Household Preferences for Residential Electricity Contracts

by

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Declaration of Originality

This thesis contains no material which has been accepted for a degree or diploma by the University or any other institution, except by way of background information and duly acknowledged in the thesis to the best of my knowledge and belief. None of the material in the thesis was previously published or written by another person except where duly acknowledged, nor does the thesis contain any material that infringes copyright.

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The research associated with this thesis abides by the international and Australian codes on human and animal experimentation, the guidelines by the Australian Government's Office of the Gene Technology Regulator and the rulings of the Safety, Ethics and Institutional Biosafety Committees of the University. Ethics Clearance No. H0016832.

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Abstract

In Australia, a trilemma has emerged among the three stated objectives of energy policy, namely maintaining high system reliability, providing affordable energy and achieving a drastic reduction in greenhouse gas emissions. These three objectives cannot be simultaneously achieved in the short to medium term. This suggests there are choices for society and potential trade-offs that can be explored in the short to medium term. This dissertation utilises two methods to investigate and simulate consumer preferences for aspects of these trade-offs as well as the potential for switching behaviours for different residential electricity contract features.

Since households are impacted by the cost of these energy policies, it is important to understand the policies they prefer. Consumer preferences are explored using a Discrete Choice Experiment (DCE) through the design of an online, multi-treatment survey of respondents from the states of New South Wales and Victoria. Each treatment involved choice tasks with the following shared contract features: the proportion of electricity sourced from renewable energy generation, investments in battery storage, information provision through the installation of smart electricity meters, and the imposition of consumption restrictions. Additional information was collected to explore potential sources of preference heterogeneity including how the status quo contract (or Business-as-Usual) is described, risk preferences, and financial literacy. Finally, an Agent-Based Model (ABM) is combined with a DCE to demonstrate a decision support tool that simultaneously simulates the likelihood of switching electricity contracts as well as the selection of a specific contract based on the DCE. Combining both models provide insights into consumer behaviours relevant to energy policy that otherwise would not have been observed if treated in isolation.

The first paper compares two treatments that presented different versions of the status quo contract. In the first treatment, respondents could select a status quo contract with no additional costs being imposed, though the contract did involve the imposition of consumption restrictions during the evening. The second treatment describes the status quo as the most expensive contract with the highest levels for each of the attributes, including no imposed consumption restrictions. The reported results for the first treatment are interpreted as the Willingness to Pay (WTP) to remove consumption

restrictions as well as increases in the levels of the other contract features presented. In the second treatment the alternative contracts offered involved lower levels for all features including cost, therefore the reported results are defined as the Willingness to Accept Compensation in the form of Lower Cost Increases (WTA-LCI). When comparing both treatments the WTA-LCI estimates are statistically larger for most of the features when compared to the equivalent WTP estimates. This result is consistent with past studies analysing differences between WTP and WTA. Both sets of the results provide unique insights regarding two contrasting policy stances of whether the financial costs of these policies should be imposed on households or not.

The second paper analyses whether a respondent's preference for risk explains differences in the WTA-LCI observed between respondents. After completing the choice tasks respondents completed a risk preference elicitation exercise. Two groups of respondents were identified, the first being those who were highly risk-averse and the second representing all other respondents. The results of the DCE suggest that the highly risk-averse group requires more compensation for reductions in contract features relative to the other group. It may be the case that this difference in WTA-LCI is due to the uncertainty respondents perceive with reductions in contract features. Addressing these uncertainties would work towards fostering public acceptance for policies that delay investments in infrastructure and that lead to the implementation of demand-side management policies.

The role of financial literacy is explored in the third paper with a range of electricity contracts. Each respondent completed a financial literacy quiz that assessed the respondent's knowledge of financial investments. The number of correctly answered questions on the quiz is used as a proxy measure of their financial literacy. A hybrid scaled mixed logit model was estimated to identify links between a respondent's socio-demographic characteristics, their score on the financial literacy quiz, and the choices they made in the DCE. Several socio-demographic characteristics including age, gender and education were identified as being correlated with the number of questions correctly answered in the quiz. Financial literacy was found to be positively correlated with how consistent respondents were in evaluating different combinations of electricity contracts and their stated WTP for contract features.

The results suggest that respondents who scored high on the quiz treated the features as investments, with costs incurred today leading to benefits being realised over time.

The fourth paper extends the DCE research by combining an Agent-Based Model (ABM) with a DCE to simultaneously model the decision to switch from an existing contract as well as the selection of electricity contracts with specific contract features. Agents in the ABM represent households with unique characteristics with respect to their propensity to switch, their average bill size, and the size of their social network. The DCE included three contracts that differed with respect to their cost and the number of consumption restrictions imposed. Feedback effects were modelled in the ABM with the contract selected in the DCE affecting the likelihood of neighbouring households also switching from their existing contract. Several simulations modelled alternative scenarios reflecting changes in the size of annual price changes, the variance in electricity bills, and the size of social networks. The results suggest that low-income households are the most likely group to switch from their existing electricity contract. The price-elasticity of contract switching was estimated as being inelastic, consistent with related studies looking at price-elasticities with respect to electricity consumption.

The findings of these papers highlight that there is preference heterogeneity with respect to contract features. Identifying what role status quo descriptions, risk preferences, and financial literacy plays in explaining preference heterogeneity is a novel element in this dissertation. The combination of an ABM and DCE demonstrate how the two methods can be utilised to simulate potential scenarios relevant to evaluating alternative energy policies, as well as fill in a gap with respect to the combination of these two methods in the resource economics literature.

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Chapter 1: Introduction

1.1 Dissertation Overview

The overall aim of this doctoral research is to estimate household preferences for energy policies with threefold objectives, namely ensuring energy reliability, increasing renewable energy generation, and slowing the increase of retail electricity prices for affordable energy. Achieving two of the previous objectives is often at the expense of the third. Rising energy prices in Australia have supported a transition towards green electricity production whilst maintaining the reliability of the electricity system. Going forward additional investment may be required to continue this trend, especially if the proportion of steady-source power (Baseload generation) decreases. Does this trend reflect what households want? This dissertation seeks to answer this question whilst also exploring how different behaviours and attitudes influence preferences for alternative polices.

1.2 Background

The Australian National Electricity Market is an interconnected system of infrastructure that allows for the generation, transmission, and distribution of electricity to consumers. The system connects the Eastern states of New South Wales (including the Australian Capital Territory), Queensland, South Australia, Victoria, and Tasmania and excludes Western Australia and the Northern Territory. The interconnection of the Eastern states allows for electricity to be traded across 40,000km of transmission lines (Australian Energy Market Operator (AEMO), 2021). A key feature of electricity markets is that supply must always meet demand to ensure stability of the grid. A spot market for electricity allows for prices to instantaneously adjust with supply and demand, signalling when changes in supply are required. Electricity generators offer bids to supply specific quantities of electricity at a particular price, which are then collected and ordered according to the lowest price. Demand forecasts, plus a reserve, are then used to accept subsequent supply bids until the market clears. Bids are received to supply electricity in five-minute intervals, with the final price paid based on the average accepted bid over a thirty-minute interval. This market structure ensures that electricity generated at the lowest cost is purchased first, encouraging competition among generators. There can also be zero or negative bidding due to low marginal costs or to ensure generators with long ramp up times do not switch off, which would limit their capacity to react to unexpected changes in demand. A financial contract market also exists allowing for the hedging of the financial risks associated with spot price volatility (Australian Energy Market Commission (AEMC), 2020a). The secondary market, separate from the spot market, allows retailers to purchase power from generators in the future at an agreed price.

Most market participants are private firms, with some state-owned electricity providers also participating. Overseeing these markets are several government agencies at both the Commonwealth and state levels, who are responsible for setting the rules, procedures, and regulations that govern the markets. The Australian Energy Market Operator (AEMO) is the main entity responsible for ensuring the physical constraints of the system are maintained. This includes managing the voltage and frequency of electricity transmitted to ensure a continuous flow of electricity, and to prevent physical damage to infrastructure. Continuity can be disrupted by extreme weather events, unexpected changes in voltage or unexpected changes in transmission flow. AEMO also intervenes in the market in cases where supply does not match demand, to enact policies that either incentivise additional supply or impose reductions in demand. In line with previous protocols (Ruiz Estrada, 2010), this thesis adopts the term policy to refer to a particular method or technical instrument formulated to solve a specific problem. The other role AEMO plays is the administration and operation of the wholesale market. The rules that guide AEMO's operations are set by the Australian Energy Market Commission (AEMC), who are responsible for designing and amending the National Energy Rules through the National Electricity Law, the National Gas Law, and the National Energy Retail Law. Most state governments have applied these laws with some exceptions, usually as a consequence of similar legislation covering issues such as consumer protections already being in effect (Department of Industry, Science, Energy and Resources, 2021a). The Australian Energy Regulator (AER) is the economic regulator and rule enforcer for the National Electricity Market. The strategic objective of the AER is to ensure competition is maximised where feasible and when this is not possible, it enforces regulations to ensure that consumer interests are protected (Australian Energy Regulator (AER), 2021a). Government ministers at both the state and federal levels oversee these agencies with the aim of ensuring that the market is designed to be as reliable and secure as possible. One objective of this thesis is to explore whether the government aims of maintaining the current level of network reliability and security are aligned with household preferences.

The Australian market has developed as a consequence of a series of legislative reforms which began in the 1990s and followed the international trend towards the liberalisation of electricity markets (Joskow, 2008; Erdogdu, 2014). Prior to these reforms, most states and territories owned and managed their own electricity infrastructure. Mostly, electricity was purchased from state-owned monopolies since the 1950s. The price of electricity in real terms had been falling from \$0.20 AUD per kilowatt hour (kWh) in 1955 to \$0.09 AUD per kWh in 1995 (Brady, 1996). Between 1991 and 1998, various reforms were put into effect through legislation, leading to the creation of the National Electricity Market. These reforms attempted to achieve multiple objectives including privatisation and the separation of retail operations from generation, transmission, and distribution. The policy objective of introducing competition in the market was that regulation could be better focussed on encouraging efficiency and stability within the market. Following these reforms into the early 2000s, the retail price of electricity was relatively stable at around \$0.15 AUD per kWh (2012 prices); however, from 2006 until recently there has been a year-on-year increase in prices (Graham et al., 2015).

1.3 Rising Electricity Bills

In the last decade, Australian residential consumption of electricity has increased by an average of 0.5% per annum (Department of Industry, Science, Energy and Resources, 2020a). Over this period, household electricity bills have increased by more than 5% per annum on average (Australian Competition and Consumer Commission (ACCC), 2018; ACCC, 2019). There are several factors that explain this change, however, they can all be classified as issues that are related to the energy policy trilemma (United Nations World Commission on Environment and Development, 1987). This trilemma highlights the trade-offs across three dimensions: stabilising or lowering the price of electricity, maximizing the reliability of the system, and encouraging the growth of renewable energy generation technologies. Often, achieving two of the above dimensions is at the expense of the third. In Australia's case, an average increase in the cost of electricity per household has supported an increase in reliability and the proportion of renewable energy electricity. The most important factor contributing to rising energy prices is the large-scale investment in transmission and distribution infrastructure. These investments, often referred to as network costs, over the period 2008 - 2019 represent 38% of the increase in household electricity bills during this time (ACCC, 2019). These cost increases are colloquially referred to as 'gold-plating' the network (ACCC, 2012; Wood et al., 2018a). Although there are several reasons for this growth in investment, it has allowed AEMO to achieve the 99.998% of forecast demand reliability standard as set in the national electricity rules (AEMC, 2020b)

Wholesale costs are the next largest component contributing to the rising prices. There are two supply-side factors working against each other, with the net effect being a fall in supply in the previous decade. There has been an increase in the quantity of electricity being supplied through renewable energy generation since 2001, mainly solar and wind technologies. There has also been some investment in gas and oil for electricity generation (Department of Industry, Science, Energy and Resources, 2020a). Increased renewable energy generation is expected to lead to a merit order effect (Figueiredo and Da Silva, 2019), whereby lower marginal-cost generation out-competes generation from fossil fuels, leading to lower wholesale prices over time. In Australia, this fall in prices has only just started to be realised and is expected to last until 2020-2021 (AEMC, 2020c). There are several reasons why large falls in wholesale prices have not been realised, including the closure of ten baseload coal-fired plants (5,319 megawatts (MW) of generation) between 2012 and 2017, with the remaining plants expected to close in the next 10 to 20 years (Jotzo et al., 2018). Some of these plants have been decommissioned in part due to reaching the end of their useful life. This form of power generation, however, is often undercut by generation technologies with lower marginal costs. This fall in supply has since been made up for, with 7,600 MW of renewable energy generation added to the market between 2017 and 2019 alone (Clean Energy Regulator, 2020a). This gain in supply does not account for the fact that renewable energy generation is not a substitute for baseload generation, which includes those generation technologies that can reliably be changed with respect to the amount of electricity generated (Joskow, 2011). Most renewable energy generation technologies are entirely dependent on weather patterns, unlike baseload generation which can be controlled. For example, fossil fuels can be burnt at a higher rate to generate more electricity. Consequently, the intermittency of renewable energy generation has led to increased price volatility when forecast demand has not been met. The high marginal-cost peak load generation (technologies that can rapidly change with respect to the amount of electricity generated) required to match demand has driven up wholesale prices (Wood et al., 2018a; Rai and Nelson, 2019). Examples of peak-load generation include gas turbines, which can rapidly change the amount of electricity generated through increasing the rate of combustion, and batteries, which can discharge when peak demand is realised. There are environmental and monetary cost implications associated with the use of gas turbines in Australia, one of the most expensive in terms of the cost per kWh of electricity generation (Campey et al., 2017). Batteries may not have the same environmental costs as gas turbines; however, they are not yet widely adopted since the installation costs are relatively expensive compared to other renewable power sources (ARENA, 2021). Hydroelectric dams can also be used for peak generation. There are, however, limitations related to transmission infrastructure in Australia that prevents this type of generation from being relied upon during times of peak demand (Hydro Tasmania, 2018). There are also consumption limitations, with hydroelectric power representing only 6% of national electricity generation (Department of Industry, Science, Energy and Resources, 2020a).

The other costs that have contributed to rising prices relate to environmental and retail costs. Investments in renewable energy generation have been subsidised through the Large-Scale Renewable Energy Target policy (Clean Energy Regulator, 2018). The policy was enacted through Commonwealth legislation and requires retailers to purchase and surrender certificates that are obtained when electricity is purchased from renewable energy generators. These certificates are created every time one megawatt hour (MWh) of electricity is generated from a renewable energy source. In 2020, this national policy resulted in 20% of electricity produced nationally in Australia being generated from renewable energy sources. There are significant differences in the proportion of renewables between states. For example, in 2019-20, Tasmania and South Australia generated 94% and 50% of their electricity from renewable energy sources, while Victoria and New South Wales only generated 19% and 21% respectively (Department of Industry, Science, Energy and Resources, 2020a). It is important to note that Tasmania and South Australia represent only 9% of the total population, whilst Victoria and New South Wales represent approximately 58% of the population (Australian Bureau of Statistics, 2020). Consequently, the national energy target has been met by averaging over the states with states such as Queensland (11%) and Western Australia (9%) being offset by small states such as Tasmania (Department of Industry, Science, Energy and Resources, 2020a).

One of the consequences of the government requiring electricity retailers to purchase certificates that ensure they have purchased electricity from renewable sources is that this additional cost has been passed onto households, with this cost explaining 22% of the rise in the cost of electricity (ACCC, 2018). Retail costs and margins in Australia are large compared to countries with similar markets (Valadkhani et al., 2018), with issues such as vertical integration (energy companies that own the generators, participate in the wholesale market, and sell to final energy consumers) and low rates of consumers switching to cheaper electricity contracts being identified in the literature as significant contributors to growing retail margins (Simshauser and Whilsh-Wilson, 2017).

Government policies have prioritised investments that maintain the reliability of the network and support the growth in renewable energy generation at the expense of rising prices over the last decade. Although there are signs that this upward trend may be slowing (AEMC, 2020c), there are concerns that the reliability of the network may start to diminish in the next decade (AEMC, 2019). The retiring of baseload generation coupled with the additional load coming from renewable energy generators means that more investment will be required to ensure the ongoing reliability of the network. The national renewable energy target of 20% has been met, yet there is currently no plan to change the target even though reducing the proportion of fossil fuels used for electricity generation would work towards meeting Australia's commitment to the Paris Accord (Riedinger, 2020). Consequently, inaction with respect to changing the current target may create uncertainty with respect to future investments without government subsidies (De Atholia et al., 2020). Future climate and energy targets are still an issue of public debate. The current federal government's policy stance focuses on lowering emissions through adaptation strategies such as technological innovation (Department of Industry, Science, Energy and Resources, 2020b), and leaving each of the states and territories to set their own renewable energy or emission reduction targets (Climate Council, 2017).

1.4 Thesis Statement

Based on the preceding discussion it is not known whether household preferences are aligned with current policy goals focusing on reliability as well as the transition towards green electricity. Electricity generation is an essential service that is regulated to ensure that households have equitable access to electricity. Borriello et al. (2019) explored the acceptability of these types of trade-offs for household consumers who face the consequences of these decisions and concluded that consumer preferences are often neglected. It is likely that households will have to accept continuously rising prices for electricity if the current policy setting of increasing renewable energy and reliability is followed. Lower price increases can only be achieved by relaxing other elements of the energy trilemma. The energy trilemma represents trade-offs across three dimensions, and policies that prioritise one dimension over others should reflect upon the preferences of households as they ultimately bear the burden or benefit from these decisions. Therefore, the research question for this dissertation was: Can household preferences for electricity contract features reflecting the energy trilemma better motivate future energy policy?

There are several policy alternatives that could be developed to ensure a more sustainable energy policy in an Australian context. These policies include an extension of the RET, increasing storage capacity through battery technologies, for example in the South Australian Hornsdale Battery Reserve which has been operational since 2017 (Sonali, 2017), and finally reducing total demand during the peak consumption period. The second policy could mitigate intermittency issues associated with increased renewable energy generation by storing excess electricity when it is relatively cheap to produce, then sell at times of insufficient supply (Keck and Lenzen, 2021). Reducing peak demand often requires costly peak generators such as gas turbines to meet demand. If demand can instead be shifted to a time in the day where demand is usually lower, the likelihood of significant spikes in wholesale prices linked to expensive sources of supply (gas turbines) may be reduced. As these policies would be paid for by households, it is important to evaluate whether households' preferences match this policy direction. Following on from this, the next question is to determine how they would pay. Currently households do not actively engage in the wholesale electricity market. There are households who own solar panels, however, their interaction with the market is passive in the sense that they receive payments for exporting excess solar energy to the grid. Battery technologies in Australia are currently not widespread at the household level, preventing the trading of stored electricity. Most interactions are through an intermediary such as an electricity retailer.

In this dissertation it is assumed that households would state their preference for specific polices through the selection of newly created contract features, which would be an extension of existing contracts. This approach would be not too dissimilar to how households already pay for changes in network infrastructure, e.g., the transmission and distribution components of the bill, as well as the costs of the LRET. The benefits of additional investment, over and above what is currently the case, would take time to realise and would incur additional costs today. The issue of contract features is investigated from two perspectives – one of which assumes an opt-in and the other allows an opt-out. This distinction is based on the future expectations set by electricity retailers, the first represents the opportunity for households to opt-in to contracts that represent paying for additional features. The second perspective assumes that retailers by default offer a maximum-cost contract that households could opt-out of, exchanging lower costs for less desirable features. The opt-out choice is relevant for developed countries, where some defined standard (e.g., the colloquial gold-plated networks) has been achieved, whereas an opt-in choice is relevant for developing countries. The choice to analyse these two perspectives highlight some of the choices available to households with respect to future investments. The first evaluates whether investments should be brought forward through additional funding, and the second considers the choice to delay investments in exchange for lower cost increases.

The previous features focused on investments in renewables and reliability, however what if price stabilisation and increasing renewables became the priorities? Demand Side Management (DSM) policies, defined as those that encourage changes in consumption patterns (Groppi et al., 2021), may be one way, as part of a suite of policies, to mitigate future price increases whilst indirectly improving the reliability of the network and reducing the risks associated with intermittency. Two DSM policies that are the focus of this dissertation involve the imposition of consumption restrictions and installation of smart meters. Both policies represent two different ways to reduce demand. Consumption restrictions provide an alternative to paying a premium for electricity consumed during the peak evening period. Depending on whether they became a mandatory feature of future contracts or a feature that can be opted into these restrictions could either be removed for a fee or accepted in return for some reduction in the household's electricity bill. In contrast, consumption restrictions information from smart meters represents a voluntary way to manage consumption through the provision of timely consumption data. The information provided by these meters would be paid for by households, therefore they would need to determine whether the benefits associated with this additional information exceed the costs to obtain it. The objective is to evaluate the households' support for both the DSM policies described in this dissertation as a means to lower peak demand.

1.5 Research Aims

Whilst estimating households' preferences is the overall research aim, it is expected that there will be significant differences in preferences for the proposed contract features. The trade-offs made between features are assumed to represent utility-maximising choices which are a function of underlying preferences, which are shaped in part by latent attitudes. Failing to account for these underlying factors can create issues with respect to estimating unbiased preference parameters. There is, however, a desire to better understand all relevant factors that affect decision-making processes beyond the omitted variable bias associated with failing to account for preference heterogeneity. Understanding why some households have a positive preference for a particular feature and others a negative preference is relevant for evaluating the impact of different policies. Assessing the welfare impacts of implementing new features will be limited if different sources of preference heterogeneity is not accounted for. Therefore, this dissertation seeks to explore several unique sources of heterogeneity across three papers to identify which factors are relevant to the evaluation of the contract features analysed.

1.5.1 Research aim one

The first research aim was to investigate whether there is a divergence between Willingness to Pay (WTP) and Willingness to Accept (WTA) estimates for electricity contract features.[1] Evidence of a divergence would suggest that the valuation of different contract features may be influenced by income effects or other behavioural explanations (Horowitz and McConnell, 2002). To test for such a divergence two different contracts were described. The first is a status quo contract with no cost increase as well as the imposition of consumption restrictions. The second is a status quo contract that includes maximum levels for all features, including cost. Under the null hypothesis, it is hypothesised that there is no statistically significant difference between each set of contract feature estimates. Rejecting this hypothesis would suggest that the value of contract features diverges when they are described as improvements versus reductions. From a policy perspective this may be problematic since an overreliance on WTP measures may underestimate the true value respondents place on each of the features presented. It is also problematic since it may provide an opportunity to pick and choose a valuation method that suits a particular agenda, which wouldn't be the case if the divergence did not exist.

1.5.2 Research aim two

The second research aim was to investigate the correlation between a household's measured level of financial literacy and their preference for different contract features. The features described could be considered as investments in the sense that costs are incurred today with the benefits realised over time. For example, more renewables could lead to lower prices in the future. It is hypothesised that financial literacy affects how households evaluate the trade-offs between alternative electricity contracts. Under the null hypothesis, there is no statistically significant difference between preferences after accounting for a households' measured level of financial literacy. If this is not the case, then it may imply that different levels of financial literacy led to different stated WTP values.

[1] In this dissertation we refer to the candidate as first author with the supervisory team who were involved in the critical decisions in the research process.

1.5.3 Research aim three

The third research aim was to investigate the impact of an individual's risk preferences upon preferences for various electricity contract features. Utilising data from the opt-out set of contracts, we consider the possibility households may prefer future energy policies that emphasise price stabilisation over reliability and renewable energy generation. This would represent a divergence from the status quo which prioritises reliability and green electricity over price. When compared with alternative policy stances, the status quo may represent the policy that is the lowest risk, with households requiring more compensation for reductions in contract features representing movements away from the status quo. It is hypothesised that a household's preference for risk is related to their preference for electricity contract features. Under the null hypothesis there is no statistically significant difference between household preferences after accounting for their preference for risk. If this was not the case, then it may be that being risk-averse is one of the reasons why households prefer the status quo.

Each of these three research aims not only look at preferences for various electricity contract features, but they potentially provide general insights into human decision-making. Status-quo framing, financial literacy, and risk preferences represent different behavioural factors that may be important when evaluating different choices (e.g., Johnston et al., 2017). The results from these surveys may either inform future cost-benefit analysis or be used to justify various policy stances. If there is evidence that these behavioural factors are important, then it may be the case that future studies relying on stated preference techniques may need to be mindful of accounting for these factors (potential omitted variables).

1.5.4 Research aim four

The previous research aims posed explore the importance of different sources of heterogeneity which in turn influence how households evaluate trade-offs. What is not considered are the practical issues associated with how households switch to new electricity contracts. In the final research aim of this dissertation, I report on combining two methodologies to create a decision support tool that can evaluate the impact of implementing different features. This tool could be used by retailers and regulators to forecast the uptake rate of new contracts based on modelled rates of contract switching.

Changes in the factors that influence the rate of switching could also be modelled, identifying relevant factors preventing or supporting specific switching rates. As an example, if consumption restrictions were offered as an opt-in contract feature, then how many households would accept the restrictions? Since it is an opt-in feature, there is the possibility that households would delay this choice, which would not be surprising as electricity contract switching rates in Australia average around 20% per annum (AER, 2020). Understanding why this is the case as well as identifying factors that could increase this rate is important if the uptake of new contract features is a priority. Therefore, the final research aim answers the following questions: What are the determinants of switching rates? How many households do we expect to switch to a new contract over a specified period? And finally, what are the distributive consequences of such a policy approach?

1.6 Research Methodology

The answers to the research questions posed in this dissertation are obtained using two methodologies. A multi-treatment Discrete Choice Experiment (DCE) was designed and analysed in the first three papers. For the final paper, the results from the first DCE paper were combined with an Agent-Based Model (ABM) to create a decision support tool for policy evaluation. Data was collected from two markets, Victoria and NSW, since the markets in these states have a significant number of electricity retailers. There are no government monopolies with respect to electricity provision, and the proportion of renewables is close to the national average. Most of the power generation, however, is from coal-fired generation. Primary data was collected through the creation of a survey that was made available online in June 2019. Figure 1 provides an overview for each of the main sections of the survey. Since electricity contracts were the focus of this research, the sampling frame included states in which there was a choice between several retail electricity providers. Households were randomly sampled, stratified by age, gender, and whether they lived within the greater metropolitan area. The Online Resource Unit (ORU), one of the panel providers in Australia, administered the survey, randomly selecting respondents from their panel based on the aforementioned criteria. The University of Tasmania provided funding to ORU to obtain responses. Every individual who completed the survey received points upon completion. Once they accumulate enough points, they can redeem gift cards as payment. Based on the funding provided to ORU, 1,200 responses were collected.

