate a ToU structure where the tariff not just drops during mid-peak, but also increases during peak hours. Consequently, in the next scenario, peak price is increased by 50% (i.e. from 0.3 to 0.45 \$ per kWh). This increases the total cost customers pay by 10% and the total consumption decreases by 0.2%.

Scenario 4: mid-peak reduced by 100% and peak price increased by 50%

In a more extreme scenario, the mid-peak price is set to zero (see right-most column in Table 4). Now, consumer cost falls by 1% while total consumption decreases by 0.6%. Thus, this outcome appears to achieve several important objectives, although a peak price that is three times as high as during mid-peak might be politically tough to roll out on a large scale.

Table 5 shows the results for the same scenarios, but when the peak period expands from 10am-2pm to 9am-4pm. Elasticities and price levels remain the same. Consumption only changes marginally, but consumer costs fall markedly. While attractive from a consumer perspective, this puts pressure on the system's budget. Alternative sources of revenue are likely to be needed since efficiency improvements are unlikely to reduce costs this much.

Table 5. Simulation results when mid-peak is from 9am to 4pm.

Elasticities during (short) peak periods

When using the average load curve for an average summer day, which is what is done in the analyses displayed in Tables 4 and 5, the peak is relatively flat from 2:30pm to 5:30pm.³ So, from a network perspective, this is the period when the price should be the highest. Compared to what is used in the

³ The shape of the load curve can be different on critical summer days.

simulations in Table 4 (2pm – 9pm) and Table 5 (4pm – 9pm), that is a substantially shorter period, but it is also longer than the 1.5 hours that has sometimes been suggested. No study has been found that looks at what the elasticity is for shorter peak periods. It is likely that the cross-elasticities will go up, but large-scale RCTs are needed to identify the actual magnitudes.

In the attached open-source simulation tool, the analytically curious reader can run additional simulations with different price levels, elasticities, and price break points.

5. Discussion points

If a *ToU tariff scheme* is used, the following issues need attention:

- The length of the peak price periods (start and end times se Table 1 for reference)
- The number of distinct price periods (typically two or three se Table 1 for reference).
- No study has evaluated entirely free electricity during off-peak hours. A relevant question, therefore, is what the behavioural difference between a very low off-peak price and a zeroprice during off-peak is.

If a *CPP tariff scheme* is used, the following issues need attention:

- Decide how a critical event should be defined. It is important to keep in mind that critical events must be predictable since consumers must be made aware of when the CPPs apply and they need that information in advance.
- How many events should be considered 'critical' within a given time interval? Based on what has been used in the literature, it seems there should not be more than one per week, on average. But this is ultimately a behavioural question and should be evaluated experimentally.
- Determine how much to increase the price during critical events.

The literature on how to change electricity consumers' behaviour is extensive and price-based interventions, including other financial incentives, is only a subpart of that literature. So far, combined interventions, e.g. a ToU and a social norm intervention, have not been properly evaluated.

Another type of behavioural intervention that has not been investigated sufficiently, is how nonfinancial, social rewards, affect consumers' behaviour. It is documented that a social reward can change individuals' behaviour substantially. A valuable project would be to investigate how social rewards affect consumers' behaviour in combination with ToU.

There are also question marks around the long-term effects of both financial and non-financial interventions.

6. Conclusions

Consumers are highly inelastic in response to ToU tariffs in electricity. Thus, the simulation results presented in this report suggest that ToU tariffs can be used adjust the economic burden on customers, but not to have a material effect on network load, and investments needed satisfy consumers' demand. Techno-economic modelling can complement the analysis presented here to give more detailed insights on how network capacity is affected in different parts of the network (both the transmission and the distribution networks).

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