1.6.1 Stated preference

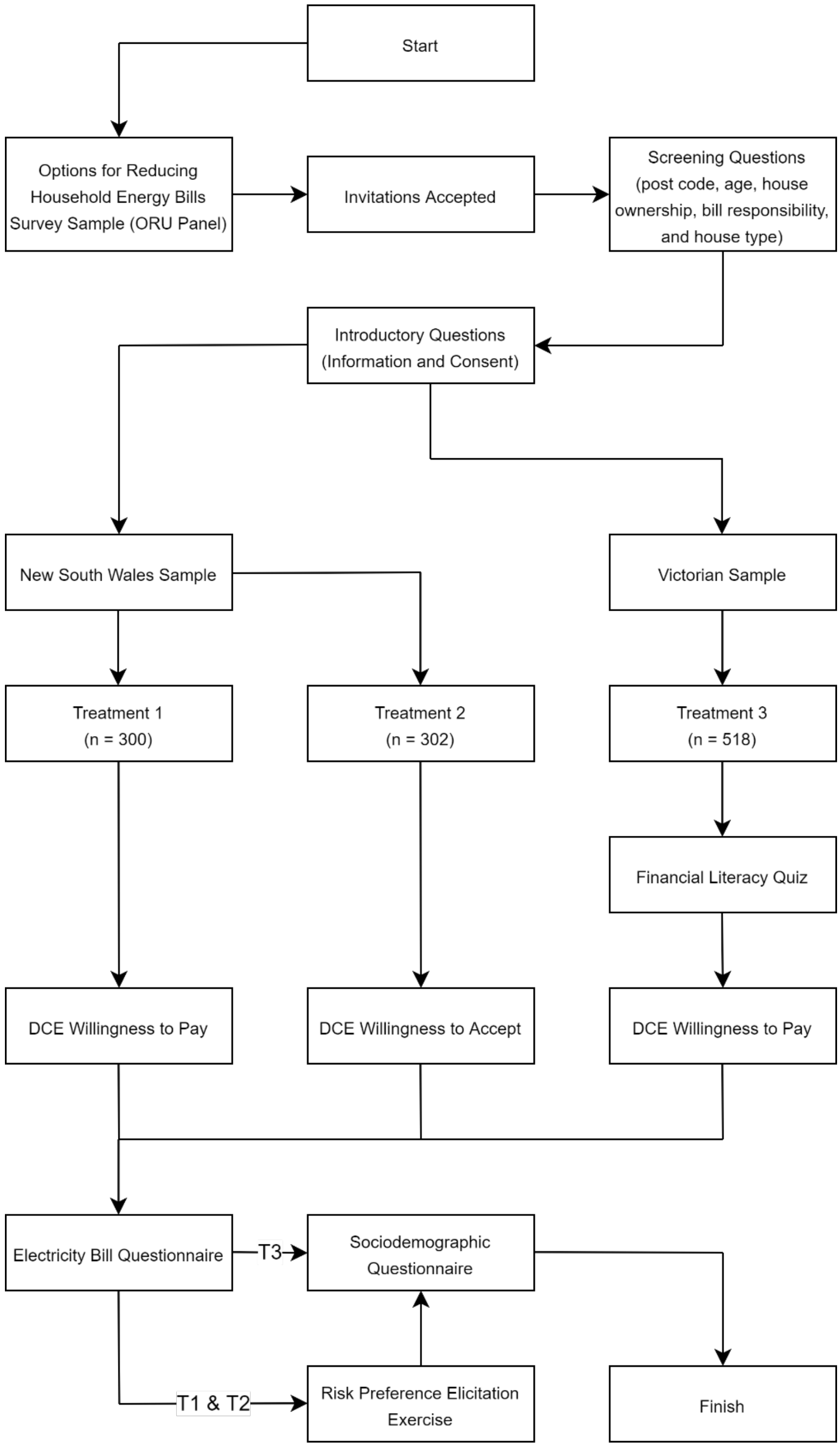
The reason for utilising a stated preference technique over revealed preference relates to the lack of information available with respect to preferences for contract features that do not currently exist. Most electricity contracts include terms that detail the contract length, the tariff rate per kWh as well as other charges, and bill payment details (AER, 2021). Some retailers do offer contracts that allow households to determine how much power is sourced from renewable energy generation. These contracts, however, do not fund additional investments. Battery storage and real-time information do exist in Australia, however, they are not currently tied to commonly available electricity contracts. Finally, DSM in the form of consumption restrictions is currently only being piloted in a limited number of projects working mainly with industrial and commercial customers. Household participation in demand reduction is voluntary (Australian Renewable Energy Agency, 2017).

1.6.2 Agent-based modelling

The final paper demonstrates the benefits of combining two methods to evaluate different decisions. Focusing on consumption restrictions, from the opt-in set of contracts, the final paper of the dissertation evaluates how many people would accept either some restrictions or higher fixed costs. This choice would only be made when they next switch from their current electricity contract. The DCE model provides parameter estimates for specific features of different electricity contracts. The ABM allows the factors driving the decision to switch to be simulated. This simulation allows for additional sources of preference heterogeneity to be modelled, and feedback effects to occur between the decision to switch as well as the choice made in the DCE. The combination of these two methods not only allowed me to gather insights that otherwise would not have been identified such as the distribution of demand response uptake by income cohorts, which I was then able to compare to real-world data collected during the dissertation.

The data collected includes whether households had switched electricity contracts, the estimated size of their electricity bill, as well as socio-demographic characteristics that may explain the variation in the intention of switching and the size of their bill. The parameters used to calibrate the model data included to what extent the variation in bills each quarter affected the intention of switching, as well as how a household's social network influenced their intention of switching.

Figure 1. Overview of the survey design



1.6.3 Survey details (survey included in the appendix 1)

After completing the screening questions, and conditional on the state they lived in, respondents were randomly assigned to one of three treatments. Given the length of the survey (41 pages) it was decided that each of the first three research questions would be addressed by a separate treatment. This was also based on a median completion time of 22 minutes observed during focus group testing and interviews. Separate treatments had a median completion time of 19 minutes in pilots. This allowed for each research aim to be addressed separately although it required that participants only see specific elements of the survey. This decision reduced the length of time each respondent spent completing the survey and may have reduced respondent fatigue. Both treatments were presented with an information sheet and consent form (Ethics Clearance H0016832). Table 1 provides details as to how each treatment relates to the research aims developed in this dissertation. Respondents in treatment three completed a financial literacy quiz based on the questions developed by Louviere et al. (2016) to elicit each respondent's knowledge of financial investments, a proxy measure of their financial literacy. In the next section of the survey all respondents were presented the DCE, starting with a primer on the problem of rising electricity costs. The primer read as follows:

Household electricity costs are on the rise across Australia. In the last 10 years, household electricity bills have increased by an average of 5.6% every year (ACCC, 2017). These cost increases are due to more gas being used to meet peak demand.

Renewable generation can reduce power prices (and our carbon footprint) but it is not as reliable. Households can influence change through their selection of electricity contracts.

Electricity retailers can offer tailored electricity contracts that:

- Change the amount of power sourced from renewable generation
- Limit appliance use during the evening peak period
- Install batteries to store electricity that can be accessed by the community
- Provide you with more frequent updates about the cost of powering your home

Each of these changes will impact on the future cost of energy for households. The next few pages provide information about each feature, and you will be asked a simple question relating to that feature. No one is going to contact you about your electricity contract.

Following this primer several electricity contract features were described as well as different status quo contracts which differed based on the treatment. Treatment one and three included the opt-in set of contracts and treatment two included the opt-out contracts. The contract features, but not the levels, were identical across each treatment and each respondent completed eight choice tasks each time comparing a status quo contract against two unlabelled contracts. The median completion time for the eight choice tasks across all treatments was 2 minutes and 32 seconds.

Table 1. Treatments analysed for each research aim

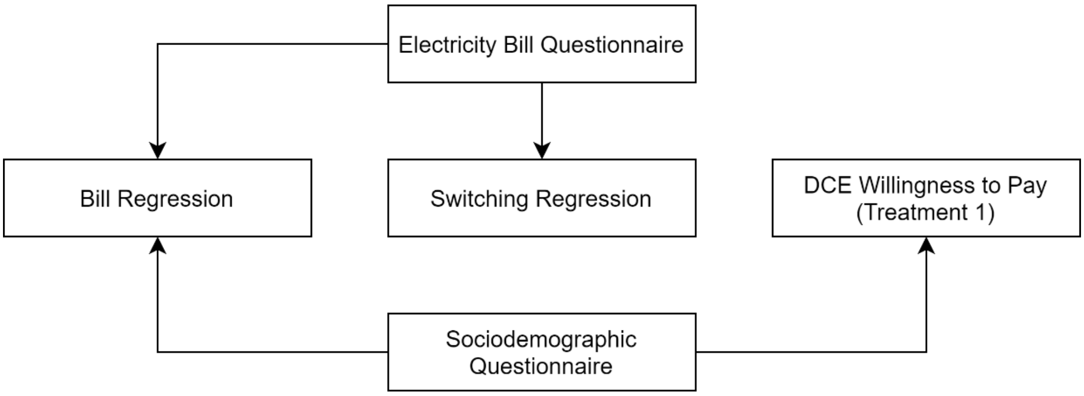
Research Aim:	Treatment Analysed:
1	1 and 2 (NSW)
2	3 (VIC)
3	2 (NSW)
4	1 (NSW)

Each treatment was unique in the experimental designs generated as well as how the status quo contracts were constructed. In treatment one and three, the status quo contracts were constructed in such a way that willingness to pay estimates could be calculated. For treatment two the role of the status quo and unlabelled contracts were reversed so that willingness to accept estimates could be estimated. After the completion of the DCE, a sub-sample of respondents were asked questions about their household's electricity use, including the size of their most recent bill and whether they had switched electricity contracts in the previous two years. The decision to not show this section to all respondents was based on early results suggesting that a quarter of the total survey time was spent completing this particular section.

Respondents in treatments one and two completed a risk preference elicitation exercise based on a multiple-price lottery game developed by Dave et al. (2010), followed by the final socio-demographic questionnaire. All treatments completed the socio-demographic questions and some attitudinal scales before finishing the survey. The placement of the quiz and risk preference elicitation exercise before and after the choice tasks was to allow for testing of conditioning effects. A comparison of the DCE results from treatments one and two is the focus of the first paper, the second paper utilises the results of the financial literacy quiz and the DCE results, and the third paper combines the risk preferences and DCE results from treatment two. In every paper a mixed logit model, with random parameters and an error component, is estimated in willingness to pay space. The first paper compares the mean parameter estimates between the two treatments, reinforcing a consistent finding in the literature with regards to differences between WTP and WTA. The second paper estimated a hybrid mixed logit model, with socio-demographic factors identified to be correlated with financial literacy, which is also correlated with the choices made in the DCE. And finally, the results of the third DCE paper suggest that highly risk-averse respondents may require additional compensation and reduced insurance associated with policies that favour price stability over reliability and green electricity.

The fourth paper in this dissertation combines the results from treatment one as part of an ABM that models the likelihood that households switch from their existing electricity contract. Figure 2 highlights how the data collected from the survey feeds into the model. The likelihood of switching in each period is a function of socio-demographic characteristics, changes in the size of bills each period, and an estimated social network effect that was based on whether neighbouring households had recently switched. Feedback effects are modelled between the decision to switch, and the electricity contract each household selects which is based on the DCE results. The simulated scenario involved three contracts that differed with respect to the amount of consumption restrictions imposed versus the additional costs of removing said restrictions. The results suggest that there are specific groups of households who will switch, with these groups defined by specific characteristics. This result demonstrates how the combination of two methodologies can be employed to obtain additional insights into household behaviours relevant for policy analysis thus reinforcing the key objective of this dissertation.

Figure 2. Survey information utilised for agent-based model



As a four-paper thesis, there will be some repetition as the papers are designed to be submitted individually to journals and have supported conference and seminar presentations. One paper is currently with Energy Economics (Paper 2: Financial Literacy, submitted 1st February 2021). As three of the papers are DCE papers there will be similarity in the modelling set-up and description of the data collection.

Chapter 2: Use of Restrictions to Manage Peak Load: Consumer Preferences and Implications for Policy

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2.1 Introduction

Climate change and energy policy are inextricably linked (Bollen et al., 2010). Climate policy remains fragmented internationally with some jurisdictions (e.g., countries, states, and cities) setting ambitious targets to reduce greenhouse gases (CO_{2e}) to achieve net zero carbon emissions by 2050 (UN Climate Change Alliance 2019). Other jurisdictions have become mired in the politics of jobs in resource extraction, resource revenues associated with coal, shale oil or oil sand projects (e.g., Australia, USA, or Canada), reliability of energy systems or lost economic growth. These issues contribute to the idea that energy policy is a deeply, divisive political issue in these countries (Pearce et al., 2017). Achieving energy security whilst meeting sustainable development targets further complicates the policy agenda (Nepal and Paija, 2019).

Investment in technologies such as wind and photovoltaic distributed generation have become a central platform of climate and energy policy of many countries (Silva et al., 2019). To achieve this transition, governments have adopted feed-in-tariffs, subsidies, and renewable energy generation targets to support investment in renewables (MacDonald and Eyre, 2018) which is counter to the push for efficiency and liberalisation of energy markets (Roques and Finon, 2017). Further, low-carbon technologies are subject to multiple sources of uncertainty, including technology types that could lead to lower costs (Wendling, 2019). Demand-side management policies exist which may be deemed a lower cost approach that achieves sustainable economic growth and an energy sector that is less reliant on fossil-fuels for electricity generation (Warren, 2018).

The purpose of this study is to investigate the acceptability of different electricity contracts with a set of Australian households. A Stated Preference (SP) approach was used, firstly, because there are non-market values associated with moving to greener technologies. Secondly, like many countries, Australia has a low proportion of renewable energy generation and minimal use of demand-side management policies. As such, a market-based observational approach is not appropriate as these contract attributes are outside the experience set of consumers. The scenarios and attributes developed for the survey require the use of willingness to accept in the form of lower cost increases and willingness to pay treatments in a Discrete Choice Experiment (DCE).

Initially we provide an overview of the literature and some context of the energy issues in Australia. The relevant components of the multiple treatment survey are described in the methods section, including details of the attributes in the DCE, the differences between treatments, the payment scenario constructed, the sampling strategy, and the experimental design. Next, the econometric models are described, and results presented. Finally, the policy implications of the results are discussed.

2.2 Background

2.2.1 Literature

Energy policy goals focusing on increasing the proportion of renewable energy generation in the energy mix, maintaining or increasing energy security, and minimising cost, constitute the energy trilemma (Brügger et al., 2015; Heffron et al., 2015; Demski et al., 2017). It has been shown in numerous studies that consumers have a positive WTP for increased renewable energy generation technologies (Mewton and Cacho, 2011; Soon and Ahmad, 2015; Sundt and Rehdanz, 2015; Ma and Burton, 2016; Borriello et al., 2019). Soon and Ahmad (2015) and Sundt and Rehdanz, (2015) are meta-analyses exploring the observed variation of willingness to pay for green electricity in existing studies and highlight many of the contextual factors that may influence differences in willingness to pay. Many factors were outlined, including the sampling design, how recent the study was conducted, and where the respondents lived were all highlighted as being important factors explaining the difference in willingness to pay. Table 1 details a list of papers post-2011 highlighting the many context factors influencing the willingness to pay for green energy. Despite differences in willingness to pay, the consensus is that households on average have a positive willingness to pay for renewable energy generation. Given existing energy generation technologies, two of the three goals (e.g., high level of reliability combined with a high proportion of renewables) in the trilemma can be achieved, however the challenge is to achieve this while maintaining affordability. For example, a more reliable network with increased renewable energy generation can be achieved through coordinated investment and systems planning (AEMC, 2020). Alternatively, costs could be held constant by maintaining the existing, coal-powered baseload generation and network infrastructure. This may, however, reduce the pace of growth in renewable energy generation and has the potential to affect the stability of the network over time. This trade-off gives rise to the first and second research questions for this study namely - Are households willing to accept less investment in renewable energy generation in exchange for lower electricity price growth (or willing to pay for an increase in renewable energy targets)? Are households willing to accept a less reliable system in exchange for lower overall costs?

An alternative to more investment in fossil-fuel generators, for example, gas-powered generators, is demand-side management policies in the form of information provision. The first policy would involve the provision of consumption information through the installation of smart meters for each household to address the salience of prices and intermittency problems associated with current billing (Gilbert and Zivin, 2014). There have been several studies that have shown a positive preference for smart meters (Gans et al., 2013; Ida et al., 2014; Pepermans, 2014). It is expected that households value these meters in the same way they value other energy saving measures, such as outdoor (e.g., solar lights) versus indoor (e.g., insulation) energy saving technologies (Poortinga et al., 2003; Banfi et al., 2008; Kwak et al., 2010). Recent papers analysing the benefits of smart meters highlight that they can often be used as a means of reducing household electricity bills by way of compensation in exchange for reduced privacy. Richter and Pollitt (2018) reported that the amount of compensation British households required varied by the degree of privacy lost through the sharing of user data with external parties. In this study we focus on the use of smart meters as a means of providing increased information, as opposed to groups outside the households using said information.

Table 1 Summary of Willingness to Pay Studies for Renewable Energy Post-2011

Author-Date:	Country:	Method:	Contextual Factors:
Abdullah and Jeanty 2011	Kenya	Contingent Valuation	Electricity source, payment vehicle, and home ownership.
Aldy et al. 2012	United States	Survey	Race, age, and political preference.
Amador et al. 2013	Spain	Discrete Choice Experiment	Experience of recent outages, education, concern for greenhouse gases, and energy saving behaviours.
Aravena et al. 2012	Chile	Contingent Valuation	Information provision.
Bhandari et al. 2020	Niger	Comparative Analysis	The ability to perform maintenance at the village level, community ownership, and information provision.
Bigerna and Polinori 2014	Italy	Ordinary Least Squares	Age, income, gender, education, household size, and policy scenario uncertainty.
Cicia et al. 2012	Italy	Discrete Choice Experiment	Renewable energy source, climate change worries. education, age, health behaviours, and past energy purchasing decisions.
Claudy et al. 2011	Ireland	Contingent Valuation	Perceptions of product characteristics, social norms, and socio-demographic characteristics.
Dagher and Harajli 2015	Lebanon	Tobit Model	Home ownership, trust in government institutions, and awareness of renewable energy.
Gao et al. 2020	Japan	Meta-analysis (Japan only)	Prefecture location and income.
Gracia et al. 2012	Spain	Discrete Choice Experiment	The type of renewable energy source.
Grösche and Schröder 2011	Germany	Discrete Choice Experiment	Levy size and fuel substitution.
Guo et al. 2014	China	Contingent Valuation	Income, electricity consumption, bid amount, and payment vehicle.
Hanemann et al. 2011	Spain	Contingent Valuation	Age and location.
Hojnik et al. 2021	Slovenia	Fuzzy-set Qualitative Comparative Analysis	Social norms, moral obligations, and knowledge of green energy.
Inanova 2012	Australia	Contingent Valuation	Renewable energy source, climate change concerns.

Table 1 (cont.)

Irfan et al. 2020	Pakistan	Structural Equation Modelling	Subjective norms, perceived behavioural control, and beliefs about renewable energy costs.
Kaenzig et al. 2013	Germany	Discrete Choice Experiment	Mix of renewable sources and location of electricity generation.
Kim et al. 2012	South Korea	Contingent Valuation	Prior experience with renewable energy.
Kontogianni et al. 2013	Greece	Contingent Valuation	Knowledge about renewable energy sources.
Kosenius and Ollikainen 2012	Finland	Discrete Choice Experiment	Attitudes on climate change and avoiding reductions in biodiversity.
Kostakis and Sardianou 2012	Crete	Logit Model	Age, gender, environmental consciousness and information provision.
Lee et al. 2017	South Korea	Contingent Valuation	Education, income, age, monthly bill amount, knowledge of renewable energies, gender, and the number of children in the household.
Liobikienė and Dagiliūtė 2021	Lithuania	Generalized Linear Regression	Environmental concern and subjective norms.
Liu et al. 2013	China	Logit Model	Income, individual knowledge levels, beliefs about the costs of renewable energy use, and age.
Mozumder et al. 2011	United States	Contingent Valuation	Total energy mix and attitude towards the environment.
Muhammad et al. 2021	Turkey	One-way Analysis of Variance	Income, environmental consciousness, age, and education.
Murukami et al. 2015	Japan/United States	Discrete Choice Experiment	Monthly bill size, greenhouse gas emissions reduction, percentage of nuclear versus renewable.
Ntatnos et al. 2018	Greece	Logit Model	Education, government subsidies, renewable expansion by the state, and institutional barriers.
Štreimikienė, and Baležentis 2015	Lithuania	Tobit Model	Information provision, employment status, income level, education, and awareness of renewable technologies.

Table 1 (cont.)

Su et al. 2018	Lithuania	Discrete Choice Experiment	Installation costs, average monthly bill, warranty period, installation considerations, and energy sharing possibilities.
Taale and Kyeremeh 2016	Ghana	Tobit Model	Monthly income, prior notice on power outages, business ownership, separate meter ownership, household size, and education.
Zhang and Wu 2012	China	Contingent Valuation	Education. Income, and location of residence.
Zorić and Hrovatin 2012	Slovenia	Censored Regression Model	Education, environmental awareness, age, and household income.

The second demand-side management policy proposed involves limiting consumption at the household level during the peak period in the evening. Consumers have been shown to be flexible in their consumption and will opt-in to price-based demand response programs (Cappers et al., 2010; Torriti et al., 2010; Kubli et al., 2018). The price signal of the program needs to be large enough for households to notice and for the programs to be successful, which is problematic since electricity consumption has been repeatedly estimated to be price inelastic (Labandeira et al., 2017). This inelasticity in electricity consumption may be related to consumption related habits and general inertia (Maréchal, 2010; Guerassimoff and Thomas, 2015; Hortaçsu et al., 2017). One alternative explored in this study is the possibility of having respondents opt into consumption limits in exchange for lower cost increase. The other treatment would have consumption limits imposed by default, requiring payment to have the limits removed. Past trials have been funded in Australia to investigate the effectiveness of imposing consumption limits based on energy signatures (ARENA, 2020a). In our study if households do not want these limits imposed, then there would be an option to opt-out at an additional cost. Alternatively, they may opt for these limits in exchange for lower price increases. Such policies could better align the costs of peak load supply with the final price paid or alternatively achieve lower power consumption during the peak period. Previous studies have looked at household preferences for this form of demand response with Broberg and Persson (2016) and Ruokamo et al. (2019) identifying that households would be willing to pay a premium in return for less control over their electricity consumption. The amount of consumption required or premium paid has been found to vary based on whether the electricity controlled relates to all uses versus just for heating (Daniel et al., 2018), the quantity and frequency of electricity controlled (Curtis et al. 2020; Broberg et al., 2021) as well as an individuals' agreement with particular social norms (Gołębiowska et al. 2020). Whether or not the premium or compensation required varies with the type of appliance is a recent issue, with Sundt et al. (2021) finding no statistical evidence that the type of appliance-control matters. In our study we postulate that it's not so much the appliance that matters, but the activities that rely on certain appliances that matter. We did not find in any of the studies reviewed evidence to suggest that activities are what mattered. It is this gap in the literature we seek to address with our proposed demand response feature.

The two demand-side management policies developed lead into the third and fourth research questions of this study namely - Are households willing to accept limits (or willing to pay to remove limits) on their energy consumption? Are households willing to forgo smart meters and better information in exchange for lower electricity bills? Compared to previous studies, the contributions are two-fold. Firstly, we focus on whether Australian households value smart meters and are influenced by consumption limits. Many of the previous studies looking at these demand-side management policies have been in European markets. Secondly, we focus on limits being imposed on activities as opposed to specific appliances or quantities of electricity.

2.2.2 Case study background - Australian market for residential electricity

Between 2008 and 2018 in Australia, residential electricity consumption grew at an average of 0.5% per annum, however in per capita terms there was an average reduction of 1.0% per annum (Department of the Environment and Energy, 2019). Meanwhile residential electricity prices increased by over 5% per annum on average (ACCC, 2018) due to several factors. In the same period, gas prices trended upwards, several coal fire power stations shut down (AER, 2018) and the national Renewable Energy Target (RET) increased to 20%. The RET is a legislated scheme which supports investments in renewable energy generation and is ultimately passed along to households, representing on average 6% of households' electricity bills in 2017-18 (AER, 2018). The additional wind and solar energy generation in Australia have been offsetting the increases in wholesale electricity prices (Csereklyei et al., 2019).

Under current national electricity rules, peak residential demand is to be met with minimal chance of load shedding (AEMC, 2018b). Recent and imminent retirement of baseload power generators, combined with greater reliance on solar and wind energy, has raised stability issues, in part due to the intermittent nature of renewable energy generators (AEMC, 2020d). High-cost solutions exist to address reliability issues, such as the installation of different energy storage technologies. These costs, however, combine with already large network costs due to the Australian energy market serving a relatively small population by international standards, spread across a large geographical area. Thus, network and distribution costs make up a large portion of the fixed cost of operations which are passed along to consumers and make up a significant proportion of household electricity bills (ACCC, 2018). Overall, these infrastructure investments ensure high reliability standards as set by the Australian Electricity Market Commission (AEMC, 2020). This significant investment is sometimes referred to as 'gold-plating' the transmission network (Bell et al., 2017).

Past studies have found that consumers are willingness to pay for improvements in service quality and supply (Morrison and Nalder, 2009; Hensher et al., 2014; Huh et al., 2015; Ozbafli and Jenkins, 2016). The primary concern for most households is that the lights turn on and appliances work when required. Further, consumers are largely unaware of the disconnect between the real-time cost in the wholesale market and the quarterly consumer bill as the regulated price is smoothed over time. One way to lower costs is to shift consumption by providing a stronger price signal such as time-of-use tariffs to encourage a consumer demand response (Gyamfi et al., 2013; ACCC, 2018). The norm for most Australian households is two-part tariffs with a fixed and variable charge (AER, 2018).

2.3 Methods

2.3.1 Survey design

The survey used in this study was developed as part of a larger, multiple treatment DCE project, investigating various aspects of consumer affordability and preferences for alternative electricity contracts. Initially, participants were provided with information as part of informed consent (Ethics Clearance H0016832). The first part of the survey described how Australian retail electricity prices have consistently increased across the country over the last 10 years, identifying some of the reasons this has occurred, followed by some warm-up questions. Participants were then introduced to the attributes included in the choice tasks with supporting rationale of the contracts to be evaluated. As standard in this literature, a reminder to carefully consider their budget and to complete the tasks as if they really had to pay, i.e., cheap talk script, (Morrison and Brown, 2009) was used to reduce the potential for hypothetical bias associated with SP and private goods (Carson and Groves, 2007). Respondents completed eight choice tasks, selecting from three different electricity contracts. Following the completion of all choice tasks, a set of socio-demographic questions were asked.

Respondents were randomly assigned to one of two treatments or versions of the survey. Each alternative in the DCE choice tasks represents a five-year contract with costs incurred over time offering different benefits. Some of the benefits were personal, for example, real-time meters provide more information to the household. Other benefits were also societal, for example increased renewables would contribute towards eliminating the externalities associated with electricity generation from fossil-fuels. The treatments share four non-cost attributes, namely - changes in the amount of power sourced from renewable energy generators, limits to appliance use during the evening peak period, installation of batteries to store electricity that can be accessed by the community, and providing households with more frequent updates about the cost of power to their home. Respondents saw a different status quo contract depending on the treatment. The list of attributes, the associated levels and status quo attribute levels for each treatment are shown in Table 2.

The policy trilemma, by definition, involves trade-offs among renewables, cost and reliability (Gunningham, 2013). Treatment one (Willingness to Accept Lower Cost Increase) specifies a renewable energy target of 60% renewables in the status quo, no consumption limits/restrictions, real-time cost information as reminders, and a fixed cost increase of $120 per month for 5 years. The non-status levels involve a lower level of services and a lower cost. Treatment two is a more traditional willingness to pay format except that it is stated that the only way to have a status quo with no cost increase requires consumption restrictions.

Table 2. Description of attributes and levels in the treatments

Attributes	Status Quo Level	Non-SQ Levels
Treatment One (Willingness to Accept Lower Cost Increase)		
Proportion of generation from renewable sources	60%	15%, 30%, 45%, 60%
Consumption restrictions	No Restrictions	Two restrictions, one restriction, no restrictions
Consumption information	Real-Time Reminders	Quarterly, daily reminders, real-time reminders
Community storage	60MWh	0 MWh, 20 MWh, 40 MWh, 60MWh
Fixed cost increase per quarterly for 5 years to your household	$120	$0, $10, $20, $30, $40, $50, $60, $70, $80, $90, $100, $110
Treatment Two (Willingness to Pay)		
Proportion of generation from renewable sources	15% (No Change from current level)	15% (No Change from current level), 30%, 45%, 60%
Consumption restrictions	Two Restrictions	Two restrictions, One restriction, No Restrictions
Consumption information	Quarterly	Quarterly, daily reminders, real-time reminders
Community storage	0 MWh	0 MWh, 20 MWh, 40 MWh, 60MWh
Fixed cost increase per quarterly for 5 years to your household	$0	$10, $20, $30, $40, $50, $60, $70, $80, $90, $100, $110, $120

During the survey period (May - June 2019), renewable energy generation constituted just over 15% of the national energy mix, with most electricity being generated from non-renewable energy sources, specifically coal. Research in the Australian market identified a target of 60% renewables by 2030 as feasible (Blakers et al., 2017), with a recent forecast suggesting that by 2030 the proportion will be 30% (De Rosa and Castro, 2020).

Australian households' peak energy consumption on average occurs between the hours of 5pm and 8pm. During this time, the cost of generation at the margin is at its most expensive (AEMO, 2018). Consumption restrictions would flatten peak demand and reduce the need to access these higher priced sources. The three activities identified as having the potential to reduce residential demand included cooking, cleaning, and entertainment. A list of common appliances associated with each activity was also detailed to provide context. Alternative contracts offered variations in the levels of use restrictions. Respondents' understanding of what these restrictions would mean for their electricity consumption habits were tested with questions and respondents were also asked to rank the activities they were most and least willing to forego during the peak period.

The community storage attribute highlighted that the batteries would serve as a substitute load source reducing the duration of blackouts. Storage technologies also have the capacity to increase the reliability of supply as the proportion of renewable energy generation technologies increases. At the time of the survey, there were 55 energy storage projects nationally, including the large-scale (100MW/129MWh) Hornsdale Power Reserve project in South Australia (Aurecon, 2018; Smart Energy Council, 2018). This battery project was widely reported in the national media for its capacity to increase energy reliability for the state with 48% wind and solar energy sources, and as a result, respondents are likely to have been aware of the potential for such battery projects (Sonali, 2017). Recent research suggests that 100kW-1MW community battery installations in Australia are likely to be financially viable from a cost-benefit perspective (Australian Renewable Energy Agency, 2020b).

Finally, smart meter technology was included as a demand-side management feature which would allow households to access their consumption information more frequently. Currently, most households only receive this information with their quarterly bill. Alternative technologies discussed included those which would allow current consumption information to be reviewed by households either once a day or in real-time.

The cost for each contract was defined as an increase in the fixed component of the household's electricity bill, paid every quarter for five years. Determining the appropriate cost levels was through focus groups, interviews, and a pilot study. The cost level for the status quo varied depending on how the status quo was described. In treatment one (Willingness to Accept Lower Cost Increase), the status quo was described as the future default electricity contract that would be offered if current trends in energy investments continued. This contract included the maximum level of battery storage and renewables as part of the national energy mix, as well as real-time billing information and no consumption restrictions. In this treatment, respondents could opt-out of this contract by selecting contracts which were cheaper than the status quo but led to lower levels of the non-cost attributes. The framing of these alternative status quos was tested using the methods discussed previously with no issues in comprehension noted.

Figure 1. Example status quo explanation and choice task - treatment one (Willingness to Accept Lower Cost Increase)

Cost to you

Based on current trends in energy investment we expect a future with more renewables, batteries, smart meters, and consumption during the peak period will not be affected. If you select "No change":

60% **of total generation** will be from renewable sources — 60%

There will be a **significant investment** in community batteries — 60 MWh

No consumption activities will be limited during the peak period. — No Limit

There will be large investment in updated smart meters
Consumption information will be **real-time** — Real-Time

This will lead to an additional cost of $120 per quarter for **the next five years**. The other contract options will also lead to less investment, however the cost increase will be smaller than the "No change" option.

$120 per quarter -----> $480 a year -----> $2400 over five years

Features	Option A No change	Option B	Option C
% of Renewable Generation	60%	30%	45%
Consumption Limits	No Limit	Low Limit	No Limit
Community Storage	60 MWh	60 MWh	20 MWh
Consumption Information	Real-Time	Quarterly	Daily
Average bill increase per quarter over the next five years	$120 per quarter	$40 per quarter	$20 per quarter

Figure 2. Example status quo explanation and choice task - treatment two (Willingness to Pay)

Cost to you

Based on current energy investments, we expect a future with the same levels of batteries, renewables, and smart meters. This will lead to less available energy during the peak period.

If you select "No change":

There will be **no new generation** from renewable sources — 15%

There will be **NO** new community batteries — 0 MWh

Two consumption activities will be limited during the peak period. — High Limit

There will be **NO** new smart meters
Consumption information will be **quarterly** — Quarterly (Mar, Jun, Sep, Dec)

This will lead to no additional cost for households over the next five years. The other contract options will lead to the **quarterly fixed cost** of your bill increasing over the **next five years**.

$40 per quarter -----> $160 a year -----> $800 over five years

Features	Option A No change	Option B	Option C
% of Renewable Generation	15%	30%	45%
Consumption Limits	High Limit	Low Limit	No Limit
Community Storage	0 MWh	60 MWh	20 MWh
Consumption Information	Quarterly (Mar, Jun, Sep, Dec)	Quarterly (Mar, Jun, Sep, Dec)	Daily (2pm: Meter Update)
Average bill increase per quarter over the next five years	$0 per quarter	$40 per quarter	$20 per quarter

In treatment two (Willingness to Pay), the status quo contract specified no increased investment in renewable energy or storage activities (as a proportion of the current energy infrastructure mix), consumption information being provided quarterly, and two consumption activities being restricted for each household. It was described to respondents as the most likely situation if there were to be no increase in the fixed costs of electricity bills. This was the only zero-cost contract available in this treatment, with the other contracts involving positive costs up to a maximum of $110 a quarter.

2.3.2 Experimental design

An efficient design was initially developed using parameter estimates obtained from the literature for renewable energy investments (Brennan and Van Rensburg, 2016; Ozbafli and Jenkins, 2016). For the other attributes, consumption limits, storage, and consumption information, no priors were available, so the parameters were calibrated to ensure utility balance and no dominated alternatives (Scarpa and Rose, 2008; Bliemer and Rose, 2016). All designs were generated using Ngene version 1.1.1 (ChoiceMetrics, 2012). Data from a pilot survey was used to estimate a simple multinomial logit model and the parameter estimates were used to update the priors for the final Bayesian D-efficient design. The final design included 48 choice tasks divided into six blocks with eight tasks. The final design has a simulated Bayesian D-efficient error of 0.003343 for treatment one and 0.002851 for treatment two.

2.3.3 Sampling

A stratified random sampling method was utilised for this survey in New South Wales based on gender, age, and urban versus non-urban (e.g., Sydney metropolitan area versus the rest of the state). The survey was administered online by Online Research Unit (ORU) (http://theoru.com/), an Australian panel provider. ORU is one of the largest panel providers in Australia. ORU continuously refreshes its panel using a combination of techniques (e.g., online and offline). Respondents were sent a general invitation to complete the survey, as well as three follow-up reminders. Screening criteria excluded renters and required participants to live in a detached house and be responsible for paying for the household's electricity bill. The choice to exclude renters was due to the plausibility of whether the cost of smart meter installation would be incurred by the renter.

2.4 Econometric Model

A Random Utility Model (RUM) is used to model household preferences for alternative electricity contracts. It is assumed in the RUM that each household selects from a discrete set in such a way that maximises utility. For each household *n* facing *c* choice tasks consisting of *j* alternatives. Each of these alternatives has an associated utility level, $\mathrm{U_{ncj}}$, which can be shown as:

$$\mathrm{U_{ncj}} = \mathrm{V_{ncj}} + \varepsilon_{\mathrm{ncj}}\ \forall\, \mathrm{j}, \mathrm{j} = 1, 2, .., \mathrm{J} \tag{1}$$

with $\mathrm{V_{ncj}}$ representing the observable component of utility and $\varepsilon_{\mathrm{ncj}}$ the unobserved component, which for the logit specification is a type-1 extreme value error term. Consequently, this specification only allows for probabilistic statements to be inferred from households' choices. Therefore, the probability that an individual selects alternative *j* for any choice task can be shown as:

$$\mathrm{P_{njc}} = \mathrm{Prob}\left(\mathrm{V_{ncj}} + \varepsilon_{\mathrm{ncj}} > \mathrm{V_{nci}} + \varepsilon_{\mathrm{nci}}\right) \forall\, \mathrm{j} \neq \mathrm{i} \tag{2}$$

Assuming a linear in parameters specification for the observable component of utility we can show this component as a function of attribute levels $\mathrm{x_{njc}}$, socio-demographic variables z_{n}. For every attribute and socio-demographic variable, a set of parameter vectors, β and θ, are estimated. Following the derivation by McFadden (1974) the probability of individual *n* in choice task *c* selecting alternative *j* can be shown as:

$$\mathrm{P_{njc}} = \frac{\mathrm{e}^{\beta \mathrm{x_{njc}} + \theta \mathrm{z_n}}}{\sum_{\mathrm{i}} \mathrm{e}^{\beta \mathrm{x_{nic}} + \theta \mathrm{z_n}}} \tag{3}$$

Equation (1) represents a function estimated in utility-space. Without interaction terms, the willingness to pay for each attribute *k* is defined as:

$$\mathrm{WTP_k} = -\frac{\beta_{\mathrm{k}}}{\beta_{\mathrm{c}}} \tag{4}$$

where, β_c is the estimated cost parameter for the cost contract feature. WTP is the ratio of parameters, therefore the standard error and covariance terms are required to determine whether each estimate is statistically significant. Given that one of the objectives of this study is to estimate the WTP for the non-cost attributes we can instead directly estimate the utility function in preference space (Train and Weeks, 2005; Scarpa et al., 2008).

Rewriting (1) we can now estimate the utility function as:

$$U_{njc} = -\beta_c p_{njc} + \omega x_{njc} + \mu z_n + \varepsilon_{njc} \tag{5}$$

where, p_{njc} is the attribute level for cost and ω represents the ratio of each non-cost parameter with the cost coefficient, and μ is the equivalent parameter for the socio-demographic variables. Direct estimation in willingness to pay space avoids the need to calculate the analytical approximation of the standard errors for parameters estimated in utility space (Daly et al., 2012). Therefore, the parameters and their associated standard errors can be used to test for statistical differences in parameters between models by comparing the confidence intervals of identical features between treatments. Using the 95% level of confidence, we have sufficient evidence to say that the estimates are different if their confidence intervals do not overlap.

One of the consequences of using the error term specified is that the estimated parameters are fixed, and preferences are therefore assumed to be homogeneous. This assumption can be relaxed by specifying a Mixed Multinomial Logit Model (MMNL) such that:

$$B_{nk} = \beta_k^m + \beta_k^s \tau_{nk} \tag{6}$$

where, B_{nk} is a population-level estimate composed of the mean preference for the attribute β_k^m, and β_k^s the spread of the parameter estimate. The final component τ_{nk} represents an error term that in part determines the shape of the distribution for each parameter. For every non-cost parameter, a normal distribution is specified. One issue with defining WTP as the ratio of two normally distributed parameters is that the mean and variance are not defined when the cost parameter equals zero (Bliemer and Rose, 2013). This issue was avoided by specifying a lognormal distribution for the cost attribute. All models estimated include j-1 alternative specific constant for the status quo (ASC status quo) and the third alternative (ASC Option C). ASC Option C is useful for detecting right-side bias. Socio-demographic variables included in the status quo alternative include gender, age, and education. Gender is a dummy variable equal to one for female, age is continuous, and education was also coded as several dummy variables representing the highest level of education attained. The base level is high school education, with each variable representing diploma (e.g., trade education), undergraduate, and postgraduate. Finally, the non-status quo alternatives include an error component. Both parameters have been included to test whether any status quo bias exists in the choice experiment (Scarpa et al., 2007). The error component is estimated as a normally distributed error term with zero mean, specifically addressing the potential source of correlation between the non-status quo alternatives (Herriges and Phaneuf, 2002). This correlation can arise due to the difference in substitution patterns when the non-status quo alternatives versus the status quo (Scarpa et al., 2007). The error component, ASCs, and socio-demographic interaction parameters are estimated in willingness to pay space.

The error term τ_{nk} is simulated as integrating over tau leads to no closed form solution for the MMNL. Therefore, the log-likelihood function is solved using maximum simulated likelihood, with the solution to equation (2) being shown as:

$$LL(\beta') = \sum_{n=1}^{N} \ln\left[\frac{1}{R}\sum_{r=1}^{R}\prod_{j=1}^{J}\prod_{c=1}^{C}\left(P_{njc}^{r}\right)^{y_{njc}}\right] \quad (7)$$

with y_{njc} representing the actual choices made and *r* the number of draws used for simulation. The draws are taken for the tau’s included in equation (6), with the probabilities calculated for each set of draws. The draws were sampled using Modified Latin Hypercube Sampling (Hess et al., 2006) with 5,000 draws to ensure the stability of parameter estimates. The final models were estimated using Python Biogeme (Bierlaire, 2016) with supporting code from Rose and Zhang (2017).

2.5 Results

Table 3 highlights the descriptive statistics of the sample, relative to the state, based on the latest 2016 census. For age and gender, we find there is no statistically significant difference between the sample and census proportions in New South Wales (α = 5%). Minor variations were noted due to difficulties with meeting quota targets for some of the categories, specifically young women. In total, 302 respondents were obtained for treatment one and 300 for treatment two. In both treatments, households were most willing to reduce/change when they undertook cleaning activities away from the peak periods and least willing to reduce/change cooking, with entertainment being the intermediate activity. These questions were asked prior to the choice tasks.

Table 3. Descriptive statistics

	Rest of New South Wales				Greater Sydney			
	Men		Women		Men		Women	
Age	**Sample**	**Census**	**Sample**	**Census**	**Sample**	**Census**	**Sample**	**Census**
18-29	2.33%	2.66%	1.83%	2.66%	6.64%	6.98%	5.81%	6.81%
30-44	4.32%	3.82%	4.48%	3.99%	10.47%	9.80%	10.30%	9.80%
45-59	3.82%	4.49%	4.49%	4.65%	8.31%	7.81%	8.64%	8.14%
60+	6.31%	5.81%	5.98%	6.31%	7.97%	7.64%	8.31%	8.64%
Activity Most Willing to go Without					**Treatment One**		**Treatment Two**	
Cleaning					81.33%		84.44%	
Cooking					8.67%		7.28%	
Entertainment					10.00%		8.28%	
Activity Least Willing to go Without								
Cleaning					7.00%		5.30%	
Cooking					54.33%		57.62%	
Entertainment					38.67%		37.09%	

The choice frequencies for each treatment are shown in Table 4. Across both treatments, most of the choices made were for the non-status quo alternatives. For treatment two (Willingness to Pay), over a third of respondents chose the zero-cost status quo, even though this alternative involved two consumption restrictions being imposed on the household. A test of the difference in proportions between treatments suggests that the status quo was chosen less for treatment one (Willingness to Accept Lower Cost Increase) and that the difference is statistically significant ($t=15.44$, $p<0.001$). This may be, in part, due to the status quo being the highest cost alternative, including no consumption restrictions with all non-cost attributes being set at their maximum level. Approximately 26% and 57% of all choices respectively made in each treatment involved an alternative which imposed two consumption restrictions on the households.

Table 4. Proportion of alternatives selected

Alternative Selected:	Treatment One (Willingness to Accept Lower Cost Increase)	Treatment Two (Willingness to Pay)
Option A (Status Quo)	16.4%	36.0%
Option B	45.4%	34.3%
Option C	38.2%	29.7%

The second column of Table 5 reports the mixed logit model results of the willingness to accept lower cost increase treatment. All the mean parameters, except for the daily reminders attribute, have signs in line with economic theory and are statistically significant. The daily reminders attribute is negative and statistically significant. This implies that disutility is associated with daily reminders and respondents would pay to remove this feature from the fixed cost of their contract. The alternative-specific constant is negative, suggesting that there is unobserved heterogeneity that leads respondents to select away from the status quo alternative. The standard deviations show that there is preference heterogeneity within the sampled population (Hensher et al., 2015). A significant error component suggests that respondent's trade-off between the non-status quo alternatives differently relative to the status quo. For the status quo, the age coefficient is positive, suggesting that older respondents are more likely to select the status quo. Gender is also significant, suggesting that women are relatively less likely to select the status quo. Finally, for the education parameters, only the undergraduate education coefficient is insignificant, with those respondents with diplomas less likely to select the status quo and those with postgraduate degrees more likely.

The third column of Table 5 reports results related to the willingness to pay treatment. Except for the daily reminders attribute, all the estimated coefficients on attributes have the expected sign and are statistically significant. The ASC for the status quo is the same sign as for treatment one, but it is relatively smaller. This result is not surprising given the higher choice frequency for this treatment reported in Table 3. In terms of the standard deviation parameters, most are statistically significant. The error component is also significant for treatment two. The coefficients for the socio-demographic factors suggest that older and female respondents are more likely to select the status quo and only those respondents with a diploma education level are less likely. Finally, compared to respondents with high school education, respondents who attained an undergraduate or postgraduate level of education were more likely to select the status quo, however, only the former level is significant. In terms of model diagnostics, there are minor differences in terms of the final log-likelihood for each treatment. The AIC and BIC coefficients, alternative methods for evaluating model fit between models, suggest that the willingness to pay model is a slightly better fit.

Table 5. MMNL estimated in Willingness to Accept Lower Cost Increase/Willingness to Pay- space by treatment

Variable	MMNL -Treatment One (Willingness to Accept Lower Cost Increase) Coef. (Robust Std. Error)		MMNL -Treatment Two (Willingness to Pay) Coef. (Robust Std. Error)	
Mean Parameters				
Daily Reminders	-1.811***	(0.209)	-0.757	(0.464)
Real-Time Reminders	5.597***	(0.220)	4.371***	(0.197)
One Consumption Restriction	9.543***	(0.196)	5.855***	(0.407)
No Consumption Restrictions	18.278***	(0.238)	10.422***	(0.404)
Renewable Generation	0.598***	(0.010)	0.342***	(0.011)
Storage	0.239***	(0.003)	0.127***	(0.014)
Household Cost ($/year)	-2.873***	(0.230)	-2.249***	(0.321)
ASC (Status Quo)	-107.151***	(2.291)	-44.978***	(1.133)
ASC (Option C)	-7.950***	(0.207)	-3.323***	(0.354)
Standard Deviation Parameters				
Daily Reminders	0.756***	(0.084)	5.018***	(0.192)
Real-Time Reminders	8.486***	(0.112)	8.515***	(0.309)
One Consumption Restriction	20.388***	(0.168)	14.313***	(0.413)
No Consumption Restrictions	34.996***	(0.291)	18.877***	(0.182)
Renewable Generation	0.935***	(0.008)	0.656***	(0.008)
Storage	0.466***	(0.006)	0.356***	(0.006)
Household Cost ($/year)	2.501***	(0.391)	1.944***	(0.502)
Error component	145.516***	(1.571)	64.082***	(1.690)
Status Quo Interactions				
Age	0.299***	(0.018)	0.319***	(0.013)
Gender	-3.660***	(1.062)	-0.678	(0.452)
Diploma	-3.140***	(0.914)	16.041***	(0.480)
Undergraduate	-1.818	(1.290)	-15.222***	(0.757)
Postgraduate	5.6111***	(0.835)	-1.169	(0.715)

Table 5 (Contd…) Variable	MMNL -Treatment One (Willingness to Accept Lower Cost Increase) Coef. (Robust Std. Error)	MMNL -Treatment Two (Willingness to Pay) Coef. (Robust Std. Error)
Diagnostics		
No. of Observations	2,416	2,400
Log-Likelihood	1,836.446	1,832.26
AIC	3,716.892	3,708.526
BIC	3,798.375	3,790.009
McFadden Pseudo R^2	0.308	0.305

*** 1% significance ** 5% significance * 10% significance.

Table 6 reports the results of tests for differences between the willingness to pay and willingness to accept lower cost increase parameter distributions. The null hypothesis of equality of mean preferences is rejected for all attributes, except for the daily reminders attribute, with the willingness to accept lower cost increase treatment having a larger coefficient. This implies that respondents need to be compensated more for reductions in the attribute levels, relative to the willingness to pay an equivalent.

Table 6. Estimated mean marginal Willingness to Accept Lower Cost Increase/Willingness to Pay and 95% confidence intervals

Attribute	Willingness to Accept Lower Cost Increase Treatment	Willingness to Pay Treatment	Parameter Difference?
Renewable Generation: 10% Decrease (Increase)	$5.99 [$5.78, $6.18]	$3.42 [$3.20, $3.64]	Yes
Storage: 10MWh Decrease (Increase)	$2.39 [$2.33, $2.45]	$1.27 [$1.00, $1.54]	Yes
Restrictions Imposed: One Restriction	$9.54 [$9.16, $9.93]	$5.86 [$5.06, $6.65]	Yes
No Restrictions	$18.28 [$17.81, $18.74]	$10.42 [$9.63, $11.21]	Yes
Daily Reminders	-$1.81 [-$2.22, -$1.40]	Not Significant	Yes
Real-Time Reminders	$5.60 [$5.17, $6.03]	$4.37 [$3.98, $4.76]	Yes

2.6 Conclusions and Policy Implications

Central to this study and the four research questions posed are the preferences of Australians for trade-offs inherent in the energy policy trilemma. We present two different scenarios in the form of treatments to unravel the complexities of preferences and to provide information to support infrastructure decision-making. In treatment one, households were presented with a non-trivial “rebate” (our willingness to accept lower cost increase) in the form of a stream of lower future fixed cost increases in exchange for varying lower targets in renewables, reliability, information, and less freedom in appliance usage and household activities. In treatment two, households were presented with a status quo contract which involved no additional fixed costs and two consumption restrictions imposed versus contracts leading to increases in service provision but with a stream of higher costs.

When considering the renewable energy generation attribute in both treatments, the estimated coefficient for renewables was statistically significant and the expected sign. This result is consistent with past willingness to pay studies reporting a consistent positive preference for more renewable energy generation (Ma et al., 2015; Soon and Ahmad, 2015; Sundt and Rehdanz, 2015). The premium Australian households are willing to pay on top of the average household electricity bill, is relatively small compared to other studies, e.g., German households are willing to pay a premium of up to 16 % (Kaenzig et al., 2013). Our results suggest a small additional premium noting the existing contribution Australian households make towards renewable energy investments, specifically through the RET (Department of Industry, Science, Energy and Resources, 2020). It may also be that since renewables are already perceived to be leading to reduced costs, there may not be any perceived benefit to providing additional funding as part of their current electricity bill. AEMO has noted that more battery storage and virtual power plants (interconnected energy resources) will be required as more renewables are installed (AEMO, 2020b).

The result for the storage attribute is consistent with past studies analysing preferences for energy reliability. One of the benefits related to battery storage is the potential flexibility in the management and operation of power systems to reduce the likelihood of a blackout event. Previous studies have shown that the premium paid varies according to the duration of blackouts avoided (Goett et al., 2000; Abdullah and Mariel, 2010; Pepermans, 2011; Amador et al., 2013). It has also been shown that willingness to pay is related to the time of day and season (Carlsson and Martinsson, 2008). Historically, the NSW grid has been very reliable, however nationally there have been rare instances of storm damage and localised load-shedding during sustained heat waves. This may explain why the WTA-LCI/WTP for this attribute is small, relative to the other attributes. From a policy perspective, this result also shows that there is public support for battery technology at the community level. Beyond the capacity to reduce the duration of blackouts, battery storage is increasingly being studied as a means to support renewable energy generation technologies (Cebulla et al., 2018; Hartner and Permoser, 2018; Soini et al., 2020).

Consumption limits have the highest willingness to accept lower cost increase estimates relative to other attributes in treatment one. Households in treatment two, similarly have a higher willingness to pay to remove restrictions relative to the other attributes in the treatment. Households required a larger rebate in the form of lower cost increases when compared to the willingness to pay to remove consumption restrictions. A recent study by Srivastava et al. (2020) also measures the compensation required to enrol in similar demand management programs, using Belgian households. Their case study focuses on multiple attributes associated with a specific demand-side management program, such as varying time lengths and different appliances being restricted. In our study, the focus is different as we vary the number of activities that are restricted during the peak period. Regardless of this difference, there is a similarity in the size of the results, with their main result suggesting that households require 41€ ($67.44 AUD[2]) per year to participate in a daily demand-side management program. This amount lies between the two estimates we obtained when considering the two consumption limit level estimates (converted to annual measures) of $73.12 and $41.68 in our study. Despite differences in the size of estimates, our study further supports the idea that households are willing to participate in demand-side management policies if they are compensated appropriately.

[2] Euro to AUD conversion rate calculated based on the EURAUD:CUR closing spot price 30th September 2020.

In Australia, there have been projects funded by the Commonwealth government to test the feasibility of several demand-side management programs (Australian Renewable Energy Agency, 2020). One limitation of these programs was that they were developed as trials with a high degree of self-selection. Our sample may be more representative of wider community preferences in so far as our respondents received a general invitation to answer a survey (limitations of online panels and DCE notwithstanding). International examples of similar programs were found to be effective only if consumers are price sensitive (Frondel and Kussel, 2019). It was also reported that for these programs, the opt-in rates were significantly lower relative to those trials where customers could opt-out (Parrish et al., 2019). Indirectly the findings of this study support the idea that respondents prefer to opt-out of demand-side management programs and require compensation to participate. It could also indicate that households may not be aware of ways that they could reduce their demand. This contract feature could be beneficial for utilities, depending on whether the revenue generated (increased revenue foregone) from removing (imposing) consumption limits would offset the projected costs (saved) of reducing peak demand.[3]

For the second demand-side management policy, the installation of smart meters, households' value smart meters that provide real-time feedback. The non-significant result for daily reminders may be due to the infrequency of the information received, relative to the real-time reminders. This is consistent with previous studies which have shown that feedback is most effective when it is provided frequently since they become aware of ways they could reduce their consumption (Fischer, 2008; Gleerup et al., 2010; Gans et al., 2013). Therefore, the negative willingness to accept lower cost increase results for the daily reminders could be interpreted as households perceiving the daily reminder as being potentially annoying.

Previous studies have shown that one of the key drivers of consumers adopting smart energy technologies is the perception that it will lead to lower bills (Wilson et al., 2017; Rausser et al., 2018). In our study, we note the potential for the experience of the neighbouring state of Victoria to be at work.

[3] This comparison is assumed for a vertically generated utility, where both the costs of generation and selling electricity are both incurred by the utility.

The rollout of smart meters in Victoria was promoted as a means of reducing industry costs related to ensuring a reliable supply of energy. Eventually, these cost savings were expected to lower prices for consumers, but according to the Victorian Auditor General (2015) this rollout had no effect on prices, and consumer benefits were not realised. Given the low willingness to pay for smart meters, a more effective policy would beto target installation to households that are energy-aware and actively focused on reducing their electricity bills, rather thana wide-spread installation of smart meters.

The previous discussion highlights that households are willing to pay more for a greener and more reliable energy system as well as support demand-side management policies. Differences in model results across both treatments raise the question - which set of results should be used in benefit-cost analysis. The disparity between the willingness to accept lower cost increase and the willingness to pay results is not surprising in the context of the wider environmental SP literature. It has been observed in numerous studies that there is a disparity between the two measures, so much so that several meta-analyses have focused solely on identifying the causes of these differences (Horowitz and McConnell, 2002; Sayman and Onculer, 2005; Tuncel and Hammitt, 2014). Explanations offered include a lack of substitutes (Hanemann, 1991), commitment costs (Zhao and Kling, 2001, 2004), bounded rationality (Hoehn and Randall, 1987), mental accounting (Thaler, 1985; Mishan and Quah, 2007) and, prospect theory (Barberis, 2013).

In this study, the difference in estimates for specific attributes across treatments is driven, in part, by the description of the status quo. This allows the methods and results to be used in settings with different infrastructure investment or demand-side management policies. Depending on the investment being considered and tolerance for the error, the estimates can be transferred, or our general DCE setup utilised to explore preferences in other settings. For example, there are situations where access to short term fossil fuel generators is being evaluated, such as the Japanese government opting to shift its nuclear/fossil-fuel/renewable energy targets post-Fukushima (Chapman and Itaoka, 2018). The WTA-LCI estimates or treatment setup may be useful and appropriate if the benefit-cost analysis for the storage attribute focuses on reductions in the reliability of the network. The WTP treatment could be an appropriate measure to use if the focus is on estimating the benefits from a more reliable grid in a developing country context. Finally, future studies could address some of the limitations of this study. The sampling frame excluded renters who may have different preferences from homeowners. The most important features are those related to removing restrictions. This may have led to a two-stage decision-making process where certain restriction levels were excluded and then the other features evaluated. Significant preference heterogeneity was noted for all features despite the means being statistically different.

Chapter 3: Measuring the Impacts of Financial Literacy on Electricity Contract Choice

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3.1 Introduction

Residential electricity prices in Australia increased by over 5% per annum on average between 2008 and 2018, with a small decrease occurring in real terms during 2018-19 (ACCC, 2018, 2019). In the decade prior to 2018, residential electricity consumption grew at an average of 0.5% per annum, however, in per capita terms, there was an average reduction of 1.0% per annum (Department of the Environment and Energy, 2019). This presents a challenge for achieving policy objectives focused on minimising costs, maintaining a reliable energy system, and transitioning towards a low-carbon economy. These objectives make up the three competing elements of the Energy Trilemma (Song et al., 2017). Australian households have been facing higher electricity prices as a consequence of ensuring high reliability of the network and supporting low-carbon transition.

Australian retail electricity prices are regulated, where retailers are required to justify changes in retail prices (AER, 2020). Regulators in the United Kingdom and Australia have increasingly been focusing on how households perceive the value of services provided by utilities (Essential Services Commission, 2016; ACCC, 2019). This in part is achieved by retailers offering retail electricity contracts in line with household preferences. Regulators have been hesitant to approve new contracts offered by retailers unless it is clear that they are in the best interests of consumers over time. One objective of this study is to evaluate whether in the service offerings represent value for money from the average household's perspective.

A Discrete Choice Experiment (DCE) was developed to evaluate different energy contracts and obtain Willingness to Pay (WTP) estimates for various contract characteristics using the case study site of the retail energy market of Victoria, Australia. These characteristics represent investments in energy infrastructure as well as the implementation of demand-side management policies. A DCE allows for the estimation of non-market values, for example, household preferences for a greener electricity mix. This method also allows for the evaluation of new or improved contract features which cannot be assessed using existing market data.

By employing these methods, the goal is to obtain reliable estimates of household preferences that could support public decision-making. Decision heuristics and preference heterogeneity are two sources of variation that could affect the reliability of these estimates (Yoo and Ready, 2014). One potential source of variation explored in this study is to understand the role of financial literacy in providing the context for evaluating choices between different electricity contracts. Financial literacy could influence the perceived benefits of various contract features and may be correlated with an individual's propensity to focus on the upfront costs of a feature and discount the benefits realised over time. There is some evidence that this is the case for decisions evaluating alternative energy-efficient appliances (Kalbekken et al., 2013). In this study, they found that providing information on the lifetime energy cost of tumble drivers led to consumers being more likely to purchase energy-efficient versions of the appliance. If financial literacy does influence the choices made between alternative features, then it could explain why some features fail to gain public support even when the feature is justified as an investment leading to future benefits such as lower energy prices. This can also create problems for regulators who may believe the features are not valued as much as they would otherwise be, leading to underinvestment in new technologies.

Respondents completed a financial literacy quiz as part of the survey instrument employed, developed by Louviere et al. (2016). Since financial literacy is inferred rather than observed, the respondents' quiz score is used as a proxy indicator of their financial literacy. We estimate a hybrid choice model to account for potential measurement errors in this proxy and to identify correlations between the socio-demographic characteristics of a respondent with their quiz score.

The DCE was designed to support decision-making processes, for example informing firms whether their consumers will fund investments in energy infrastructure, or perhaps assist regulators in determining whether households' value similar contract features (Khosroshahi et al., 2021). The results suggest that a respondent's financial literacy influences how respondents evaluate contracts within the DCE. Lower levels of financial literacy are found to lead to lower stated willingness to pay for all contract features.

3.2 Background

Over the last 20 years, there have been numerous studies analysing consumers' willingness to pay for policies that reduce $\mathrm{CO}_{2-\mathrm{e}}$ emissions, including increased investment in renewable energy generation technologies (Roe et al. 2001; Alberini et al., 2018). One of the issues related to increased renewable energy generation is that they are often intermittent in nature, which is especially problematic when these sources of energy generation replace baseload generation technologies (Edenhofer et al., 2013). One solution to this problem is the installation of battery storage technology to allow low marginal cost renewable energy to be stored and sold in the peak period when demand is at its highest (Sioshansi, 2010; Ratnam et al., 2015; Hanser et al., 2017). Rather than focusing on the trading opportunities related to storage technologies, they can also be perceived as additional investments that increase the reliability of the existing supply (Kaschub et al., 2016; Comello et al., 2018). It may also be possible to ensure that the electricity network is more interconnected. It is important to note that given the population distribution and physical distance between towns and cities in Australia, this may not reflect the most cost-effective option.

In addition to supply-side investments, demand-side management policies could reduce or shift demand away from the usual peak periods in the evening when generation is sourced from peak-load generators (Broberg and Persson, 2016). Numerous market-based instruments have been developed over time, with mixed results regarding their efficacy in reducing or shifting aggregate consumption (Strbac, 2008; Richter and Pollitt, 2018). One specific problem relates to customer inertia, in that consumers tend not to actively review and change their electricity contracts to reduce costs (Yang, 2014; Hortaçsu et al., 2017; Giraudet, 2020). These observed behaviours have been postulated as one potential explanation for the observed energy-efficiency gap (Jaffe and Stavins, 1994; Gillingham and Palmer, 2014). Some studies have observed that consumers do value having additional information about their electricity consumption, even if it does not prompt them to search for cheaper contracts (Gerpott and

Paukert, 2013; Kaufmann et al., 2013; Buchanan et al., 2016; Richter and Pollitt, 2018). It is possible that having access to more information represents an investment that could be used to manage consumption over time.

There is a growing literature analysing consumers' willingness to be flexible in their consumption habits to reduce electricity costs in exchange for the disutility associated with changing habits (Kubli et al., 2018). This research, however, focused on prosumers, households that both produce and consume electricity (Bergman and Eyre, 2011; Parag and Sovacool, 2016). As of 2021 in Australia, this represents around 30% of all Australian households who have rooftop solar photovoltaics installed (Department of Industry, Science, Energy, and Resources, 2021b). Related to this research focus is the scope for policies that encourage flexibility with respect to household consumption habits, irrespective of the availability of prosumer technologies. Tjørring et al. (2018) also found that households were willing to shift their use of cleaning appliances to different times. Finally, Ruokamo et al. (2019) found that households required compensation for having their electricity consumption affected during the evening. This study explores the respondent's WTP to avoid the need to change existing behaviour and for energy investments.

The study further explores the extent to which the respondent's financial literacy influences the consistency of choices made between contracts selected in the DCE. We define consistency as the variance in the error term for a consumers' utility function (Dellaert et al., 1999). It is postulated in this study that financial literacy is correlated with consistency, that is, respondents who are more financially literate make more consistent choices (smaller error variance) relative to those who are less financially literate. In this study we see if financial literacy is a determinant of how consistent households are when evaluating different electricity contracts, using Australia as a case study.

Financial literacy is important since it determines an individual's capacity to evaluate financial information. It has been shown to be correlated with effective retirement planning and positive savings behaviour (Behrman et al., 2012; Clark et al., 2015). It has also been shown as a predictor for determining the ability of individuals to make investment decisions (Stolper and Walter, 2017). Meier and Sprenger (2013) investigate the relationship between financial literacy and time preferences. They find that individuals who participate in financial education programs have relatively lower discount rates when making investment decisions. Sutter et al. (2013) designed an incentivised experiment eliciting children and adolescents' time preferences, with their results suggesting a link between impatience (higher discount rates) and poor saving choices. This link is also suggested in Lührmann et al. (2018), where a statistically significant relationship was found between financial education and the proportion of time-consistent choices. A recent paper by Brent and Ward (2018), the only study identified in the literature that identifies a link between choice and financial literacy within choice experiments, finds that financial literacy influences the consistency of choices made when evaluating alternative hot water systems. Respondents who were less financially literate were more likely to purchase systems that had a lower upfront cost, but higher running costs over time. In this study our contribution to this literature is twofold. Firstly, it is one a few papers that expands on the idea that financial literacy may be important to account for when households evaluate DCEs. Secondly, to the best of our knowledge, it may be the only study to evaluate whether financial literacy is a factor in decision-making when households evaluate alternative electricity contracts.

3.3 Methods

3.3.1 Model specifications

A random utility framework underpins our model of consumer preferences for electricity contracts. With this framework, each decision maker *n* is expected to obtain a level of utility from a specific alternative *j* for choice task *c* equal to $\mathrm{U_{njc}}$. The most common functional form assumed is a linear relationship among attribute levels for each alternative and their respective parameters, as shown in equation (1):

$$\mathrm{U_{njc}} = \beta' \mathrm{x_{njc}} + \varepsilon_{\mathrm{njc}} \ \forall \ \mathrm{j}, \mathrm{j} = 1, 2, .., \mathrm{J} \tag{1}$$

Based on this specification, $\mathrm{x_{njc}}$ is a matrix of attribute levels and β' represents a vector of parameters to be estimated, and $\varepsilon_{\mathrm{njc}}$ is the unobserved error term. Following the approach in McFadden (1974), our equation (2) shows that the probability of individual *n* selecting alternative *j* in choice task *c* as:

$$\mathrm{P_{njc}} = \mathrm{Prob}\left(\mathrm{V_{ncj}} + \varepsilon_{\mathrm{ncj}} > \mathrm{V_{nci}} + \varepsilon_{\mathrm{nci}}\right) \forall \ \mathrm{j} \neq \mathrm{i} \tag{2}$$

In this study, the choice model is directly estimated in Willingness to Pay Space (WTPS) (Train and Weeks, 2005; Scarpa et al., 2008), as shown in equation (3):

$$\mathrm{U_{njc}} = -\alpha \mathrm{p_{njc}} + \alpha\omega \mathrm{x_{njc}} + \varepsilon_{\mathrm{njc}} \tag{3}$$

where α is the estimated cost parameter and p_{njc} represents the cost attribute and ω is defined as the ratio $(\frac{\beta'}{\alpha})$. To account for preference heterogeneity, a mixed multinomial logit specification was employed utilising both random parameters and an error component. Preference heterogeneity for each attribute is modelled through the preference parameter as expressed in equation (4):

$$\beta_{\mathrm{k}} = \bar{\beta}_{\mathrm{k}} + \varphi_{\mathrm{k}} \upsilon_{\mathrm{nk}} \tag{4}$$

where, β_k is a population-level estimate composed of the mean preference for the attribute $\beta_{\mathrm{k}}^{\mathrm{m}}$, and φ_{k} is the spread of the estimate. For every non-cost parameter, a normal distribution is specified for the error term υ_{nk}. A lognormal distribution is specified for the cost attribute's error-term to avoid the issues associated with defining the ratio of two normally distributed parameters (Bliemer and Rose, 2013).

For this study, a three-alternative unlabelled choice experiment has been created with one of the alternatives specified as the status quo. To control for left-right bias and/or status quo bias, three additional parameters have been included in the model. Two alternative-specific constants are estimated for the status quo contract and the third contract (Option C). Further, a zero-mean normally distributed error component has been included for the two non-status quo alternatives to account for potential differences in substitution patterns between the status quo and non-status quo alternatives (Herriges and Phaneuf 2002; Scarpa et al., 2007).

To model how financial literacy influences choice, a scaled mixed logit model, which is a reduced form specification of the Generalised Multinomial Logit model is specified (Keane, 2006; Fiebig et al., 2010; Greene and Hensher, 2010). It is assumed that there is a common source of correlation that affects an individual's preference for all the parameters specified in equation (3). This correlation, sometimes referred to as individual scale heterogeneity, is specified as:

$$\sigma_n = \exp(\overline{\sigma}_n + \tau\vartheta_{\mathrm{n}}) \quad (5)$$

where $\overline{\sigma}_{\mathrm{n}}$ is the mean level of scale heterogeneity, the parameter τ measures the spread of scale heterogeneity, and ϑ is a zero-mean normally distributed error term. As τ approaches zero, the model reduces to a model with scale homogeneity, and as it increases, the degree of randomness in choice at the individual level increases (Fiebig et al., 2010). Randomness is defined in relation to the choice probabilities predicted by the model. For three alternatives, assuming for simplicity that $\mathrm{E}(\sigma_{\mathrm{n}}) = 1$, as choices become more random, the probability of selecting an alternative is equal to the multiplicative inverse of the number of alternatives, as shown in equation (6):

$$\sigma_{\mathrm{n}} \to 0 \Rightarrow \mathrm{P}_{\mathrm{njc}} = \frac{\exp[\sigma_{\mathrm{n}}\beta' \mathrm{x}_{\mathrm{njc}}]}{\sum_j \exp[\sigma_{\mathrm{n}}\beta' \mathrm{x}_{\mathrm{njc}}]} \to \frac{1}{3} \quad (6)$$

To analyse whether financial literacy influences scale, the τ parameter is now assumed to be a function of both the mean level of scale heterogeneity as well as the respondents' measured level of financial literacy ($\tau = \tau + \delta\mathrm{Fin_n}$). As a final modification to equation (5), the mean level of scale heterogeneity is normalised so that the expected value of σ_n is equal to 1, allowing for the β coefficients to be interpreted without having to adjust for scale. The final specification for measuring scale heterogeneity is defined as:

$$\sigma_n = \exp\left(-\frac{(\tau + \delta\mathrm{Fin_n})^2}{2} + (\tau + \delta\mathrm{Fin_n})\vartheta_n\right) \tag{7}$$

To evaluate whether financial literacy influences the consistency of choice, the hypothesis developed postulates that the sign of the δ parameter is negative, suggesting that as a respondent's financial literacy score increases, so does the consistency of their choices when evaluating alternatives.

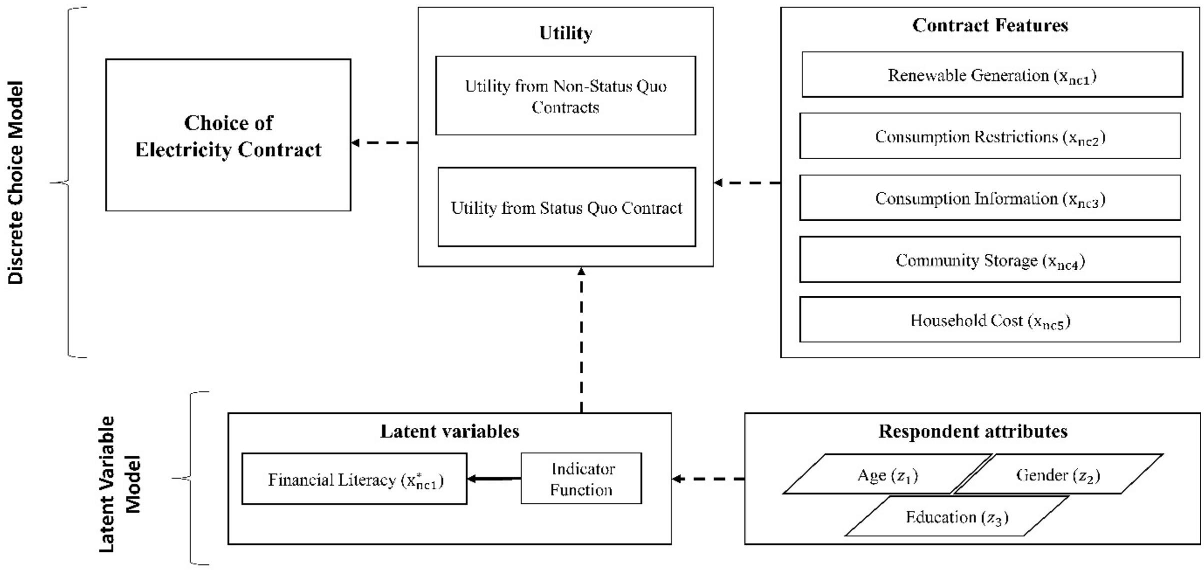
We can now reformulate the probabilities noted in equation (2) to account for the aforementioned parameters to be estimated, with the probability of selecting an alternative as shown in equation (8):

$$P_{njc} = \frac{e^{(\sigma_n(-\alpha p_{njc}+\alpha\omega x_{njc}+\phi_{1|2}))}}{\sum_j e^{(\sigma_n(-\alpha p_{nic}+\alpha\omega x_{nic}+\phi_{1|2}))}} \tag{8}$$

where $\phi_{1|2}$ represents the ratio of a zero-mean error component included in the non-status quo alternatives and α.

Financial literacy cannot be directly observed and as such, it is a latent variable, and can only be indirectly measured as responses to questions designed to measure the latent variable. To allow for the latent nature of financial literacy, a hybrid choice model can be used to simultaneously measure the latent variable analysed as well as its effect on the discrete choice experiment (Ben-Akiva et al., 2002; Daly et al., 2012). This modelling approach can also address issues related to measurement error with latent variables (Budziński and Czajkowski, 2017). Figure 1 shows an overview of how the latent variable model fits in with the current discrete choice model.

Figure 1. Overview of hybrid scaled mixed logit model



Financial literacy is modelled using a structural equation estimating the correlation between literacy and socio-economic characteristics, as shown in equation (9):

$$\mathrm{Fin}_n = \rho z_n + \eta_n \tag{9}$$

where, ρ is a vector of estimated coefficients for the matrix z_n of socioeconomic characteristics for respondent *n*, and η is a normally distributed error term. For this study, the characteristics modelled for each respondent include their age, gender, and education level. Education is recorded as three separate dummy variables, with high school the base level which is compared against higher levels of education including TAFE (post-high school, technical skills training), undergraduate and postgraduate (Honours year, Masters and Ph.D.) studies. With this structural equation, correlations among the financial literacy score and the socio-demographic characteristics of the respondents can be estimated.

The latent variable is also linked to an indicator function, in this case, the individuals' score for the financial literacy quiz via equation (10):

$$\mathrm{I}^*_m = \mu_m + \gamma \mathrm{Fin}_n + \zeta_m \tag{10}$$

with I_m^* representing the individual's score on the quiz, μ is a vector of threshold parameters, γ is a vector of coefficients to estimate and zeta is an extreme value distributed error term.[4] As the financial literacy score is an ordinal variable, a linear specification linking the score to socioeconomic characteristics would lead to a misspecification error. Therefore, an ordered logistic function is used to calculate the probabilities for each level of the indicator variables as shown in equation (11):

$$
\begin{aligned}
&P(I_m = 1) = 1 - \frac{1}{e^{(-\mu_1 + \gamma Fin_m)}} \\
&P(2 \leq I_m \leq 6) = \frac{1}{e^{(-\mu_{k-1} + \gamma Fin_m)}} - \frac{1}{e^{(-\mu_k + \gamma Fin_m)}} \qquad (11) \\
&P(I_m = 7) = \frac{1}{e^{(-\mu_6 + \gamma Fin_m)}}
\end{aligned}
$$

Both the choice model and latent variables are solved simultaneously. The log-likelihood function is solved using simulated maximum likelihood, with the combined solution to equation (8) and (11) being shown as:

$$
LL = \sum_{n=1}^{N} \ln \left[\frac{1}{R} \sum_{r=1}^{R} \left[\prod_{j=1}^{J} \prod_{c=1}^{C} \left(P_{njc}^{r}\right)^{y_{njc}} \times \prod_{m=1}^{M} P(I_m^r) \right] \right] \qquad (12)
$$

where, y_{njc} denotes the actual choices made and r the number of draws used for simulation. The draws are taken for the errors mentioned above, with the probabilities calculated for each set of draws. The draws were sampled using Modified Latin Hypercube Sampling (Hess et al., 2006) with 5,000 draws to ensure the stability of parameter estimates. The final model was estimated using Python Biogeme (Bierlaire, 2016) with supporting code from Rose and Zhang (2017).

3.3.2 Survey design

The survey used in this study was developed as part of a larger, multi-treatment project, investigating various aspects of consumer preferences for alternative electricity contracts. We use one treatment in this analysis. After reading a general information screen about the project, the households who provided informed consent [Ethics Clearance H0016832], proceeded to view information and

[4] For all the error terms included in the hybrid model specification it is assumed that they are mutually independent (Vij and Walker, 2016)

answer questions across a four-part survey. The financial literacy quiz was the first part of the survey. The second part of the survey described how Australian retail electricity prices have increased across the country over the last 10 years, as well as describing some reasons why this has occurred. The third part explained the contracts to be evaluated and their associated features. A cheap talk script was provided following the feature descriptions as a reminder to respondents to make choices as if they really had to pay. Following this reminder, respondents were asked to look at the combination of features and make a choice. Respondents then completed eight choice tasks selecting from three different electricity contracts. The fourth part of the survey involved answering attitudinal and socio-demographic questions. In the development of the survey, focus groups and in-depth interviews were conducted with paper copies of the survey to test wording and survey length. The final version of the survey was programmed by the Online Research Unit (ORU) as an internet survey.

The contracts that would be offered by retailers included a combination of the following features, namely changes in the amount of power sourced from renewable energy generation, limiting appliance use during the evening peak period, installation of batteries to store electricity that can be accessed by the community, and finally the installation of smart meters that would provide households with more frequent updates about the cost of powering their home.

Each feature was described as having the potential to lower future electricity prices within the national electricity market in the long run. During the time period when the survey was in-progress, renewable energy generation made up just over 15% of the national energy mix, with the majority of electricity generated from burning coal.

Peak energy consumption for households in Victoria, on average, occurs between the hours of 5pm and 8pm. During this time, peak load generation leads to substantially higher prices being demanded by generators. One way to lessen the need to access these higher priced sources is to restrict how much power can be consumed during this peak period by households. By default, to keep prices constant, all electricity retailers would restrict two of three possible consumption activities. The three activities mentioned included cooking, cleaning, and entertainment. A list of common appliances associated with each activity was also detailed to provide context. As part of the feature description, households would get to choose which activities they would restrict. Alternative contracts would allow for one or both sets of restrictions to be lifted, however, these options never had a zero-cost associated with them. Several questions queried whether respondents understood what these restrictions would mean for their electricity consumption habits. Based on how this feature was described, the estimated parameters measure the WTP for removing restrictions.

Another feature presented was related to community storage. At the time of the survey, there were few large-scale batteries operating nationally. A major battery project had been built in South Australia which was widely reported (Sonali, 2017), therefore, respondents are likely to have been aware of the potential for such battery projects. The description of this feature was based on the assumption that batteries would be usable as a replacement source of power during a blackout as well as a substitute for peak-load power sources in the evening.

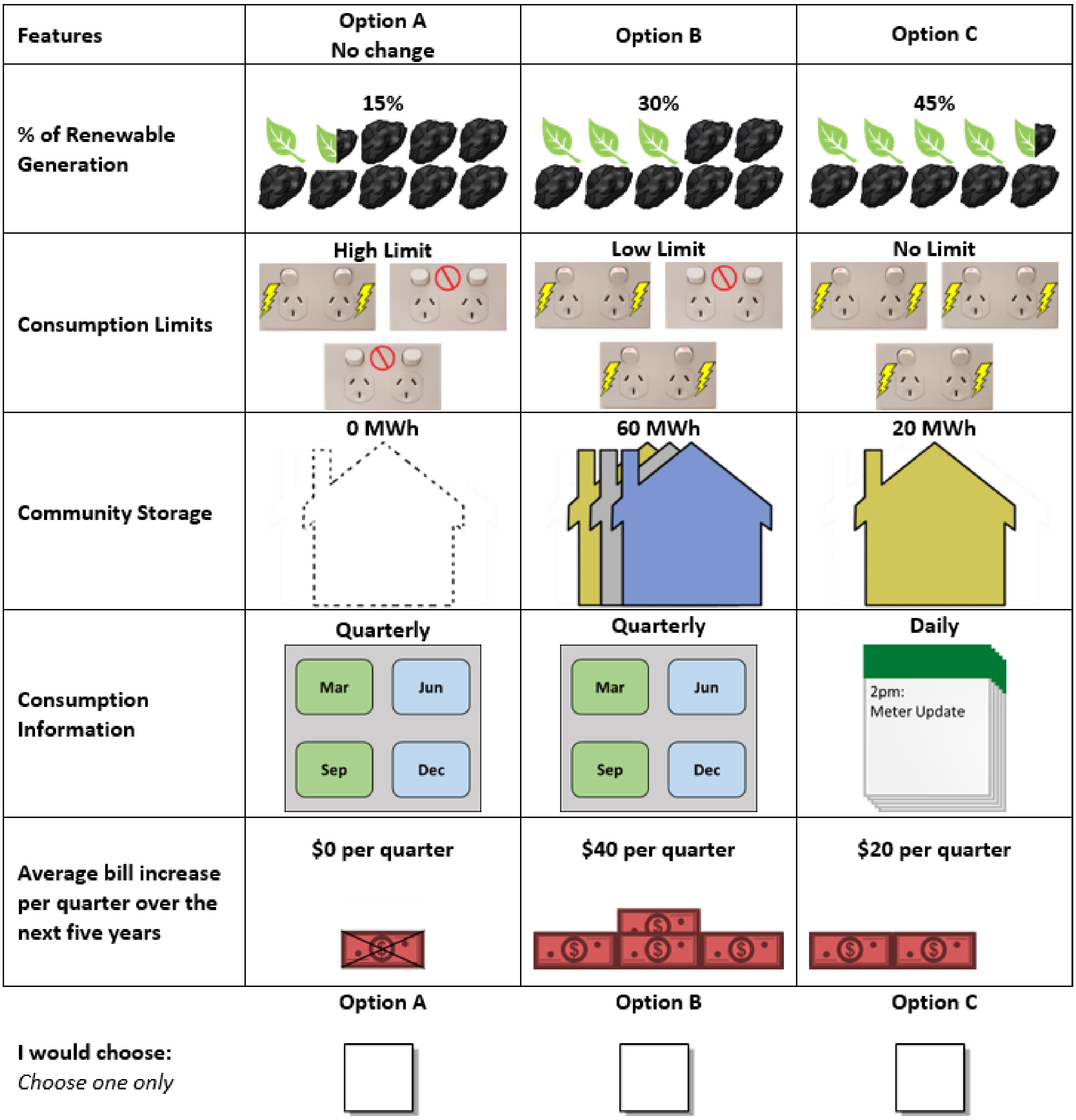
The final feature described would allow households to access their consumption information more frequently through the installation of smart meters. Currently, most Australian households only receive this information with their quarterly bill, whereas the smart meters would allow consumption information to be received either daily or in real-time, depending on the type of meter and frequency households prefer. For each of the contracts offered, except for the status quo contract, there is a cost imposed on the household. The cost was defined as an increase in the fixed component of the household's electricity bill, paid every quarter for five years.

There was a business-as-usual, status quo contract, with no additional cost being imposed on households. This option resulted in no increased investment in renewable energy or storage activities (as a proportion of the current energy infrastructure mix), consumption information being provided quarterly, and two consumption activities being restricted for each household. The list of features and their associated levels are shown in Table 1. An example of the choice tasks is shown in Figure 2. Between each respondent, the order of contract features, apart from costs, was randomised to eliminate potential order effects.

Table 1. Description of features and levels (status quo levels are in bold)

Features:	Levels (Non-status quo):	Levels (status quo):
Proportion of Generation from Renewable Sources	15%, 30%, 45%, 60%	15%
Consumption Restrictions	Two Restrictions, One Restriction, No Restrictions	Two Restrictions
Consumption Information	Quarterly, Daily Reminders, Real-Time Reminders	Quarterly
Community Storage	0 MWh, 20 MWh, 40 MWh, 60MWh	0 MWh
Fixed cost increase per quarterly for 5 years to your household	$20, $25, $30, $35, $40, $45, $50, $55, $60, $65, $70, $75	$0

Figure 2. Example choice task



3.3.3 Survey sample and experimental design

A stratified random sampling method was utilised across Victoria based on gender, age, and rural versus urban location. The survey was administered online by Online Research Unit (ORU) (http://theoru.com/), an Australian panel provider who continuously refresh their panel using a combination of techniques to reduce issues of self-selection bias.

An efficient design, based on a multinomial logit model, was initially developed using priors obtained from the literature, specifically priors relating to renewable energy investments (Brennan and Van Rensburg, 2016; Ozbafli and Jenkins, 2016). For the other features, namely consumption limits, storage, and consumption information, no priors were available. The expected sign for these parameters was positive, so they were calibrated to ensure utility balance and no dominated alternatives (Bliemer and Collins, 2016). All designs were generated using Ngene version 1.1.1 (ChoiceMetrics, 2012). All designs estimated included the main effects only.

The initial design was piloted, and a basic model was estimated with the significant estimates included as priors in a Bayesian D-efficient design. For the parameters related to billing information, storage, and no consumption limits, the estimated coefficients were not significant in the simple multinomial logit model estimated using pilot data (n = 56). It is not always possible to know if a statistically insignificant parameter is due to the small size of the pilot or due to the feature being unimportant to respondents. These parameters were set to be positive to balance utility and ensure no dominated alternatives. The final design included 48 choice tasks divided into 6 blocks with a simulated Bayesian D-efficient error of 0.003448.

3.3.4 Measurement of financial literacy

Several methods have been developed to measure a respondent's financial literacy. The most prevalent approach involves test-based measures (Hung et al., 2009), whereby responses to a set of questions pertaining to specific financial concepts are often aggregated. Other methods include estimating effects using indicator variables (Jappelli, 2010; Gathergood, 2012), principal component analysis (Behrmann et al., 2012; Lusardi et al., 2014), or cluster analysis (Lusardi and Tufano, 2015).

Self-assessed measures of financial literacy are another approach, whereby financial literacy is inferred from a respondent's self-assessment (Stolper and Walter, 2017).

A set of questions assessing each respondent's knowledge of financial investments were used to measure financial literacy. The quiz was designed for Australian respondents with experts in financial planning to assess the likelihood that a consumer could make sound, independent financial investment decisions (Louviere et al., 2016). Seven questions from the quiz related to financial investments were included in the survey and were answered by all respondents. The order of the questions was randomised between respondents to eliminate potential ordering effects. Each question was worth one point, with a maximum score of seven points, representing the highest level of financial literacy. Although higher scores imply higher levels of financial literacy, the scores themselves are ordinal. Each question has an unequal weighting in terms of their importance in assessing an individual's financial literacy. Consequently, including the scores as interaction terms would lead to measurement error. The choice of modelling these scores as part of a hybrid choice model can address the measurement error issue (Vij and Walker, 2016). In addition, it allows for the linking of socio-demographic factors with the respondents' scores. It was assumed that a high level of financial literacy may be necessary to evaluate electricity contracts involving multiple features associated with investments in energy infrastructure and policy. The non-status quo contracts incurred costs every quarter for five years. The benefits of increased renewables and battery storage, however, are long-term. For example, increased renewable energy generation leads to less reliance on fossil fuels, reducing the associated negative externalities over time. The costs of installing smart meters could be offset through cost savings as consumption information allows households to understand how to lower their future electricity bills. Finally, paying for the removal of restrictions could better align the high costs of generation during the peak period with the final prices paid by households.

3.4 Results and Discussion

In total 18,250 invites (random sample of the ORU panel stratified by urban/rural, age and gender) were sent out with reminders in three waves to obtain 518 respondents in total. Socio-demographic targets were used in estimating the required number of observations, but not imposed as quotas. To be eligible to complete the survey, the respondent had to be owner-occupier (with or without mortgage) of a single-family, detached house and responsible for the electricity bill (thus excluding renters and occupants of apartments, townhouses, etc).

The sample respondent characteristics reported in Table 2 are compared with state proportions based on the 2016 census. For each category we fail to reject any statistically significant difference between the sample and census proportions at the 5% level of significance. Therefore, based on the reported proportions, we are confident that the sample population is representative of the population of the state of Victoria.

Table 2. Comparison of sample to population proportions for Victoria

	Rest of Victoria				Greater Melbourne			
	Men		Women		Men		Women	
Age	Sample	Census	Sample	Census	Sample	Census	Sample	Census
18-29	2.12%	1.84%	2.12%	1.75%	8.69%	8.37%	8.30%	8.24%
30-44	3.09%	2.59%	2.51%	2.70%	11.58%	11.34%	11.58%	11.43%
45-59	3.67%	3.01%	3.47%	3.17%	8.11%	9.06%	8.49%	9.53%
60+	4.83%	3.94%	3.47%	4.28%	8.69%	8.69%	9.27%	10.06%

For the financial literacy quiz, each respondent completed seven questions as shown in Table 3. When compared to the results reported in Louviere et al. (2016), the percentage of correct answers is comparable for most questions. There was an exception with one question regarding the tax consequences of dividend income where we added “I do not know” as a response, which was not the case in Louviere et al. (2016). This response was added based on feedback received in focus groups. These responses were then randomly assigned to the remaining results in a similar proportion of correct responses.

Table 3. Financial literacy percentage of correct answers comparison

Question:	% Correct	
	Current Survey	Louviere et al. (2016)
Normally, which of these assets exhibits the highest fluctuations over time? [Multiple Choice]	82.8%	85.6%
Which of the following is ALWAYS true when dividend payments are received? [Multiple Choice]	76.8%	76.8%
It is usually possible to reduce the risk of investing in the share market by buying a wide range of shares. [True/False]	85.7%	85.5%
If you invest $1,000 in a managed fund, is it possible to have less than $1,000 when you withdraw your money? [True/False]	84.6%	79.9%
Is an investment with a high return likely to be high risk? [Yes/No]	92.5%	94.0%
If a friend inherits $10,000 today and her sister inherits $10,000 three years from now, who will be richer in three years because of the inheritance? [Multiple Choice]	69.7%	61.9%
If you own shares in an Australian company, which ONE of these statements is true about the tax you will pay on dividend income? [Multiple Choice]	44.4%	58.9%

The choice frequencies for each of the contract alternatives are shown in Table 4. More than a third of all choices involved selected the status quo contract. This result suggests that there is a significant proportion of respondents selecting the status-quo contract despite having two consumption restrictions imposed on the household. An analysis of all choices evaluated by respondents found that approximately 60% of all choices made involved selecting a contract with two restrictions being imposed. Of all the respondents who completed the survey, 26 (5%) selected a contract that involved at least one restriction being removed for every choice task.

Table 4. Proportion of alternatives selected

Alternative Selected:	Proportions:
Option A (Status Quo)	35.67%
Option B	35.76%
Option C	28.57%

The socio-demographic factors included in the structural equation model are all statistically significant, as shown in Table 5. Older, male, and more educated respondents were more likely to be financially literate. In terms of the relative magnitude of the education parameters, the results suggest that the undergraduate education level has the strongest correlation with financial literacy. The negative coefficient for gender (female = 1) is consistent with past studies (Agnew and Harrison, 2015; Klapper et al. 2015; Bucher-Koenen et al., 2017). The sign on education is also consistent with past studies (Christelis et al., 2010; Lusardi et al., 2010; Lusardi, 2019). The positive relationship between age and financial literacy is less clear, with some studies suggesting a non-linear relationship, with financial literacy increasing up until a certain age, then falling (Gamble et al., 2015; Finke et al., 2017). A quadratic term for age was included in an alternative model, however, the final log-likelihood for this model was inferior. For the measurement equation, the gamma parameter is positive and significant, suggesting that higher levels of the latent variable lead to a greater likelihood of scoring higher on the financial literacy quiz. The threshold parameters are all significant except for two levels, which correspond to lower scores. This is not surprising given the relatively few respondents who correctly answered a maximum of up to four questions.

Table 5. Structural and measurement equation results

Variable	**Coefficient (Robust Standard Error)**
Age	0.0459*** (0.0004)
Gender	-0.6268*** (0.0054)
Trade Qualification (TAFE)	0.2233*** (0.0053)
Undergraduate Education	1.0759*** (0.0109)
Postgraduate Education	0.8518*** (0.0071)
μ_1	-2.4890*** (0.4791)
μ_2	-1.2591 (0.7972)
μ_3	0.4084 (0.4706)
μ_4	2.0247*** (0.3268)
μ_5	3.6913*** (0.2342)
μ_6	5.6265*** (0.2162)
Γ	1.5836*** (0.0053)

*** 1% significance ** 5% significance * 10% significance.

The results of the Hybrid Scaled Mixed Logit Model are reported in Table 6. Starting with the mean parameters, all features are statistically significant and have the expected sign except for the daily reminders mean parameter, which is negative. The alternative-specific constants are negative, suggesting that there is unobserved heterogeneity that leads respondents to select contracts that are not the status quo or option C. In terms of the relative importance of features, removing consumption restrictions was the most important for respondents, as evidenced by the relatively large WTP values.

For the remaining feature, it was assumed that more frequent information would allow households to better optimise their consumption (Filippini et al., 2018). Based on the mean parameter estimates for real-time meters, households are willing to pay $1.36 per year for real-time information about their electricity consumption, however, this would require compensation of $0.11 per quarter if the meters only provided daily reminders. Gerpott and Paukert (2013) found that German households were willing to pay a one-time levy for consumption information, but not an ongoing monthly fee. Kaufmann et al. (2013) found that Swedish households were willing to pay up to 1.55 CHF on top of their existing tariff for real-time information shown on an in-home display. The difference in mean estimates suggests that there is no value in obtaining daily reminders with regards to household electricity consumption. For many households, such a reminder may be perceived as a nuisance, as opposed to a useful source of information that can be used to manage consumption.

In terms of consumption restrictions, the results suggest that consumers would rather have no restrictions on their consumption activities. This being the first study to estimate this specific type of restrictions, there are no direct comparisons. Kavousian et al. (2013) identified numerous factors that influence household consumption based on smart meter data. They confirm previous studies concluding that energy consumption is driven by behaviour rather than perceived efficiency gains (Cramer et al., 1985; Gouveia et al., 2012). These findings suggest that households are opting out of consumption restrictions to preserve habits, rather than considering the efficiency gains from shifting some activities to other times of the day. The information regarding the type of tariff the household incurred was not collected in this study, although, it could be a useful piece of information for any future research analysing consumption restrictions with price-incentives.

Table 6. Model scaled hybrid mixed logit (WTPS)

Variable	**Coefficient (Robust Standard Error)**	
	Mean Parameters	**Standard Deviation Parameters**
Daily Reminders	-0.1115***	2.4299***
	(0.0188)	(0.0267)
Real-Time Reminders	1.3605***	4.1675***
	(0.0397)	(0.0136)
One Consumption Restriction	3.2244***	6.0315***
	(0.0402)	(0.0272)
No Consumption Restrictions	5.2948***	7.3329***
	(0.0227)	(0.0685)
Renewable Generation	0.1993***	0.2551***
	(0.0012)	(0.0016)
Storage	0.0675***	0.1130***
	(0.0012)	(0.0013)
Household Cost ($/year)	-1.2788***	2.0866***
	(0.1715)	(0.2589)
ASC (Status Quo)	-38.3984***	
	(0.1356)	
ASC (Option C)	-4.1703	
	(0.0350)	
Error Component		32.6508***
		(0.1282)
Tau		1.8391***
		(0.0065)
Financial Literacy		-0.6566***
		(0.0053)
Diagnostics		
No. of Observations		4,144
Log-Likelihood		-3,100.05
BIC		6,312.600
McFadden Pseudo R^2		0.319

*** 1% significance ** 5% significance * 10% significance.

The WTP estimate for the community storage feature has limited comparability with previous studies. In part, this is due to how we described the feature as a technology that reduced the duration of blackouts. Goett et al. (2000) estimated that households were willing to pay a value of $1.21 cents per kWh to reduce outages from four 30-minute periods to two of the same length. Carlsson and Martinsson (2008) estimated that Swedish households are willing to pay 7.81 SEK to reduce power outages to a maximum of four hours over the weekend, although they noted a significant heterogeneity with respect to the WTP, depending on when the outage occurs, as well as the length. The estimate in our study is closer to the lower end of the studies compared, with households found to be willing to pay between 9 and 32 cents per year on top of their existing bills. There could be several reasons for this low estimate. The first could relate to the existing reliability of the infrastructure, with up to 44% of the cost of bills going towards supporting existing infrastructure and ensuring system reliability (AEMC, 2020b). Another potential reason is that batteries are not new sources of generation, but rather allow for energy to be stored and discharged later. Baseload renewable energy sources of generation such as pumped hydroelectric dams already exist in Australia and may be suitable substitutes. Finally, the relationship between large-scale battery storage and electricity prices may not be well-understood by consumers. Energy storage technologies, excluding pumped hydro storage, make up a small proportion of most countries' existing energy infrastructure (International Renewable Energy Agency, 2017). In Australia, the only large-scale battery storage in operation is the Tesla-Neoen 100MW lithium-ion battery, however, new installations are being considered (Climate Council of Australia, 2018). Much like household solar panels when they were first being developed for residential markets, it could be some time before households perceive the value of battery storage technologies as they become more integrated within the existing energy infrastructure.

Finally, for the renewables WTP feature, we can compare the results with other studies focusing on renewable energy technologies, independent of the type of technology. Ivanova (2012) estimated that Queensland households are WTP an additional $28 AUD on top of their quarterly electricity bill to support renewable energy sources. Roe et al. (2001) found that US households were willing to pay an annual $21 US premium on top of their existing electricity costs. Our results are relatively lower in real terms. A general finding by Sundt and Rehdanz (2015) is that estimated WTP is generally lower in studies which do not specify the type of renewable energy technology. Another factor that may explain this result is that we expressed the change in renewable energy technologies as a percentage change, which previous studies did not.

For every feature, the associated standard deviation parameters are statistically significant, implying preference heterogeneity within the sampled population (Hensher et al., 2015). A significant error component suggests that respondents trade-off between the non-status quo alternatives differently relative to the status quo. The final results indicate the tau parameter suggesting scale heterogeneity within the sampled population. The financial literacy parameter suggests that individuals who are relatively financially literate make more consistent choices, at least when comparing features within this discrete choice experiment.

To illustrate the previous point, the scale parameter for the sampled population is simulated based on the parameters reported in Tables 5 and 6. These parameters allow us to simulate a distribution based on equation 9, which would then be multiplied by the mean parameters for each feature. Table 7 reports the result of this simulation, with three sets of results based on the minimum, mean, and maximum scale parameters. Taking the renewable energy generation parameter as an example, the minimum WTP is $1.85, compared to a maximum value of $2.39.

Table 7. Simulation of mean willingness to pay by scale parameter

	Minimum	**Mean**	**Maximum**
Scale Parameter	0.93	1.00	1.20
Daily Reminders	-$0.10	$0.11 [-$0.07 – -$0.15]	-$0.13
Real-Time Reminders	$1.26	$1.36 [$1.28 – $1.44]	$1.63
One Consumption Restriction	$2.99	$3.22 [$3.15 – $3.30]	$3.87
No Consumption Restrictions	$4.90	$5.29 [$5.25 – $5.34]	$6.35
Renewable Generation (10-unit increase)	$1.85	$1.99 [$1.99 – $2.00]	$2.39
Storage (10-unit increase)	$0.63	$0.68 [$0.67 – $0.68]	$0.81

It is not possible to identify the specific respondents representing the extreme values mentioned. The probabilistic statements can, however, be made based on the structural equation results as well as the parameters related to financial literacy. In terms of financial literacy and its effect on choice, the only other paper that can be compared is the recent study by Brent and Ward (2018). Utilising a similar methodology, they find that people who are financially literate make more consistent choices. There are however two important points to note when comparing results. In the Brent and Ward (2018) study, they estimate a Generalised Mixed Logit without the hybrid specification, and they do not allow for the scale parameter to interact with the standard deviations of the taste parameters. They also conclude that financial literacy is a source of scale heterogeneity. On the contrary, we find evidence that suggests that financial literacy may influence the consistency of choice.

From a policy perspective, accounting for a respondent's financial literacy can be important when considering policies that represent financial investments, such as investments in energy infrastructure. These investments are gradual, with the benefits sometimes not realised until many years after the costs have been incurred. This study finds evidence that the valuation of the features included in this choice experiment are correlated with the financial literacy of the respondent. Although the measure of financial literacy modelled in this paper is a proxy, nonetheless, it provides additional evidence that financial literacy does affect choice. If respondents do not consider the benefits associated with the features evaluated, they may only focus on the cost or complete preference elicitation exercises in a manner reflecting indeterministic preferences. One question that could be the focus of future research is - if a respondent becomes more financially literate, would they have the same preferences?

3.5 Conclusions

Over the past decade, Australian households have been facing rising electricity costs. This study shows that there is still broad support for increasing investments that improve the existing network despite the rising energy prices for consumers. From a policy perspective in Australia, there appears to be a scope for increasing households' energy bills to support additional subsidies for renewable energy generation. In Australia, this is achieved through the long-run renewable energy target. In addition to funding more renewables, households are also willing to pay to support investments in battery storage. In this choice experiment, storage was presented as one way that would increase the reliability of the network. Battery storage, however, could also be used to partially address intermittency issues associated with renewable energy generation, thereby improving their perceived value within the national energy mix. From a regulator's perspective, the significant WTP estimates suggest that consumers perceive battery storage as value for money.

The choice experiment also led to estimates of WTP to remove consumption restrictions as well as install smart meters. The results suggest that households do not want to change their habits during the peak evening consumption period. Consequently, this reluctance to change consumption, as well as the willingness to avoid change, could be considered support for paying a demand charge. In some states in Australia, two- and three-part tariffs are already in place, with the volumetric charge increasing based on the time of the day. This study shows that there is support for an additional quarterly fixed charge. In addition, there is also support for smart meters to monitor consumption habits. The benefits of smart meters relate to monitoring real-time consumption through daily reminders, which however did not lead to a positive WTP in this study.

Finally, this study also looked at how financial literacy influenced the choices made in the choice experiment. The results suggest that those respondents who were less literate, as proxied by the low scores on the financial literacy quiz, were less consistent in their choices. Consequently, their stated preference for each of the features was likely to be lower when compared with those respondents with high levels of financial literacy. This result suggests that financial literacy has some influence on choice. Increasing the financial literacy of respondents could lead to the wider acceptance of contract features that reflect investments in the future, as opposed to features that merely reflect costs to be borne by households today. Related to this idea, for future studies, it may also be worth trying to link a household's financial literacy with their knowledge of other facets of the electricity network, or environmental problems more generally. Exploring these relationships may provide richer insight into the other factors that determine which households make consistent decisions.

Chapter 4: Risk Preferences and the Reliability of Electricity Networks

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4.1 Introduction

Over the last 20 years, increasing levels of investment have enhanced the ability of the Australian Electricity Market to provide a reliable supply of electricity to households as well as support the transition towards a greener energy sector. In terms of reliability, between 2008 and 2019, there were only two years where the 99.998% reliability standard was not met (AEMC, 2021). Australia also achieved its Large-scale Renewable Energy Target of 20% in January 2021, as legislated by the Commonwealth to subsidise investments in renewable energy (Australian Clean Energy Regulator, 2021). Internationally, this target is lower when compared to other countries, however, Australia's due date is relatively ambitious (International Renewable Energy Agency, 2015; Afful-Dadzi et al., 2020).

Although this is a positive outcome for reducing carbon emissions within the electricity sector, these investments have created risks, defined here as multiple outcomes with known probabilities (Park and Shapira, 2017) which may impact future policy decisions. One such risk is the intermittency issues associated with renewable energy generation, for example, wind and solar generation. These technologies can create supply-side issues that can be mitigated with technologies such as batteries or pumped storage (Trainer, 2018). Spikes in demand pose a risk to the electricity network if demand exceeds supply. Again, such risks can be reduced with new technologies such as smart meters. These meters can provide effective ways to manage or even reduce consumption at the household level, especially when combined with demand charges or rebates when consumption is restricted. These investments may not only support the transition towards a greener, reliable supply of electricity, but they can also reduce the risks associated with mismatches between supply and demand, as well as promote greater household engagement.

One consequence of continual investment is the consistent increase in the cost of electricity, which is ultimately passed onto households. If this trend continues, then it is likely that a greater proportion of household budgets could go towards paying electricity bills, even if the trend of consumption over time continues to fall (Department of Industry, Science, Energy, and Resources, 2020a). Energy poverty is one consequence of rising prices (Australian Council of Social Service, 2018), especially if the rate of growth exceeds rates of wage growth, prompting policy makers to potentially explore alternative policies. One such policy could involve reducing the rate of investment within the electricity sector to limit or even reverse the upward trend in costs. This proposed reduction in investment may also need to be supported by demand-side management policies so that delays in investment do not jeopardise the stability of the network. These policies, coupled with reductions in investment, could slow the rate of transition towards a green energy sector, make existing infrastructure less reliable, and reduce household autonomy with respect to their electricity consumption. This trade-off, however, may be preferred by households if they are compensated through a reduction in the rate of growth in their electricity bills. Therefore, the objective of this study is to estimate the reduction in the rate of cost increases required by households in exchange for reductions in energy investment as well as for the imposition of demand-side management policies such as consumption restrictions.

Willingness to Accept lower cost increases (hereafter referred to as WTA-LCI) estimates were obtained from Australian households in the state of New South Wales through the evaluation of alternative electricity contracts as part of a Discrete Choice Experiment (DCE). The contract features included within the DCE do not currently exist within the Australian market, prompting the use of stated preference methods. The features included are - the proportion of electricity sourced from renewable energy generation, the amount of community battery storage available to increase the reliability of the network, the installation of smart meters, and the potential imposition of consumption restrictions. In the status quo contract scenario, existing policies were pursued where households experienced higher cost contracts due to the highest levels of investment and no consumption limits being imposed. In addition to the status quo contract option, households could select from two alternative contract options which traded off lower cost increases against lower levels of investment as well as the potential for consumption limits to be imposed. A random parameter with error component mixed logit with full correlation was modelled in the willingness-to-accept space to directly estimate WTA-LCI estimates for each contract feature.

The contract features described in the status quo scenario insure against issues associated with reliability and green electricity, as well as require no changes in consumption and obtain more timely information with respect to consumption. A proportion of a household’s preference for these features may represent insurance against negative outcomes such as interrupted consumption or indirect environmental degradation. In this case, a household’s aversion to risk may be correlated with their preference for these features. Assuming this correlation exists, then the results would be consistent with past studies identifying the demand for insurance products being in part determined by a household’s preference for risk (Outreville, 2014). This correlation was tested through a risk preference elicitation exercise completed by the households after the DCE, which was a modified version of the Eckel and Grossman (2002) multiple-price lottery (Eckel and Grossman 2002; Dave et al. 2010). Based on the distribution of stated risk preferences, we identified one group of households who were highly risk-averse. A set of interactions were included within the DCE to estimate the difference in WTA-LCI for those households who were highly risk-averse versus the baseline group.

Our results suggest that highly risk-averse households require more compensation for reductions in energy investment as well as for the imposition of consumption limits. Respondents in this group were also found to be more sensitive to the cost levels presented relative to the baseline group. These results are novel in that they focus on the risk preferences for households in energy markets, in contrast to previous studies looking at risk in electricity markets from the supply-side. If the policy goal is to keep the services affordable, by delaying investments in maintenance of the service quality, then failing to account for risk preferences may lead to lower acceptance rates than anticipated.

The next section in the paper provides an overview of the literature focusing on risk and its relationship with electricity markets and consumer preferences. The methods section presents a description of the survey components, including the contract features of the DCE, construction of the payment scenario, sampling strategy, experimental design, and a description of the risk preference elicitation exercise. Next, the estimation of the econometric model is described followed by the results. Finally, the results are discussed and, concluding remarks are presented.

4.2 Case Study and Literature Review

Determining whether an individual's risk preference is linked to their preference for various electricity contract features could inform future policy decisions. In the context of this study, these decisions relate to the trade-offs between additional investment within electricity markets today (potentially reinforcing the upward trend in electricity prices) and delayed investment to achieve price stability or even a gradual decline in prices. This study analyses this trade-off using Australia as a case study, specifically households from the state of New South Wales. Within the context of Australia, most electricity expenditure by households goes towards network and transmission costs (AER, 2020). Most of the electricity generated is from non-renewable energy sources such as coal and gas, however, the transition towards renewable energy generation is ongoing, with approximately 20% of the national supply coming from renewable energy sources such as solar, wind, and hydro (AER, 2020). New technologies at the household level such as smart meters are being utilised, especially in states like Victoria, with mixed results. At the network level, battery storage represents the next iteration of technologies that are designed in part to increase the firming capacity of the network. Here we define firming capacity as any policies or technologies that can address short-term supply gaps related to the intermittency of some renewable energy generation sources (Pantos et al., 2017). In November 2020, there was 6,724 MW of existing, committed, or proposed capacity within Australia (Australian Electricity Market Operator, 2020).

Early papers analysing the influence of risk preferences on decisions in electricity markets focused on the supply-side. These studies define risk generally and do not specify the measurability of risk. The uncertainty of risk is referred to across two domains, namely uncertainty related to prices (Vehviläinen and Keppo, 2003) and uncertainty around forecasting demand and supply (Neuhoff and De Vries, 2004). It has been suggested that if firms are risk-averse, then efficient levels of investment with respect to generation capacity will only occur if they can enter into long-term contracts with consumers (Neuhoff and De Vries, 2004). This can have implications for long-term prices though it does not necessarily suggest that consumers will be worse off. Downward et al. (2016) demonstrate through a multi-stage model of retail electricity competition that risk-aversion under specific circumstances can in fact lead to a drop in prices. This is because the more risk-averse electricity suppliers are, the more likely they are to believe the worst-case market outcomes will occur. Consequently, they adjust their prices to reduce the likelihood that these market outcomes will occur. This result is conditional on how financial markets are integrated within electricity markets. This result is conditional on how financial markets are integrated within electricity markets. Other factors that are relevant to determining how risk aversion influences prices are whether investment is directed towards peak load versus baseload technologies (Meunier, 2013), the design of related carbon permit allocation schemes (Fan et al., 2010; 2012), and whether individual consumers (not households) represent significant sources of consumption (Zare et al., 2010).

This focus on the supply-side of the market has shifted with recent studies focusing on individual households within residential electricity markets. Specifically, they have looked at how the risk preferences of individual households influence the selection of retail electricity contracts. Schelich et al. (2018), building on the arguments made by Defuilley (2009), found that a household's risk preference may explain the low rate of contract switching observed in EU countries. Yang et al. (2018) discuss the possibility that risk-averse households may perceive the risks of entering into an electricity contract based on peak/off-peak pricing. Qiu et al. (2017) elicit risk preferences through a multiple-price lottery and identify that risk aversion affects the decision to enrol in voluntary time-of-use programs. Scleich et al. (2019) focus on the extent to which risk aversion, as well as factors such as discounting and loss aversion, may explain the energy efficiency paradox (Gillingham and Palmer, 2014; Gerarden et al., 2017). These findings together suggest that risk aversion leads to below-optimal rates of uptake with respect to energy efficient technologies such as insulation (Farsi, 2010; Fischbacher et al., 2021) or retrofit and appliance upgrades (Qiu et al., 2014; He et al., 2019). These studies suggest that risk aversion should be negatively associated with smart meters, leading to the hypothesis that risk-averse households require relatively less compensation if smart meters are removed.

It is necessary to evaluate the impacts of respondents' risk aversion on electricity consumption for other features of contract. A recent study by Niromandfam et al. (2020) suggests that the concavity of a household's utility function is a function of diminishing returns and risk-averseness of a household. This latter factor suggests that risk-averse households would pay a premium to hedge against potential fluctuations in the price of electricity. The features in our study do not directly influence the consumption of electricity, however, there is an indirect effect on the use of battery storage to ensure uninterrupted supply of energy, and consumption restrictions on certain times of the day. It is assumed that consumption restrictions and lower network reliability due to less battery usage would increase the risk of lower energy consumption. If these assumptions are valid, it is expected that households would insure themselves against the risk that consumption is affected by paying a premium to ensure investments in battery storage occur and consumption restrictions are avoided. Alternatively, if these features were reduced, then it is hypothesised that the more risk-averse a household is, the more compensation they would require for reductions in these features.

Past studies looking at risk aversion as a determinant of various behaviours suggest that the willingness to avoid potentially negative outcomes is expected. Guiso and Paiella (2004) showed that a consumer's attitude towards risks is a predictor of numerous household decisions. Examples of decisions include the choice to work in occupations perceived to be safer with respect to job security, the amount of insurance a household purchases, and how much time they invest in educational attainment. In each of these examples, consumers were paying a premium to avoid an unfavourable outcome. In the context of electricity markets, Itaoka et al. (2006) identified that consumers were willing to pay a premium to reduce the mortality risks associated with fossil fuel generation. However the consumer's preference for risk was not explicitly modelled. Several studies have identified that households are willing to pay a premium to avoid a negative event such as a power outage (Carlsson and Martinsson, 2007; Abdullah and Mariel, 2010; Hensher et al., 2014).

The attributes of renewables and the cost of the contract are the two remaining features that have not been linked with risk aversion. Assuming an increase in renewable energy technologies would contribute to climate change mitigation, then it is hypothesised that risk-averse households would require more compensation for reductions in the proportion of renewable energy generation. Ha-Duong and Treich (2004) show in a theoretical climate-economy model that as the utility function becomes more concave, the degree of relative risk-aversion and the amount of effort exerted to control emissions increases. Viscusi and Zeckhauser (2006) found that respondents who estimated the risk of climate change to be higher than other respondents were willing to pay more to mitigate these risks. Although this study did not model a respondent's risk aversion, their willingness to pay more to avoid these risks suggests that a premium would be paid to avoid a negative outcome. Anthoff et al. (2009) identified that the social cost of carbon may be positively associated with how risk-averse society is, however, this result is conditional on how much the future has already been discounted. Bartzcak et al. (2017) analysed the impacts of financial loss aversion and risk preferences on the WTP to avoid renewable energy externalities. They found that the more risk-averse a respondent is, the more compensation is required before they accept the negative externalities related to renewable energy. This finding, however, is conditional on whether the price change is represented as either a rebate on an electricity bill or a surcharge to be avoided, with the latter leading to respondents requiring less compensation.

Finally, with respect to the cost feature, previous studies have shown that the more risk-averse an individual is, specifically looking at financial risks, the more sensitive they are to cost (Bartczak et al., 2015; Zawojska et al., 2019) and consequently their stated willingness to pay for attributes decreases (Erdem et al., 2010). The novel aspect of our study is that we simultaneously consider the effect of risk aversion on the preference for all features. It is possible that risk aversion leads to a stronger preference for a non-cost feature, by the average increase in the sensitivity to cost leads to a net willingness to accept that is in fact lower.

4.3 Methods

4.3.1 Survey design

The survey used in this study was developed as part of a larger project consisting of multiple treatments to evaluate a range of factors that could influence preferences for different electricity contract features. Before opening the survey, respondents needed to provide informed consent [Ethics Clearance H0016832]. The first part of the survey described how Australian retail electricity prices have changed nationally during the previous decade, as well as highlighting some of the reasons explaining this change. Following some warmup questions, a set of contract features were described, with each being bundled together to represent potential future electricity contracts. The next selection involved the completion of eight choice tasks involving three different electricity contracts. A cheap talk script was employed before completion of the survey as a reminder to respondents to complete each choice task as if they really had to pay (Morrison and Brown, 2009). After the choice tasks, respondents then completed a risk preference elicitation exercise, selecting from six different investments. The final sections of the survey involved answering several attitudinal and socio-demographic questions.

The first section of the survey provided a summary of the major changes within the Australian electricity market over the past decade, highlighting the year-on-year increase in prices as well as the growth in renewable energy generation. Consequently, it was discussed that electricity retailers could offer contracts with features which could impact the future cost of electricity for households. The features included changing the amount of power sourced from renewable energy generation, the limiting of appliance use in the evening, increased battery storage investment, and the installation of smart meters.

The survey was conducted between May and June 2019, when renewable energy generation represented just over 15% of the national energy mix. The description of renewable energy generation was technology-neutral, in the sense that one technology was preferred over another. The differences in the proportion of renewable energy versus non-renewable energy generation sources among the states were highlighted. The maximum level of renewable energy generation within Australia which was included in the experimental design was 60%, based on previous research noting this proportion as feasible (Blakers et al. 2017).

Across Australia, there are two peaks in residential consumption, the first during the morning between 7 and 10 am and the second during the evening. This second peak is relatively larger, with the hours between 5pm and 8pm representing peak daily demand. Consequently, this time of the day is often when the marginal cost of generation is at its highest (AEMO, 2018). In the absence of real-time pricing, households pay an average price which is passed along through annually regulated price increases (AER, 2019). One potential solution would be to have consumption limiting be a contract feature that households could select.

As part of this feature description, respondents were provided a list of three activities that could be restricted during the peak period. The activities were cooking, cleaning, and entertainment, with a list of common appliances, described that could be associated with each activity. Different contracts could lead to either no activities being restricted versus one or two activities being restricted. Households were told that if they selected either level of restrictions then they would be able to select activities, preventing specific sets of appliances from turning on during the peak period. Following the feature description, respondents were asked to state the activity they would restrict first and last.

The next feature represented increased investment in battery storage at the community level. The description of this feature highlighted the technology's potential to increase the reliability of the network by reducing the duration of blackout events. These two points serve to reinforce the idea that battery storage is a means of increasing the reliability of the network. During the time that the survey was in-progress, there were four grid-scale battery storage projects in operation across Australia (AER, 2020), with the most notable being the Hornsdale power reserve in South Australia, which received wide national media coverage (Sonali, 2017). Since 2017 the battery has to led to cost savings for customers and earned sufficient revenues to offset the cost of the investment (Hareyan, 2020).

The last non-cost feature described was the installation of smart meters so that households could monitor their consumption at an increased frequency. Depending on the billing cycle of the retailer, households generally only know how much they consume every month or quarter. Installing these meters would provide more frequent consumption information, either as a daily reminder or in real-time. These levels were also effects-coded, with the base level representing quarterly consumption information.

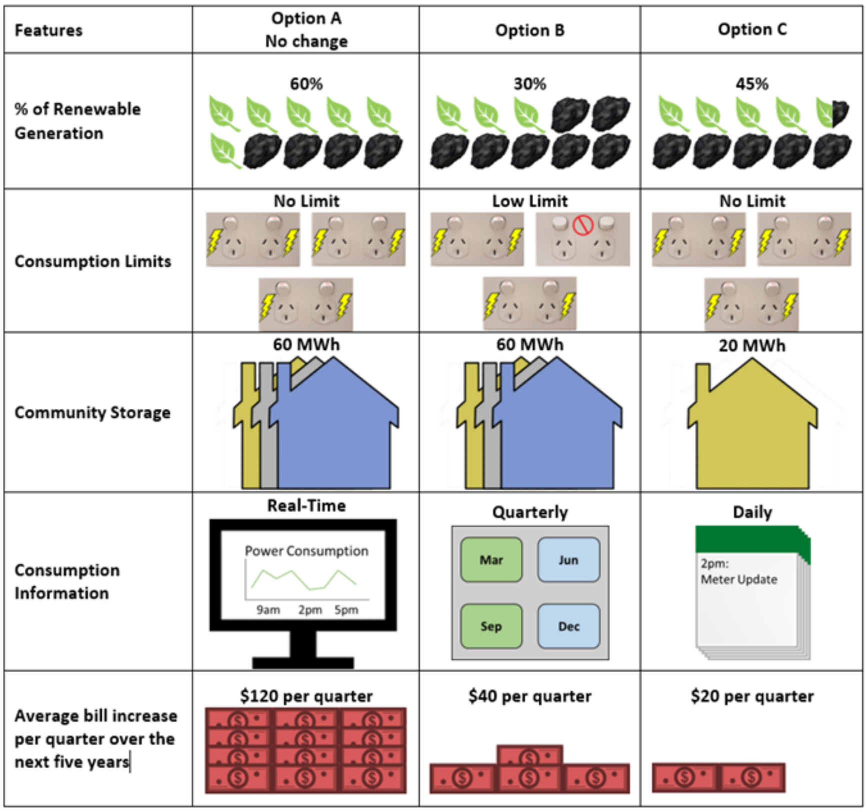
In each of the contracts, there is a fixed cost imposed on the household. This payment vehicle was selected because nearly all household electricity contracts in Australia involve a two-part tariff, with a fixed cost as well as a daily supply charge[5]. The fixed cost for the status quo contract was fixed at a maximum of $120 per quarter and included the maximum levels for all contract features as shown in Table 1. This represented the expected future default electricity contract if there is no change in policy direction or committed investment at the national level. Consequently, the market will have more renewables, battery storage, smart meters for every household, and no consumption restrictions imposed. The cost of this default contract could be avoided by selecting one of the two unlabelled contracts. These contracts traded off lower cost increases for lower levels of each of the features, including the potential for accepting consumption restrictions. This trade-off led to the framing of the subsequent Willingness to accept measures a respondent's willingness to accept lower cost increases. An example of one of the choice tasks respondents faced is shown in Figure 1.

Table 1. Description of attributes and levels

Attributes:	**Levels:**
Proportion of Generation from Renewable Sources	15%, 30%, 45%, 60%
Consumption Restrictions	Two Restrictions, One Restriction, No Restrictions
Consumption Information	Quarterly, Daily Reminders, Real-Time Reminders
Community Storage	0 MWh, 20 MWh, 40 MWh, 60MWh
Fixed cost increase per quarterly for 5 years to your household	$0, $10, $20, $30, $40, $50, $60, $70, $80, $90, $100, $110
Status Quo Contract Levels:	60%, No Restrictions, Real-Time Reminders, 60MWh, $120

[5] Time of Use tariffs do exist in Australia; however, they still include a daily supply charge.

Figure 1. Example choice task



4.3.2 Survey sample

A stratified random sample of New South Wales households was taken from the online panel by Online Research Unit (ORU) (http://theoru.com/) based on gender, age, and rural versus urban location. The Online Research Unit is a panel provider in Australia who continuously refresh their panels utilising an assortment of techniques designed to address self-selection bias issues. Potential respondents were sent invitations to complete the survey, as well as three follow-up reminders. To be eligible to complete the survey, the respondent had to be a homeowner, live in a detached house, and be responsible for paying for the household's electricity bill.

4.3.3 Experimental design

An efficient design, based on a multinomial logit model, was initially developed using priors relating to renewable energy investments, obtained from the literature (Brennan and Van Rensburg, 2016; Ozbafli and Jenkins, 2016). For other features, namely consumption limits, storage, and consumption information, no priors were available, so the parameters were calibrated to ensure utility balance and no dominated alternatives (Scarpa and Rose, 2008; Bliemer and Collins, 2016). All designs were generated using Ngene version 1.1.1 (ChoiceMetrics, 2012). All designs estimated included the main effects only. The consumption information and restriction features were effects-coded, with the base levels representing quarterly consumption information and two consumption restrictions. All other contract features were included as levels.

The initial design was piloted to obtain updated priors to be included in separate Bayesian D-efficient designs. For the parameters related to billing information, storage, and consumption limits, the estimated coefficients were not significant in both pilot models using pilot data. These parameters were set to be positive to balance utility with no dominated alternatives. The final design included 48 choice tasks divided into 6 blocks with a simulated Bayesian D-efficient error of 0.002851. Various designs were evaluated with lower D-errors representing designs that are expected to produce smaller parameter variance and covariances as recommended by Scarpa and Rose (2008). Out of the 48 choice tasks, only one included a contract with both features of a zero cost and no consumption restrictions, while all other zero-cost contracts involved at least one restriction.

4.3.2 Risk preference elicitation exercise

Following the completion of the DCE, respondents evaluated different gambles based on the Eckel and Grossman (2002) lottery, with their chosen gamble implying varying appetites for risk. A set of instructions was provided to respondents prior to the gambles appearing, explaining that they needed to select the gamble that they preferred the most. After a five-second delay, the six gambles were displayed, as shown in Figure 2, with the order of the gambles randomly assigned between respondents to eliminate ordering effects.

Figure 2. Example of online version of risk preference elicitation exercise

	Result	Payoff	Chance
Investment F1	X	28	50%
	Y	28	50%
Investment A6	X	2	50%
	Y	70	50%
Investment E2	X	24	50%
	Y	36	50%
Investment C4	X	16	50%
	Y	52	50%
Investment B5	X	12	50%
	Y	60	50%
Investment D3	X	20	50%
	Y	44	50%

The gambles were phrased as investments and there was the potential for respondents to obtain a monetary reward above what was received for completing the survey. Respondents earned points for completing the survey which they can redeem for gift cards through the survey provider. Additional points could be earned based on the investment selected as well as what result occurred. The monetary value of the additional points ranged between $1 and $2 AUD. The results of this task were coded from one to six, with one representing the highest level of risk aversion and six representing a preference for risk seeking gambles.

Utilising the Eckel and Grossman lottery was based on past studies highlighting its effectiveness in eliciting risk preferences with samples that have a wide range of educational experiences (Barr and Genicot, 2008; Dave et al., 2010). One alternative approach is the Holt and Laury (2002) multiple price list. This method, relative to the Eckel and Grossman lottery, allows for a more expansive set of risk preference categories. This is often at the expense of an increase in the perceived complexity of the elicitation task, increasing the likelihood that a respondent’s stated preference for risk differs from their actual preference (Holzmeister and Stefan, 2020). In this study, we are not concerned with obtaining a detailed distribution of risk preferences, therefore the benefit of reduced complexity offsets the loss of precision. In addition, given the length of the survey and the fact that respondents had to complete the exercise after the choice tasks, we wanted to minimise non-completion or inattention due to the difficulty of the task.

4.4 Econometrics

In this study we estimate household preferences for electricity contract features utilising a Random Utility Model. We assume that households are utility-maximisers, however, acknowledge that their choices may include factors not explicitly accounted for (Thurstone, 1927; Manski, 1977). Using this model, we can express a respondent's utility function as follows:

$$U_{njc} = \beta' x_{njc} + \varepsilon_{njc} \ \forall j, j = 1, 2, .., J \quad (1)$$

Here the utility of each household *n* for alternative *j*, choice task *c* is expressed as function of a vector of attributes x_{njc}, multiplied by a vector of parameter weights β'. In addition, the unobserved portion of utility is assumed to be represented by an extreme value type 1 error term which is Identically and Independently Distributed (IID). Following the derivation by McFadden (1974) the probability that a household selects a particular contract can be calculated as:

$$P_{njc} = \frac{e^{\beta' x_{njc}}}{\sum_i e^{\beta' x_{nic}}} \quad (2)$$

Given that one of the objectives of this study is to estimate the WTA-LCI differences due to risk-averse preferences, we can instead directly estimate the utility function in preference space (Train and Weeks, 2005; Scarpa et al., 2008). Rewriting equation 1, the utility function is expressed as:

$$U_{njc} = -\beta_c p_{njc} + \omega x_{njc} + \varepsilon_{njc} \quad (3)$$

where, p_{njc} is the cost attribute, and omega represents the ratio of each non-cost parameter with cost, as shown in equation (3). Direct estimation of willingness to accept space avoids the issues associated with simulating the standard errors for parameters estimated in utility space (Daly et al., 2012). In addition, the parameters and their associated distributions can be directly compared between models.

So far, the model specification assumes that preferences are homogenous and there are no behavioural heuristics influencing choice. Given the restrictiveness of these assumption we have estimated a Mixed Logit (MMNL) with preference heterogeneity and error component. Consequently, the fixed parameter estimate for each parameter is now expressed as the following:

$$B_{nk} = \beta_k^m + \beta_k^i s_n + \Upsilon\tau_{nk} \tag{4}$$

Each attribute now involves three components to estimate, the first component β_k^m is the mean preference for the feature, the second component β_k^i is an interaction term with the socio-demographic characteristics s_n included in the model. The interaction term included for all contract features will include the respondents' risk preference, which allows for the testing of whether risk preferences explain preference heterogeneity with respect to the WTA-LCI of each feature. Random taste variation is represented by a vector of zero-mean random variables τ_{nk} as well as a lower-triangular matrix Υ that estimates the covariances between random parameters. For each contract feature a distribution is assumed, which defines how τ_{nk} will be specified to simulate the individual-specific deviation for each feature. In this study a normal distribution is specific for each of the non-cost parameters. For the cost parameter, a lognormal distribution is specified to constrain cost as always being negative.

In this study the off-diagonal elements of Υ are not restricted to zero, therefore the matrix can be used to calculate the variance-covariance matrix of the random parameters. Alternatively, we can calculate the standard deviations of each random parameter directly from the lower-triangular matrix. To do so we define σ as a column vector of functions that for each row i of the matrix are a function of the j-column elements. For each row i the standard deviations are calculated as:

$$\sigma_i = \sqrt{\left(\sum_{j=1}^{J} \gamma_{ij}^2\right)} \tag{5}$$

where γ_{ij}^2 is a parameter from the lower-triangular matrix. Since the standard deviations are now a function of several parameters the Delta method is used to calculate their associate standard errors, accounting for each parameter's variance as well as the covariances between each set of parameters (Daly et al., 2012). The partial derivative for each row element of σ_i' with respect to γ_{ij} is equal to:

$$\sigma_i' = \frac{\gamma_{ij}}{\sqrt{\left(\sum_{j=1}^{J} \gamma_{ij}^2\right)}} \tag{6}$$

using this formula, the standard error of each row element can be calculated as:

$$\text{Std. Error}(\sigma_i) = \sqrt{\frac{\sum_{j=1}^{J} \gamma_{ij}^2 \operatorname{Var}(\gamma_{ij}) + 2\sum_{j=1}^{J}\sum_{m=1}^{l-1} \gamma_{ij}\gamma_{im} \operatorname{Covar}(\gamma_{ij}\gamma_{im})}{\sqrt{\left(\sum_{j=1}^{J} \gamma_{ij}^2\right)}}} \tag{7}$$

In addition to preference heterogeneity an alternative-specific constant is included in the status quo alternative as well as an error component with the non-status quo option C alternative. The alternative-specific constants are included in part to capture left-right bias, but also estimate the propensity for respondents to select away from the status quo contracts. Given that this contract has the largest cost, we expect that most respondents will select away from this contract. The error component is a zero-mean, normally distributed error term that allows for correlation between alternatives. The justification for this approach is based on the idea put forward by Scarpa et al. (2007) that the inclusion of an ASC for the status quo does not identify both the systematic and stochastic components of the status quo effect. The inclusion of an error component allows for differences in how respondents evaluate the non-status quo alternatives relative to the status quo alternative.

Since random parameters are being included, there is no closed-form solution for the model. Therefore, simulated maximum log-likelihood estimate is required, with the solution to equation (2) being shown as:

$$LL(\beta') = \sum_{n=1}^{N} \ln \left[\frac{1}{R}\sum_{r=1}^{R}\left[\prod_{j=1}^{J}\prod_{c=1}^{C}\left(P_{njc}^{r}\right)^{y_{njc}}\right]\right] \tag{8}$$

With r being the number of draws used for simulation. The draws were sampled using Modified Latin Hypercube Sampling technique (Hess et al., 2006) with 5,000 draws to ensure the stability of parameter estimates. The estimation strategy involved initially estimating a simple Multinomial Logit Model. Next a random parameters model was estimated using the prior model parameters included as priors as well as resitting the off-diagonal elements of the covariance matrix to zero. The final model used the priors from the random parameters model, however now the covariance matrix had the prior restrictions relaxed.

4.5 Results

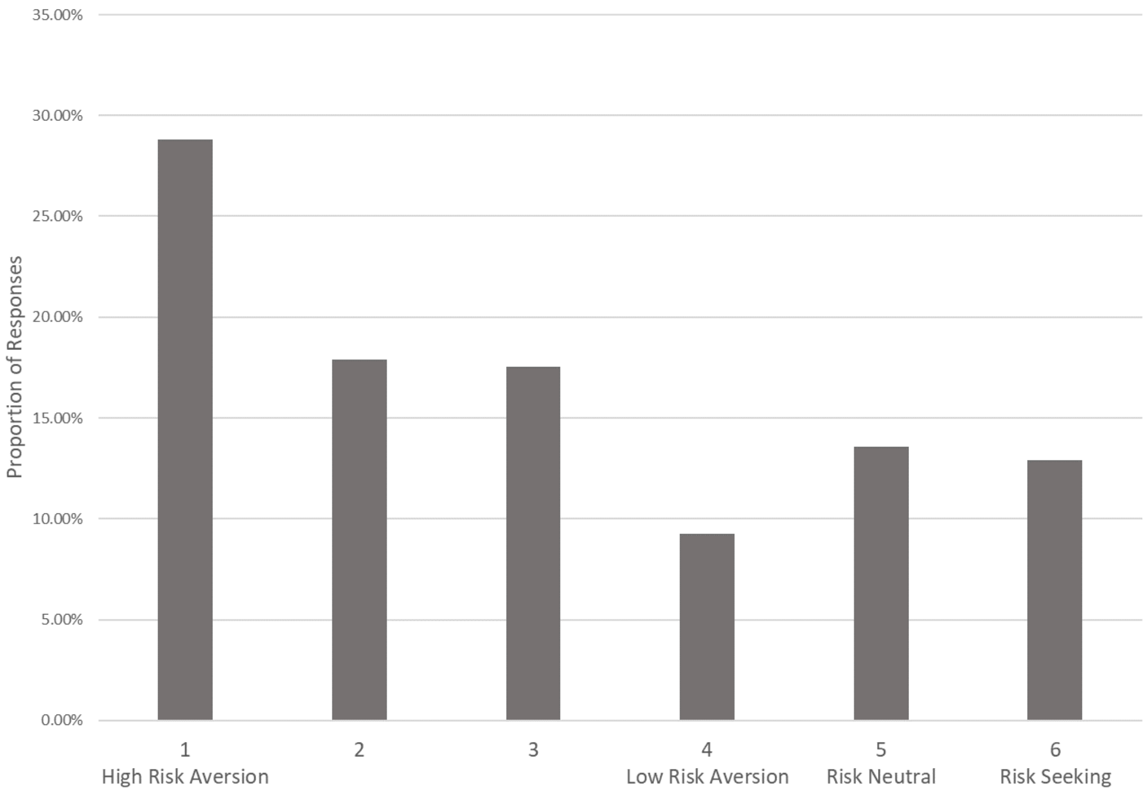
In total, 9,125 invites were sent out, followed up with three reminders to obtain 302 responses in total. Table 2 shows the sample respondent characteristics relative to state proportions, based on the 2016 Australian census. A statistical test of the difference in means suggests that there were no statistically significant differences between the census and sample proportions. In terms of activities that respondents wanted to limit first, an overwhelming preference was for limiting cleaning activities. The activity that was least likely to be limited was cooking activities.

Table 2. Comparison of sample to population proportions for New South Wales

	Rest of New South Wales				**Greater Sydney**			
	Men		**Women**		**Men**		**Women**	
Age	**Sample**	**Census**	**Sample**	**Census**	**Sample**	**Census**	**Sample**	**Census**
18-29	2.82%	2.66%	2.16%	2.66%	6.15%	6.98%	5.48%	6.81%
30-44	5.32%	3.99%	5.48%	3.99%	9.47%	9.80%	9.30%	9.80%
45-59	4.15%	4.32%	4.98%	4.65%	7.97%	7.81%	8.14%	7.97%
60+	7.14%	5.98%	6.81%	6.31%	7.14%	7.64%	7.48%	8.64%
Activities Most and Least Willing to go Without (Full Sample)					**Most**		**Least**	
Cleaning					84.44%		5.30%	
Cooking					7.28%		57.62%	
Entertainment					8.28%		37.08%	

In terms of the distribution of risk preferences, Figure 3 shows that most respondents selected an investment option that would imply risk-averse preferences. The first investment option was selected the most, representing 28% of total responses. A progressively smaller proportion of responses was observed for the less risk-averse options. Around 25% of respondents preferred the risk neutral or risk seeking option. Overall, 45% of respondents selected either option 1 or 2, representing relatively higher levels of risk aversion.

Figure 3. Distribution of risk preferences



Ideally, each level of risk would be modelled as a separate interaction parameter. Preliminary modelling suggested this was not possible due to small sample sizes for several categories. This issue was addressed by creating two categories of respondents. The first group is made up of all respondents who selected either option one or two, labelled as the highly risk-averse group. The second group represented all other respondents. A dummy variable was created equal to one if the respondent was in the highly risk-averse group and zero otherwise. The proportion of respondents in each category was approximately 47% for group 1 and 53 % for group two.

The next set of results reported are for the Mixed Multinomial Logit, as shown in Table 3. All of the mean parameters, with the exception of the daily-reminders parameter, are significant with the expected sign. Since this model is measuring WTA-LCI, the interpretation is that households require compensation, in the form of lower cost increases, in exchange for reductions in the levels of these features. The daily- reminders mean is negative and significant, suggesting that households would pay to have daily reminders removed as a contract feature. Both the alternative-specific constants are negative, suggesting that the unobserved heterogeneity leads to respondents being less likely to select these alternatives[6].

Table 3: Mixed Multinomial Logit (MMNL) results

Attributes	Parameter (Robust Standard Error)		
	Mean	**Interactions**	**Standard Deviation**
Daily Reminders	-5.841***	6.100***	11.840***
	(0.374)	(0.281)	(0.107)
Real-Time Reminders	5.235***	3.071***	7.926***
	(0.318)	(0.265)	(0.126)
One Consumption Restriction	0.891***	9.954***	19.867***
	(0.247)	(0.318)	(0.277)
No Consumption Restrictions	15.571***	11.394***	33.244***
	(0.255)	(0.306)	(0.267)
Renewable Generation	0.682***	0.038***	1.026***
	(0.011)	(0.013)	(0.006)
Storage	0.242***	0.076***	0.504***
	(0.007)	(0.008)	(0.004)
Household Cost ($/year)	-3.185***	1.018***	2.643***
	(0.212)	(0.349)	(0.344)
ASC (Status Quo)	-128.912***		
	(2.005)		
ASC (Option C)	-7.657***		
	(0.225)		
Error Component			-145.377***
			(1.321)
Diagnostics			
No. of Observations			2,416
Log-Likelihood			-1,789.654
AIC			3,669.308
BIC			3,836.277
McFadden Pseudo R^2			0.326

*** 1% significance ** 5% significance * 10% significance.

The next set of results include the risk aversion interaction effects for each of the attributes. For all the non-cost contract features, the interaction is positive and statistically significant. This suggests that the risk-averse group, relative to the baseline group, requires relatively more compensation, or greater reduction in cost increases, for both reductions in energy investments as well as the imposition

[6] An alternative model was estimated which included socio-demographic factors being interacted with the status-quo ASC. A log-likelihood test showed no statistical difference between this model and the one reported in this study.

of consumption restrictions relative to the baseline group. Interestingly, for the ‘consumption restriction’ feature, the risk-averse group requires the most compensation and the baseline group significantly less than the risk-averse group. The interaction parameter between risk aversion and cost is positive and significant. For the baseline group, the median cost coefficient is equal to -0.041 and for the risk-averse group is -0.1145. This result suggests that the risk-averse group is more sensitive to cost and therefore would have a lower WTA for each of the attributes if no other interactions were accounted for.

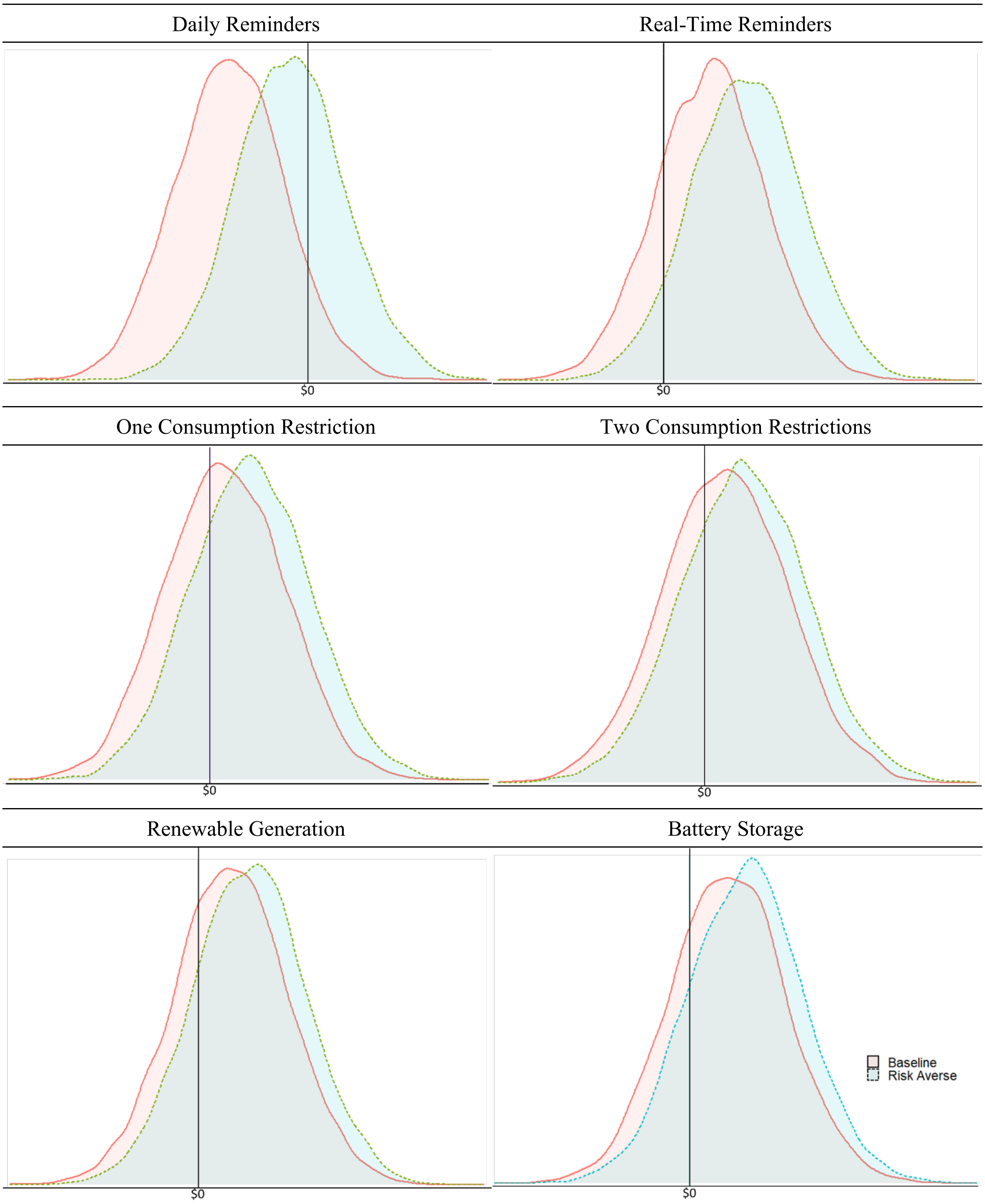
For every contract feature, the corresponding standard deviation parameter is statistically significant, suggesting heterogeneity in WTA-LCI is required at the individual level. In addition, the reported error component is statistically significant, suggesting that there is a substitution pattern shared between the non-status quo alternatives. Full covariance was modelled and the correlations between the random parameters are reported in Table 4. Using a threshold value equal to 0.5 in absolute terms, the correlations suggest that individuals who care about daily reminders also care about real-time reminders and renewable energy generation. The same applies when comparing real-time reminders with renewable energy generation. Individuals who are concerned with having no restrictions imposed also care about more storage and are less concerned with cost, as can be seen with the negative correlation between cost and no restrictions.

Table 4. Correlation matrix random parameters

	Daily Reminders	Real-Time Reminders	One Restriction	No Restrictions	Renewable Generation	Storage	Household Cost
Daily Reminders	1.00						
Real-Time Reminders	0.62	1.00					
One Restriction	-0.08	0.01	1.00				
No Restrictions	0.03	0.11	-0.08	1.00			
Renewable Generation	0.68	0.57	-0.22	-0.25	1.00		
Storage	0.19	-0.22	-0.04	0.79	-0.12	1.00	
Household Cost	-0.07	-0.05	0.22	-0.51	0.15	-0.35	1.00

Finally, to emphasise the difference between the risk-averse and baseline groups for each of the non-cost contract features, the distributions of WTA-LCI values were simulated. Two sets of simulations were performed using both the means and standard deviations reported previously, with the difference being the inclusion of the interaction parameter. Figure 4 shows that for every feature, excluding the daily reminders feature, many of the WTA-LCI values are positive. In addition, the proportion of the distribution that is negative for the highly risk-averse group is less, reaffirming that risk references as measured in this study explain some of the preference heterogeneity within the sample.

Figure 4. Simulated WTA-LCI distributions by contract feature



4.6 Discussion and Conclusions

4.6.1 Eliciting risk preferences

In a number of previous studies on risk preferences, the risk seeking option (option 6 in Figure 2) was not included. A study by Dave et al. (2010) is an exception where the six-option version of the lottery is utilised. The most striking difference is the proportion of respondents in our study who select options one (29%) and two (18%), which are the most risk-averse options. This is in contrast to 10.7% and 11.2% for each option as reported in Dave et al. (2010), which is also similar to Eckel et al. (2012) reporting similar proportions with approximately 20% of respondents selecting options one and two. Although a different number of risk categories were used by Brick et al. (2012) they found that 38% of respondents selected an option suggesting that they were highly risk-averse. In contrast to the above results, Ball et al. (2010) identified a very small proportion of respondents selecting risk-averse options, although they included the same number of options, the low and high payoffs differed in magnitude, with some options potentially leading to negative payoffs.

The variation in the results among studies may be attributed to differences in the number of options, description of payoffs, and whether the lottery was completed in a laboratory versus the field. Some of these differences lead to different implied constant relative risk-aversion ranges. Another reason for the difference noted in our study is the possibility that the survey introduction and choice tasks primed respondents to think about risk in a certain way. Specifically, the issues associated with reliability and green energy may have led households to evaluate choices in way that reflects higher levels of risk aversion. Irrespective of the aforementioned reasons why there are differences. The critical issue for this study was to be able to identify groups of respondents with similar risk preferences so that relative comparisons between groups can be made as part of the discrete choice model.

The highly risk-averse group, those who selected options one and two, make up nearly half of all respondents within the sample. This may be surprising since they selected the safest option in a lottery which involves a guaranteed win. It is possible that this result is a consequence of the payoff mechanism associated with the lottery, specifically the fact that a guaranteed win is possible by selecting the option with the lowest risk. The size of the reward was phrased as the potential for additional survey completion points, which are the standard currency for completing online surveys. The additional points had a value between $1 and $2 depending on the option selected and the outcome materialised. Although the lowest payoff is relatively small, it is nonetheless guaranteed. This payoff mechanism is expected to distort respondents' behaviours (Cox et al., 2015). It is, however, not clear how this distortion would affect the distribution reported. Arguably, a guaranteed gain would lead to excessive risk taking, not the opposite as observed in this study. An alternative explanation is that there is a background risk associated with these tasks (Harrison et al., 2007; Guiso and Paiella, 2008) related to the experience of completing the choice tasks before the lottery exercise. The choice tasks represented contracts that offered lower cost traded-offs for diminishing levels of various features. There is a possibility that the background risk associated with the choice tasks affects the foreground risk of the lottery task (Harrison and Rustrom, 2008; Lusk and Coble, 2008). Previous studies have described this conditioning effect as a form of risk vulnerability (Eeckhoudt et al., 1996; Gollier and Pratt, 1996), which makes risk-averse respondents more risk-averse relative to situations where sources of risk are independent. If this conditioning has occurred, then it does provide context for what the group of respondents identified as "highly risk-averse" represent in this study. Either they represent those who really are just highly risk-averse, or they represent those who are highly risk-averse conditional on the task of trading off lower costs as compensation for diminished electricity services.

4.6.2 Risk aversion interactions with contract features

The overall objective of this study was to determine whether risk-averse consumers required more compensation for reductions in the quality of electricity contracts offered. The results suggest that this is the case, however, this result needs to be considered in the context of each contract feature. Although the WTA-LCI for each non-cost feature is greater for the highly risk-averse group, the cost interaction term suggests that the same group is more sensitive to cost, which *ceteris paribus* would lead to a lower stated WTA-LCI. These results are consistent with past studies (Bartczak et al., 2015; Zawojska et al., 2019), however, when considering both non-cost and cost interactions, the net effect suggests that the amount of compensation required is greater for all non-cost features. A potential explanation for this result is that some of these contract features have not been experienced before, with past studies showing that risk-averse consumers are influenced by their experience with the goods (Che, 1996; Erdem and Keane, 1996). When considering the status quo contract there were two features that have already been experienced by most respondents, specifically no consumption restrictions and higher costs. The other features are not so well experienced, at least at the levels described in this specific contract. This may have made it difficult for respondents to appropriately assess the value of these features, leading to an aversion away from the highest cost contract, resulting in the higher sensitivity to cost. It may also be possible that households have had limited experience with large blackouts, therefore they do not see the benefits in increasing the reliability of the network. This effect may have occurred in other contracts also and it is in part accounted for in the estimation by including an error component that is shared between these alternative contracts.

In terms of the storage attribute, respondents were trading off reliability as measured through different sizes of community (battery) storage. These technologies could be used to address emerging reliability issues in part related to the additional planned and in progress renewable energy generation expected to come online in the coming years (AEMO, 2020). These technologies require either more baseload generation or energy storage, including batteries, or a combination of both. In Australia there is currently an ongoing debate on the optimal mix of energy sources, more so the result of political discourse as opposed to feasibility in a technical sense (Li et al., 2020). Regardless this issue overlooks the fact that Australia has one of the most reliable networks in the world (AEMC, 2020d). This 'gold-plating' of the network has come at a cost to the consumers who end up paying for the additional network infrastructure investments (ACCC, 2012; Wood et al., 2018b).

It is perhaps no surprise that this investment has occurred with previous studies suggesting that consumers are WTP more for increased reliability in the network across several domains. Carlsson and Martinsson (2008) found evidence that Swedish households are willing to pay to reduce the duration of outages at any time in the day, especially when they had recently experienced outages (Carlsson et al., 2011; Amador et al. 2013; Huh et al. 2015). This premium is even larger when comparing shorter and fewer outages compared to longer and more frequent outages (Abdullah and Mariel, 2010; Hensher et al., 2014). There is also some evidence to suggest that this premium is positive even when respondents report using self-generation as their main source of power (Oseni, 2017). Since avoiding outages is a consistent finding, acknowledging differences in the size of WTP values, it stands to reason that those respondents would require compensation for any policies that increase the duration and/or frequency of outages. This is exactly what we find in our study, as well as identifying larger WTA-LCI values for highly risk-averse respondents. This is interesting since in Australia the number of blackouts nationally per annum has steadily declined, in part due to extremely high reliability standards being set by the Australian Energy Market Commission (AEMC, 2020d). As the proportion of renewables continues to increase, households may consider the premium necessary to ensure that more renewable energy generation does not affect the reliability of the network. This is especially the case for highly risk-averse households, who require on average an additional AUD $3.24 for every 10 MWh reduction in community storage relative to the baseline group.

This additional premium may be considered as insurance for a less reliable network; however, it is not just the reliability of the network that is of concern to households. The interaction parameter for the renewable energy attribute and risk aversion suggests additional compensation would be required to reduce the proportion of electricity supplied by renewable energy generators. It is possible that renewable energy generation is thought of as an investment like technologies that improve the reliability of the network. Apart from the smaller states and territories in Australia, the status quo does not involve a large proportion of energy generation provided by renewable energy sources. Therefore, the comparison with a reliable network is not as clear. Another explanation that may explain the higher WTA-LC relates to how respondents consider the risks of climate change. If it is believed that more renewable energy generation insures against the risks of climate change, then this is an expected result. As the number of renewable energy generators increases, the externalities associated with generation from fossil fuels become internalised, which has historically not been the case in Australia, reducing private costs of generation (Byrnes et al., 2013; Hua et al., 2016). Therefore, the risks associated with reversing this current trend may explain why the highly risk-averse group requires more compensation.

For the restrictions feature, it may be difficult to understand how the household will be affected and if it will have any impact on household energy bills. It could be the case that smart meters have the potential to lower bill costs over time. Removing a technology that is valued is therefore expected to lead to not only some compensation, but also more compensation for households who are already risk-averse with respect to the risk of fluctuating electricity bills. With the consumption restrictions feature, status quo bias in the context of preserving existing habits may explain the higher WTA-LC (Samuelson and Zeckhauser, 1988; Kahneman et al., 1991). Past studies have identified status quo bias as a barrier to increasing residential energy efficiency (Blasch and Daminato, 2018), supporting renewable energy projects (Linnerud et al., 2019), and influencing the decision to switch electricity contracts (Grabicki and Menges, 2017). Frederiks et al. (2015) identified risk aversion as one factor that could lead households to favour decisions which are considered low risk, in this case, moving away from contracts that contain no restrictions. Having no restrictions, although costly, is preferred to a decision involving some restrictions in exchange for lower cost increases. If this latter decision is relatively riskier, then this could explain the higher compensation observed for the highly risk-averse group.

The smart meters feature was the only feature that had an estimated interaction sign that was not expected. The result implied that households require more compensation for removing the use of meters as a contract feature. It may be because unlike previous studies, which are considering the adoption of new technologies, in this study it is the reverse. The decision to adopt a new technology is avoided if the status quo contract is selected and any behavioural reasons for not adopting this technology are not relevant.

4.6.3 Policy implications and future research

Using Australia as a case study, we identified that households value contract features that influence the pace of energy investment, therefore compensation in the form of lower-cost increases would be required if the features offered were reduced. The compensation provided would allow for a slower transition towards a renewable energy sector, reduce the reliability of the network over time, and potentially lead to some level of consumption restrictions being a default contract offer. Risk preferences are correlated with the amount of compensation required. Highly risk-averse individuals require more compensation relative to those who are less risk-averse. The results in this study suggest that failing to account for a household's risk preferences leads to lower acceptance rates with respect to potential contract offerings. If not accounted for, it is possible that a slower rate of energy investment occurs yet prices in the long-term still increase, potentially failing to achieve the original policy goal. Looking beyond the immediate contract features, these results suggest that there is a cohort of individuals who want to manage the risks associated with consuming electricity, whether it be regarding investment changes at the national level or changes to the time in the day when energy is consumed at the household level. More generally, the results of this study suggest that any policy change that encourages households to make choices with downside risks should account for their preference for risk. Policymakers need to identify the best policy design and communication strategy, to convince households that these risks are either unfounded or can be mitigated.

For future research, several avenues could further break down the relationship between risk preferences and consumer attitudes or behaviours. Previous studies have suggested that there is a positive association between risk aversion and pro-environmental attitudes or behaviours (Paladino, 2005; Barile et al., 2015; Alcock et al., 2017). It could be that pro-environmental attitudes are correlated with being risk-averse, which is resulting in the larger compensation required for reductions in renewable energy generation. Another possibility alluded to is that the highly risk-averse respondents are resorting to heuristics when making choices (Müller, 2001; Louviere and Meyer, 2008). Linking the potential relationship between risk preferences and choice heuristics could further decompose what has been identified in this study as highly risk-averse households into more distinct groups. Identifying these groups and their motivations could help in designing effective policy messages that further increase the acceptability and eventual acceptance of these policies. Finally, there is the possibility that completing a set of choice tasks can influence the responses in a risk-preference elicitation and vice versa. In this study we only focus on the former, future studies may wish to compare and evaluate if there is evidence of a conditioning effect

Chapter 5: Who will Pay a Demand Charge? Combining an Agent-Based Model and Discrete Choice Experiment for Scenario Simulations

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5.1 Introduction

Liberalisation of the Australian electricity market since the 1990s has led to the privatisation of state-owned utilities (Joskow, 2008; Erdogdu, 2014). One of the benefits of this transition is the growth in retail competition, resulting in households having a greater menu of electricity contracts available (Sirin and Gonul, 2016). Prior to the global financial crisis, increased competition contributed to a fall in electricity prices in real terms. However, this trend has completely reversed with the rise in electricity prices exceeding inflation year-on-year (Simhauser and Nelson, 2013; Valadkhani et al., 2018). There are several contributing factors that in part explain this upward trend in prices. Regulated investment has contributed to what is termed the 'gold-plating' of the network, with the rates of return for investments in transmission and distribution being above those that would occur if the regulation did not exist (Averch and Johnson, 1962; Simhauser, 2019). Additional investments into network infrastructure may continue in response to growing concerns about whether reliability can be ensured with renewable energy generation surpassing 20% of total generation in Australia (Clean Energy Regulator, 2020b).

The overall objective of this study is to evaluate demand response at the household level as one solution to the interrelated issues of renewable energy generation intermittency and network stability. The reliability of the network is influenced by unexpected increases in short-term demand, due to factors such as extreme weather events or unplanned disruptions to supply. The pertinence of considering intermittency and stability is driven in part by the inability to accurately forecast demand (Li et al., 2020; Taieb et al., 2020). Significant increases in wholesale prices due to spikes in demand may justify the need for potential intervention by energy market operators to prevent network-wide failures. This study focusses on demand response as a solution to reduce the risks associated with demand spikes. A regulated peak demand charge levied on residential households makes this demand charge unique in that it would be an additional feature of new electricity contracts that households could opt-out of. Smart meters once installed, can provide households with the real-time cost of electricity. To be able to opt-out, households would have to agree to have their electricity consumption limited by their retailer through their smart meter. This limitation would only apply during the evening peak period, which in Australia is between 5pm and 9pm (AEMC, 2018c).

One of the benefits of implementing such a charge is that households have the option to change their existing energy consumption habits or cross-subsidise other households' peak consumption (Strbac, 2008). Previous studies have shown that the acceptability of demand response policies, such as demand charges, is in part related to the way they are communicated (Steinhorst and Matthies, 2016), and the way consumers engage with these policies, for example with simplifying tariff information or switching procedures (He and Reiner, 2017; Parrish et al., 2019). The charge proposed in this study would be an opt-in charge. Households would not have to evaluate this contract feature until they next intend to switch from their current electricity contract. It may be the case that households choose to delay their intent switch indefinitely, in effect opting out of the decision. Other households may intend to switch immediately, seeing this new feature as one way to limit future bill increases.

One problem with relying on households to opt-in to new features as described is that it assumes high levels of contract switching. Although retail competition has increased substantially following the liberalisation of energy markets, it has not resulted in sustained levels of households actively engaging in switching contracts, with the average annual switching rate in Australia averaging around 20% per annum (AER, 2020). Although this rate does not imply that the Australian market is not competitive, improving the proportion of households who actively engage in contract switching has been identified as one method of increasing the amount of competition within markets, as well as promoting ongoing innovations with respect to the types of contracts offered (Hiteva and Sovacool, 2017). Observing that households do not actively switch contracts leads to the following research questions - which households are most likely to intend to switch from their current electricity contract? Do bill shocks arising from price changes, as well as increases in the variance of their bills influence the intention of switching? Can their choice of the new regulated contract features affect the intention of those in their social network to switch?

We developed a decision support tool to answer the research questions posed in this study that simultaneously models a households' intention to switch from their existing contract as well as the features they would prefer as part of their new contract. The intention to switch is simulated with an Agent-Based Model (ABM) and the new contract features are based on the parameters from a Discrete Choice Experiment (DCE) where households trade off consumption restrictions against higher costs. Both models utilise data from a random sample of households living in New South Wales. The amalgamation of an ABM and DCE combines the strengths of each modelling approach into a decision support tool. ABMs and DCEs have previously been combined to analyse problems related to solar panel diffusion (Araghi et al., 2014), explore market dynamics for roundwood tree markets (Holm et al., 2016), as well as assess the acceptability of digitalized services associated with grocery purchasing (Gatta et al., 2020). As noted by Le Pira et al. (2017) there are several benefits with combining both methods. DCEs allow the estimated stated preferences at a fixed point, however dynamic behaviour is not modelled. ABMs can simulate dynamic interactions between agents and can allow for collective phenomena to emerge. Combining these methods allows for policies to be analysed as both a function of preferences elicited from real-world data as well as emergent behaviours modelled over time. In this study both models allow for preference heterogeneity with respect to the intention to switch as well as the likelihood of selecting a particular contract. A household's individual intention of switching and the size of their electricity bill are simulated using parameters from regressions. A process is defined to model how bill shocks between quarters and social network effects affect the intention of switching. Feedback effects are modelled with the choices made in the DCE affecting the likelihood of future switching behaviour in other households.

The results of our modelling with no price changes suggest that on average 60% of households switch electricity contracts after five years. When modelling different price changes, the price-elasticity of switching is estimated to be equal to 0.19, implying that the intention of switching is price-inelastic, in line with previous studies estimating the price-elasticity of demand for electricity consumption. Bill shocks due to annual increases in electricity prices, increases in the variance of realised bills, as well as the size and configuration of households' social networks are positively associated with the aggregate switching rate. Finally, the majority of households who do switch contracts are from the low-income category. This last result is interesting in that it does not correspond with real-world data. It does, however, highlight the potential for implementing contract features which account for a household's capacity to pay may be social welfare maximising in that it provides an option for households to avoid higher electricity bills.

The next section in the paper provides an overview of the literature, highlighting research gaps addressed by this study. Section 3 discusses the methods employed and the data collected. Section 4 presents the results of the data collected and the key outputs of the simulation, including sensitivity analysis, as well a discussion of the key findings. Concluding remarks and the limitations of the study are discussed in section 5.

5.2 Literature Review

5.2.1 Electricity contract switching

Past studies show that contract switching is one way to assess the competitiveness of a market (Waterson, 2003; Littlechild, 2006). Despite the numerous waves of deregulation observed in energy markets around the world, the rate of households switching to new contracts has remained low (He and Reiner, 2017; Hortaçsu et al., 2017; Ziegler, 2020). The main impediment to switching is often explained by search costs incurred to identify and evaluate new contracts, with household welfare potentially falling in a deregulated market where search costs are high (Brennan 2007). Defeuilley (2009) categorises consumers as being dynamic or inert with respect to their reaction to changes in retail electricity markets. The former is price-responsive and encourages retailers to innovate and develop contracts that better match consumer preferences, whilst the latter are loyal to the incumbent and reinforce their existing market share.

There have been many factors proposed in past studies that influence switching rates. To overcome potential switching costs, the expected economic benefits from switching need to be significant (Giuletti et al., 2005; Ek and Söderholm, 2008; Gamble et al., 2009). The types of benefits vary between studies, with Gärling et al. (2008) highlighting that higher switch rates result from the provision of high-quality information that details each household's consumption patterns, tariffs, and available electricity retailers (Wieringa and Verhoef, 2007; Six et al., 2017; Yang et al., 2018). Wilson and Waddams Price (2010) identified that even when goods have few attributes, customers often make errors when deciding to switch based solely on price, often acquiring less than half of the potential savings related to lower tariff rates (He and Reiner, 2017). Several studies have identified that in addition to the provision of information, preference heterogeneity of determinants is not related to switching costs. Other determinants include whether customers are switching contracts with their existing retailer or externally (Scleich et al., 2019), their knowledge of market reforms (Daglish, 2016; Shin and Managi, 2017), recent experiences with switching in related markets (Vesterberg, 2018; Fontana et al., 2019; Harold et al., 2020), and status quo effects (Yang, 2014; Ndebele et al., 2019).

The research gap that our study addresses is the role of household bills and income in determining the propensity to switch. Previous studies have identified conflicting results, with both high and low-income households more likely to be active in the market (Ek and Söderholm, 2008; Gamble et al., 2009). More recent studies have identified that income is positively associated with higher switching rates (Daglish, 2016; Hortaçsu et al., 2017; Shin and Managi, 2017), however, a recent study by Schleich (2019) shows that this association only holds for households with the highest levels of income, not those households with average levels of income. Although these households may have greater economic resources, the higher opportunity cost of time may exceed the potential savings, especially if their expenditure is already a relatively small proportion of their income (Waddams Price et al., 2013). This may explain the inverted U-shape observed by Giuletti et al. (2005) when comparing income and search costs (He and Reiner, 2017). Based on this observation, we hypothesise that it is the ratio of household electricity consumption, measured by the size of their electricity bill, and income that determines their likelihood of switching. Households with a high electricity bill relative to their household income have a greater motivation to switch to contracts with lower-rate tariffs, whereas households with bills representing a marginal proportion of their total income will be less likely to switch due to the high opportunity cost of time relative to potential cost savings. This hypothesis is novel in that we have not found any other study to date that focuses on switching rates differing due to differences in household bills as a proportion of their income.

The second research gap in the literature addressed in this research is whether social networks influence switching rates. Ek and Söderholm (2008) present evidence to suggest that social descriptive roles, or the perception that others around me are switching, influence the decision to switch. A recent study by Ziegler (2020) found that social preferences are relevant when considering the switch to green electricity contracts. In this study, we test the hypothesis that the size of a household's social network matters since a household's previous experience with switching could be communicated within the network and potentially increase the likelihood that others would switch. This hypothesis is in part driven by past studies identifying that the greater the number of social links, the higher the probability that information will diffuse within a network (Katona et al., 2011; Halberstam and Knight, 2016). In our model, we allow for both positive and negative experiences with switching to affect switching rates, allowing for the possibility that repeated communication of negative experiences would reinforce a state of inertia with respect to switching.

5.2.2 Agent-based modelling

The justification for combining ABM with a DCE is based on the capacity of each method to address issues associated with modelling decisions and behaviours within electricity markets. Although they are not unique to electricity markets, issues such as imperfect information, strategic behaviour, and multiple equilibria are not always solvable with traditional econometric techniques (Tesfatsion, 2006; Fagiolo et al., 2019). There is also the effect of preference heterogeneity, which if not accounted for, can lead to biased estimates. All the factors listed here can be mitigated using an ABM, and when combined with parameter estimates from a DCE can be used to create enhanced decision support tools as compared to equivalent tools utilising only one of these methods. One potential weakness with ABMs is the issue of ensuring the validity of the simulation results. Often, this weakness is addressed by calibrating the parameters of the model so that the results reflect real-world data (Jackson et al., 2017). In the case of our study, this is problematic when considering preferences for contract features that do not exist. Addressing this problem relies on the use of stated preference techniques, and in the case of our study, the results of a previously estimated DCE. The results of this model are included as a component of the ABM simulating when households switch contracts as well as predicting their preferred contract features.

Various aspects of electricity markets have already been analysed using ABM. Weidlich and Veit (2008) review several studies related to wholesale electricity markets, focusing on the issue of electricity contract switching, where they identified a range of sources of preference heterogeneity that affect the likelihood of switching. As noted below, several studies have used ABMs to investigate determinants of contract switching. Roop and Fathelrahman (2003) model the process of households switching from a fixed rate to time-of-use tariffs. They explain this process as several steps where households compare their expected bill amount for each period with the realised amount. If the realised amount exceeds the expected amount, then it is possible that a household will switch. For the switch to occur, not only does the difference need to be large enough, but also the expected savings arising from a new contract need to exceed some threshold. Implicitly, Roop and Fathelrahman's model included switching costs through the requirement of thresholds to be exceeded. Müller et al. (2007) go one step further by utilising survey data to calibrate switching costs as well as other aspects of customer's behaviour, acknowledging that switching is a multi-step process. The findings of their simulation suggest that customer inattention is the reason retailers are not incentivised to lower prices. Linking the results to real-world data, they postulate that this inattention explains why there has been no significant changes in the annual switching rate despite the observed slow increase in prices. Zhang et al. (2011) in their study evaluate the United Kingdoms' smart metering policies to identify various psychological factors that influence the rate of smart meter adoption and show how ABM can be used for policy evaluation, which is similar to our study. Kowalska-Pyzalska (2014) explores the role of past opinions in the adoption of dynamic tariffs, reaffirming the finding that indifference with respect to electricity contracts is one factor that explains the empirically observed intention-behaviour gap. This study extends the literature with respect to the application of ABMs in residential electricity markets where we model preference heterogeneity, the likelihood of switching and household bill amounts based on socio-demographic characteristics linked to real-world data. We define a process where bill shocks may impact the intention of switching, with these shocks caused by variations linked to annual price changes as well as weather effects. Social network effects are modelled with choices made resulting from the DCE model influencing the likelihood of switching behaviour in a household's neighbours. Finally, the switching rates observed in the model are externally validated to real-world switching rates published by the Australian Energy Market Commission (AEMC, 2020c). These extensions go beyond what has been explored in previous studies and work towards providing additional insights into customer switching behaviours. It is also possible to identify which households will switch, highlighting different groups of households who not only would be more likely to switch, but also how different contract characteristics determine the switching behaviours of particular groups in relation to consumption restrictions or additional demand charges.

5.3 Methods

The model description below has been written using the ODD+ protocol for describing Agent-Based Models initially developed by Grimm et al. (2006) and extended by Muller et al. (2013).

Overview

I.i Purpose

The purpose of this study was to combine an Agent-Based Model (ABM) with the results of a Discrete Choice Experiment (DCE) to determine what proportion of households would accept consumption restrictions. The ABM models a household's probabilistic intention to switch from their current electricity contract. If they realise their intention, the parameters from the DCE determine the likelihood that households will select from one of three contracts, which vary in terms of cost and the amount of consumption restrictions imposed. Both models are linked in that switching in the ABM leads to a choice made in the DCE and the choice made in the DCE affects the switching rate of neighbouring households.

This model is designed for decision makers who are concerned about electricity contracts, including electricity retailers and market regulators. Several use cases for the model include forecasting changes in aggregate switching rates over time, understanding what factors influence contract switching rates, and calculating own-price elasticities with respect to contract switching. The model is also used to test two hypotheses. Both hypotheses test whether bill shocks and social networks affect aggregate switching rates.

I.ii Entities, state variables, and scales

Individual households are the main agents in the model. Each household is characterised as having a unique set of socio-demographic characteristics and bill size. They may also be connected to a series of social networks of varying sizes. All households initially start with a pre-regulation electricity contract. As the simulation evolves, households realise their intention to evaluate a new set of contracts that only vary in terms of cost and the level of consumption restrictions imposed. The regulator is another agent in the model that serves two purposes. Its first purpose is to impose annual changes in the price of electricity. The second purpose involves requiring electricity retailers to provide three new contracts for households that only differ in terms of the previously mentioned features. The final agent in the model is nature. This agent introduces stochasticity with respect to the size of realised electricity bills each quarter. The source of this stochasticity is the weather, with some quarters having above or below average temperatures. Differences in temperatures implicitly mean more electricity is required for heating.

There are two exogenous drivers in the model. The first driver is the annual price changes imposed by regulators. The second driver is the stochastic changes in the weather each quarter, which affect the variance of realised electricity bills. One step in the model represents three months (one quarter), and each simulation was run for 20 quarters. 10,000 households are included in each simulation. 40 versions of the model are run to test the previously mentioned set of hypotheses as well as to perform sensitivity analysis. Each version is simulated 200 times to account for simulation error and produce confidence intervals for key outputs. Spatial resolutions are modelled through the social network, with each household having a maximum number of social links, with those links being in part determined by whether neighbouring households have similar ages and incomes.

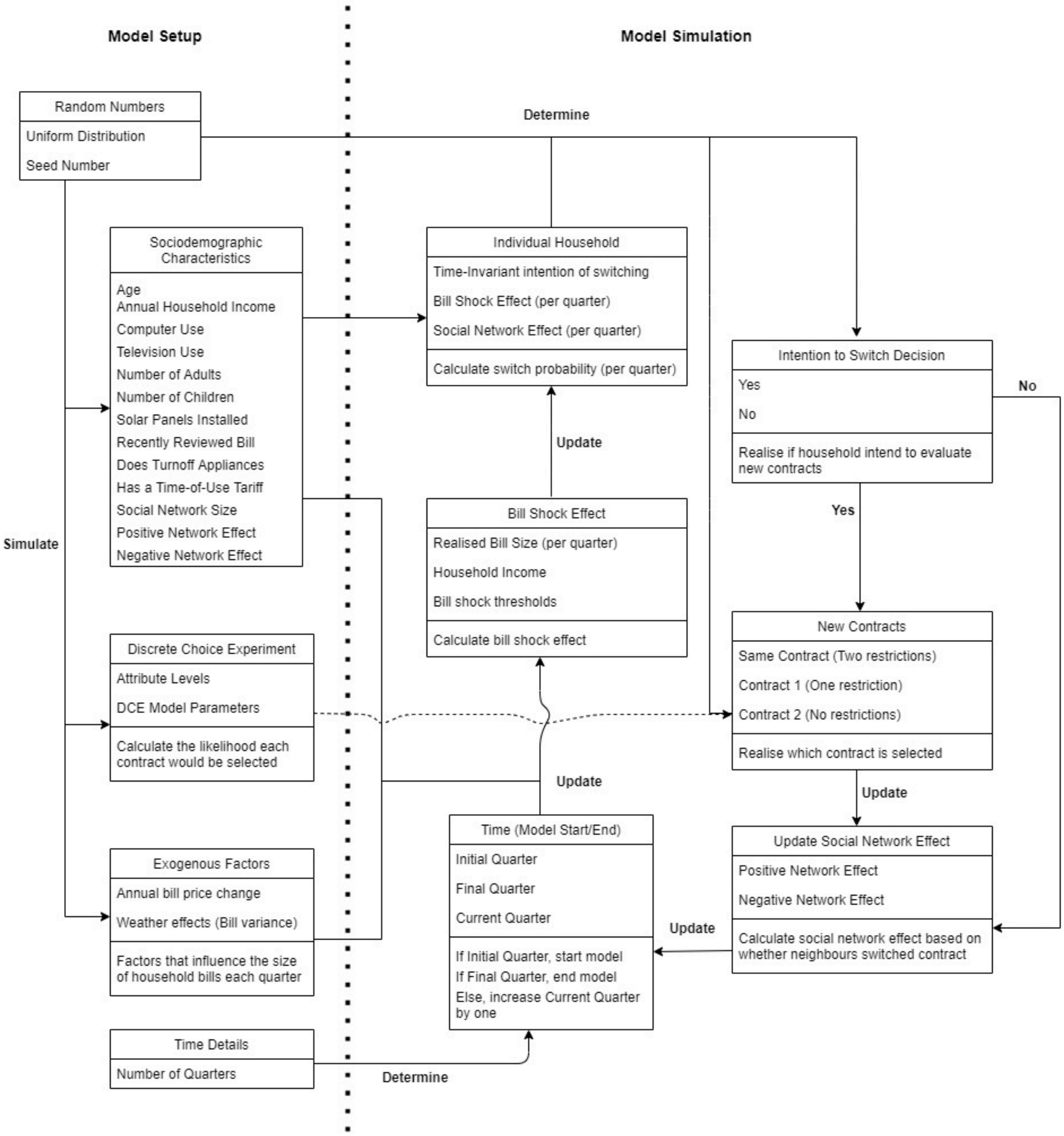
I.iii Process overview and scheduling

Figure 1 provides an overview of the process detailed below. In each quarter of the model, households evaluate several choices based on updated information. The first piece of information is whether their realised as a proportion of their household income exceeds a set of thresholds. The realised bill may change due to cumulative regulated price changes and or weather effects. If the realised bill proportion is above or below the specified threshold, their intention to switch may change in the current quarter. They also observe which of their neighbouring households switched in the previous quarter, as well as whether their neighbours' experiences were positive or negative. All this information is used to update their intention of evaluating new contracts in the current quarter. This updating process does not occur if the household had switched in any previous quarter.

When they realise their intention to switch, they evaluate the new set of regulated electricity contracts. They then probabilistically select one of the new contracts required by the regulator. If they select the status quo contract, the fixed component of their electricity bill will not change, however, they will now be prevented from using specific sets of appliances during the peak evening consumption period. Selecting this contract will be considered a negative experience and will impact the social network at the end of the quarter. If the household selects one of the other contracts, it will have a positive effect within their social network.

After determining which households switch to new contracts, the social network effect is calculated. Each household identifies which neighbours switched and whether the experience was positive or negative. The net effect is the simple aggregation of positive and negative experience. A net positive effect increases the likelihood a household will intend to switch in the next quarter. A net negative effect lowers the intention. After this calculation is completed, the model switches to the next quarter and repeats until the last quarter.

Figure 2 Model Process Overview



Design Concepts

II.i Theoretical and Empirical Background

Households are assumed to make a contract switching decision based on the associated economic and psychological benefits and costs (Bansal et al., 2005). As noted in Yang (2014), there are four main factors that influence the switching decision: customer loyalty, the cost of switching, service recovery, and the economic attractiveness of alternatives. For the last factor, we assume that households make decisions consistent with Random Utility Maximisation theory (Marschak, 1960) when selecting from the offered regulated contracts. The choice to consider these different contracts, as well as deciding which regulated contract to select represents a probabilistic choice based on the alternatives provided as well as the features of each alternative.

Households experiencing a bill shock, whereby their realised bill is greater than their average bill have been documented as a relevant factor in markets where the product purchased is a service, for example, mobile phone contracts (Grzybowski and Pereira, 2011; Lunn and Lyons, 2018). In one study by Hortaçsu et al. (2017), bill shocks were found to lead to a marginal increase in a household's intention to switch from their current electricity contract. This was the only paper found to focus on bill shocks in the context of electricity markets. Related to the issue of bill shocks is whether a household income influences the intention to switch. Past studies have identified mixed results with respect to the role income plays (Ek and Söderholm, 2008; Gamble et al., 2009). In this study we assume that it is the ratio of bill size to household income that determines whether bill shocks affect a household's intention to switch. It is assumed that greater variations in the size of the electricity bill is also caused by extreme weather. The greater the variation, the more electricity is required to maintain a standard of comfort.

The size of the social networks is based on Dunbar's number, whereby households have on average five people within their inner social circle (Gonçalves et al., 2011). It is assumed that only those individuals within the circle would be the only ones whose contract switching decision would influence a household's intention to switch from their current contract. Three types of social network structures are constructed (Corbae and Duffy, 2008). The first structure is a small-world network, whereby the likelihood that households are neighbours is determined by having a similar age and income. The second network structure represents local uniform matching, whereby households are randomly paired subject to some maximum number of links. The last structure represents uniform matching in that every household is linked together. For this last structure, the average social network effect is calculated each quarter and applies to all households.

A household's time-invariant intention to switch as well as their average bill size is based on a set of regressions on data collected from a survey in June 2019. In total, 241 observations were collected from randomly sampled households living in the Australian states of Victoria and New South Wales. The survey included several sections, three of which are relevant to this paper. A discrete choice experiment was created to elicit household preferences for alternative electricity contract features. The second section asked a set of questions related to when they did or did not recently switch from their current electricity contract as well as the reasons why. The third section was a set of questions asking about the socio-demographic characteristics of the household. The data was pooled due to insufficient statistical evidence suggesting that differences in intentions and bills were based on the state the household lived in.

Several assumptions are made about the broader retail electricity market. The market is assumed to be in equilibrium, in that there are no significant changes in supply or preferences during the simulation. Other contract features relevant to electricity contracts are assumed to be constant. This means that if households do select a contract with some restrictions, they will substitute when they perform specific activities. For example, they may choose to do cleaning activities earlier in the day. It assumes that only the regulated features are being considered by households. Finally, it is assumed that once a household switches during the model simulation, they will not switch again. This assumption is based on international evidence suggesting low contract switching rates and the timeframe of the simulation being five years. This simulation only considers the switching to regulated contracts and no other innovations that may emerge in retail electricity markets, for example, other new contract features.

II.ii Individual Decision Making

Households make several probabilistic decisions throughout the model simulation. At the end of each quarter, households first realise their intention to switch. If they do decide to consider switching, they then decide which of the three regulated contracts on offer they will select. They then realise which contract is selected. Households are assumed to be rational decision makers in that they do not make decisions that are not in their best interest. Social norms or cultural values do not play any role in the model. Realised bill amounts vary each quarter and can influence whether a bill shock is experienced. In addition, previous periods' social network effects can affect a household's intention to switch in each quarter. The social network is the only spatial element in the model, with each household having a varied number of links with other households.

II.iii Learning

Households update their intention of switching each quarter based on their social network. Once their neighbours start to switch this can have a cumulative effect on their intention to switch as the simulation progresses. The bill shock only happens in the quarter that it is experienced and is therefore not cumulative. Regulated price changes are cumulative and average bill sizes do adjust to reflect past price changes.

II.iv Individual Sensing

Individuals observe their realised bill every quarter and calculate what proportion of their household income it represents. If this proportion is above or below a pre-determined household-specific threshold, then their billing intention is modified. Households only observe when their neighbours switch to a regulated contract. They cannot sense switching outside of their social network, except in the set of simulations that assume a uniform matching network. This sensing process is also not erroneous. The mechanisms by which households obtain information are modelled explicitly as described above. Costs for cognition or gathering information are not included in the model.

II.v Individual Prediction

Households are not forward-looking in that they do not predict when their intention to switch is realised, nor the regulated contract they would select.

II.vi Interaction

The interactions are direct through households being linked within a social network. The interactions are dependent on households being linked within a social network. They are also dependent on at least one of the linked households evaluating one of three new contracts. At the end of a quarter, each household identifies which of their neighbours evaluated the new set of contracts as well as which new contract was chosen. This last point determines whether there is a positive or negative social network effect.

II.vii Collectives

The social network effect aggregates the switching decisions of linked households. The degree of aggregation is imposed by the modeller, however, the net social effect for each household emerges during the simulation.

II.viii Heterogeneity

Households are heterogenous with respect to their socio-demographic characteristics, average bill size and social network. All households make the same set of decisions, however, the probability of each household realising a decision varies. Heterogeneity is imposed when the model is initialised.

II.ix Stochasticity

The variance in realised bills is a stochastic process. When the model is initialised, random draws from a triangular distribution are drawn. The realised bill amount is multiplied by the random draw to represent variations in the bill due to changes in the weather each quarter. Based on what version of the model is run, one of two sets of draws are calculated. The first involves a minimum variation of 90%, a maximum variation of 120%, and a most likely variation equal to 100%. The second set changes the maximum variation to 160%, representing more extreme weather that requires more electricity to maintain a comfortable temperature at home.

When the model is initialised, random draws from a uniform distribution are utilised to simulate each households' socio-demographic characteristics. Random draws from a triangular distribution are used to determine each quarters weather effect. Random uniform draws are alsostored for each household to be compared against each set of decisions they evaluate to determine if said decisions are realised.

II.x Observation

All the data used to initialise the model was stored, including the random numbers utilised and the random seed number that was specified in both GAMS and R. At the end of each quarter, data for every household is stored. This included whether their intention to switch was realised each quarter as well as the actual probability of their intention. If they had a bill shock or non-zero network effect, that was also recorded. Finally, if their intention to switch was realised, the contract they selected was recorded.

All of this was recorded to calculate the aggregate switching rate for each version of the model. This allowed for comparisons in switching rates due to different price changes, variable sizes of the weather effect, as well as differences in social networks assumed. For each household that switched contracts, it was possible to look at what factors influenced their switching behaviour as well as determine which groups of households did or did not switch.

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Details

II.i Implementation Details

The simulations are run in GAMS Distribution 34.2.0. The data that is inputted into GAMS is simulated using R version 4.0.3 within RStudio version 1.4.1103. Microsoft Excel is used to transfer the data from R to GAMS. The machine that ran this simulation was using Windows 10 Education edition with an Intel(R) Core(TM) i7-7700 CPU @ 3.60GHz, 3600 Mhz, 4 Core(s), 8 Logical Processor(s), and 16GB of RAM. For 10,000 agents and 200 runs of the model to account for simulation error the average processing time was just over three hours. Physical RAM was the limiting factor with increasing the number of households.

III.ii Initialisation

There are two GAMS files, the first is used to create the social network, mapping the links between households. The second file runs the rest of the simulation. The code for the models is available from the authors on request. The model starts at q=1, which represents the first quarter of the year and ends when q=20. Initialisation does vary due to the random number seeds used in each run of the model. The seeds used for each unique simulation have been recorded and included in the appendix.

The thresholds for determining whether a household's bill as a proportion causes a bill shock is arbitrary. It is assumed that if the bill represents less than 1% of a household's income, it will reduce their intention to switch by 1%. If the bill exceeds 5% of a household's income, it will increase their intention by 10%. If the proportion lies between these ranges, there is no bill shock. The percentage change in intention is also arbitrary. The ranges for the weather shock in terms of the minimum, maximum, and most likely percentage were arbitrary.

In the small-world social network, the specification that households are more likely to be neighbours of other households with similar ages and incomes is based on previous studies highlighting these characteristics as a source of homophily (Mele, 2021). How important each neighbours social network effect was in influencing their neighbour's intention to switch is somewhat arbitrary. Using the aforementioned survey data, the relative importance of each reason for switching or not switching was used to calculate an absolute value to be included in the social network effect. For example, approximately 48% of respondents who did not switch stated their reason for not switching was that they wanted a lower price. This meant that in the model, before any scaling their negative network effect would reduce their neighbour's intention to switch by 48%. The various switching reasons and relative frequencies are reported in Appendix 3. To reduce this large of an effect, each social network effect, positive or negative, was multiplied by the parameter omega. This parameter was set to 0.1, which was arbitrary. This meant that the negative effect ranged from 0.2% - 4.8% and the positive effect was 0.7% - 0.32%.

III.iii Input Data

The regressions used data collected from the DCE survey (results from chapter 2 of the thesis). The estimated parameters, irrespective of their statistical significance, were used to produce a synthetic dataset of individual intentions to switch as well as average bill sizes. Where possible, data from the latest Australian census was used to obtain the actual distributions for some of the characteristics so that a true distribution could be simulated (Australian Bureau of Statistics, 2016). Table 1 in the Appendix highlights where the sample data and the census data were used to create the synthetic datasets. Using frequency distributions for each variable, either from census data or the survey, random numbers were used to create synthetic households that had characteristics that reflected the simulated distributions.

The DCE uses parameters estimated from survey data. Using these parameters, the average probabilities for each contract were calculated. Although the averages are reported in this paper, the actual probabilities will vary since the status quo contract includes several alternative-specific parameters as interactions with socio-demographic characteristics. Specific probabilities are calculated during the simulation.

III.iv Submodels

Billing Equation:

For every household *h*, an expectation of their average quarterly bill is simulated. Every respondent in the survey was asked to state their most recent electricity bill amount, based on which the following log-linear regression was estimated:

$$\ln(Bill_h) = \alpha + \beta s_h + \varepsilon_n \quad (1)$$

where the logarithmic transformation of the bill amount for every household was chosen due to better model fit being obtained, α represents the average bill amount holding all other factors to be zero, β is a vector of parameters estimating associations between the bill amount and a matrix of socio-demographic characteristics s_n, and ε_n is a normally distributed error term. The estimated parameters were then used to simulate the expected bill amount for each household, in the same way as described previously, defined as Bill(E).

During the simulation, each households' expected bill amount, as well as their stock of appliances was fixed. This assumes that each household intends to maintain their electricity bill to be a fixed proportion of their household income. This proportion represents a utilisation rate based on their stock of appliances and existing consumption patterns. Although these assumptions do not allow for expectations to evolve over time, it does not mean households are not price responsive. Differences between a household's expected bill amount and the realised amount each quarter can affect their propensity to switch. The realised bill is a function of annual prices and a weather shock as shown in equation 2:

$$Bill(R)_{hq} = \left(1 + \delta P_q\right) Bill(R)_{hq-1} \varphi_q \quad (2)$$

where the realised bill amount in every quarter q is a function of the previous quarters realised bill multiplied by an annual price change and weather shock. In the first period the realised amount is set to be equal to Bill(E). A dummy variable P_q is equal to one if a particular quarter involves a price change and δ is the specified price change expressed as a percentage. The final term φ_q is a randomly generated error term every quarter drawn from a triangular distribution with this error term affecting all households.

Discrete Choice and Social Network Model:

In the ABM, households faced contracts which included only two features, the potential for consumption restrictions and changes in the fixed cost component of their bill. Using the parameters from the solved DCE the likelihood of selecting a particular alternative is shown in Table 1.

Table 1. Policy scenario modelled including average probability of contract selection

Feature:	Contract A (Status Quo):	Contract B:	Contract C:
Consumption Limits	High Limit	Low Limit	No Limit
Average bill increase per quarter over the next five years	\$0 per quarter	\$40 per quarter	\$80 per quarter
Probability of selecting contract	40.95%	48.32%	10.73%

Over half of all respondents who complete the DCE are expected to select away from the status quo, which is important for considering how the network effect works.

The choice between the status-quo contract and the other contracts, determines whether the network effect is positive or negative. If the status quo contract is not selected, then the effect it positive, otherwise it is negative, as households do not actually switch to a new contract and retain their existing contract with two consumption restrictions. This may be based on the probabilities mentioned in Table 2, but it does not explain the rationale for this choice. Respondents are asked further questions in the survey to assess the reasons for recent switching or not switching from their existing contract along with the category of responses reported in Table 3.[7] The reported frequencies were used as ordered rankings of importance for (not) switching. It was assumed that the positive reasons for switching would increase the likelihood of neighbours' intentions to switch, and the reasons for not switching a negative effect. The equation for calculating the network effect is shown in equation (3):

$$Network\ Effect_{hq} = \Omega \sum_{n=1}^{N} \left(Switch_{n(q-1)} Reason_n - No\_Switch_{n(q-1)} Reason_n \right) \qquad (3)$$

For each household and quarter the network effect is the summation of all their neighbours positive or negative reasons for switching, multiplied by a scalar omega. Both $Switch_{n(q-1)}$ and $No\_Switch_{n(q-1)}$ are dummy variables equal to one when the neighbour had switched in a previous period. If they selected the status-quo contract $No\_Switch_{n(q-1)}$ will be equal to one, otherwise $Switch_{n(q-1)}$ will be equal to one. The term Ω scales the importance of the network effect when calculating the individual household's likelihood of switching. For the global matching social network whereby all households are linked

[7] Appendix 3 details the proportions for each of the responses.

together equation (3) does not change except for the fact that the network effect is divided by the number of households to obtain an average network effect that applies to all households.

5.4 Results and Discussion

5.4.1 Descriptive statistics

The individual likelihood of switching and the average quarterly bill were simulated for each household utilising both survey and census data. Table 2 reports the regression results for each equation as well as the average values for each of the characteristics simulated. The average switching rate was 21.10%, which is slightly higher than the 2018/19 rate of 20.63% reported by the Australian Electricity Market Commission (2020). For the switching model, the estimated parameters for many of the characteristics are statistically insignificant, however, they have the expected signs. The most important characteristic for this model is whether respondents recently reviewed their current electricity bill, potentially signalling their intention to switch in the future. Daily computer use was also negative and statistically significant.

Table 2. Switching and billing model regression results

Variable:	Switching Model:	Billing Model:	Average (A) or Mode (M):
Annual Switching Rate (1 = Yes)			21.10%
Constant	-2.2188 (1.8330)	4.0165*** (0.2116)	
Age (Continuous)	0.1229 (0.0758)		47 (A)
Age Squared (Continuous)	-0.0012* (0.0007)		
Quarterly Household Income (Categorical)	-0.0003 (0.0002)	0.00009 (0.00006)	$27,000 (M)
Daily Computer Use (1 = Yes)	-1.0169** (0.4102)	0.41207*** (0.1218)	81.55% (A)
Daily Television Use (1 = Yes)	-0.6240 (0.4350)		85.24% (A)
Number of Adults (Continuous)		0.2270*** (0.0506)	2 (M)
Number of Children (Continuous)		0.1052** (0.0491)	1 (M)
Own Solar Panels (1 = Yes)		0.4046*** (0.1097)	27.32% (A)
Reviewed Bill Recently (1 = Yes)	2.120*** (0.3618)		62.99% (A)
Turnoff Appliances (1 = Yes)		0.3664*** (0.0963)	
Time-of Use-Tariff (1 = Yes)	-0.3743 (0.3080)		47.26% (A)

Diagnostics:		
Number of Observations	241	
R-Squared		0.22
McFadden R-Squared	0.18	
AIC	1.1936	2.2453
BIC	1.3230	2.3460

The billing equation, when compared to the switching regression, is relatively better with respect to the number of statistically significant coefficients. The only coefficient that is not statistically significant at 5% is the income coefficient, which however has the anticipated sign indicating higher income households are more likely to have higher electricity bills. The regression results suggest that larger households, in terms of the number of adults and children who utilise more appliances, were more likely to have larger electricity bills. Interestingly, these are also the households most likely to own solar panels and regularly turn off appliances, potentially to reduce already large electricity bills. Based on the survey data, the majority of the respondents use computers and televisions daily and regularly review their electricity bills. Just over a quarter of all households have solar panels installed and just under half stated that their current electricity tariff was a time-of-use tariff.

Utilising these two regressions, the individual switch probabilities, before any billing or social effects, can be simulated to obtain a distribution of switching probabilities, as shown in Figure 2. There are two modes of switching probabilities, the first having an average likelihood of switching in any given quarter equal to approximately 2%. The second mode has an average likelihood of switching equal to approximately 8%. The next set of probabilities shown in Figure 3 report the same distribution for the 20th quarter in the simulation considering the bill shock effect. This figure relates to the baseline version of the ABM; however, the pattern is consistent for the other versions, in that there is the third cohort of households who have an individual likelihood of switching within a given quarter in excess of 15%.

Figure 2. Distribution individual switch probabilities

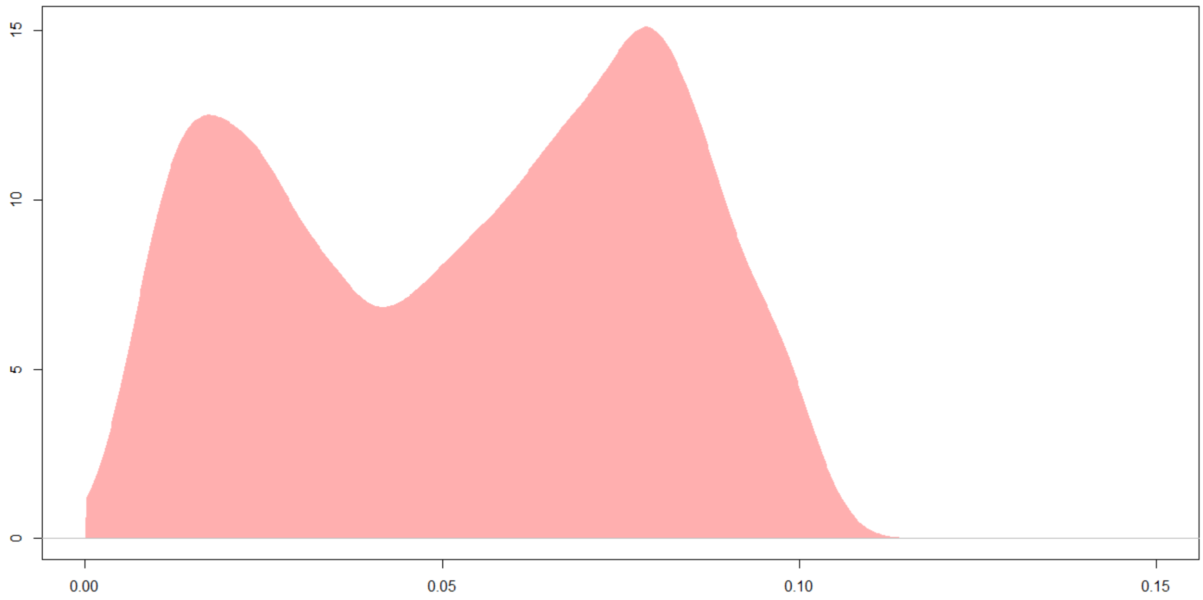
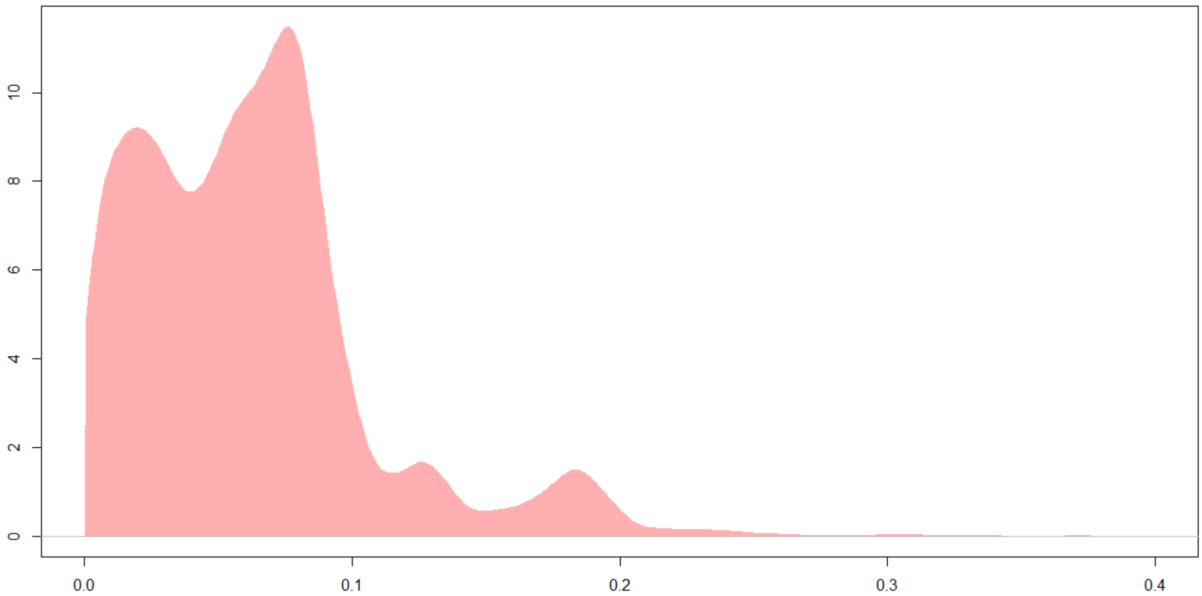
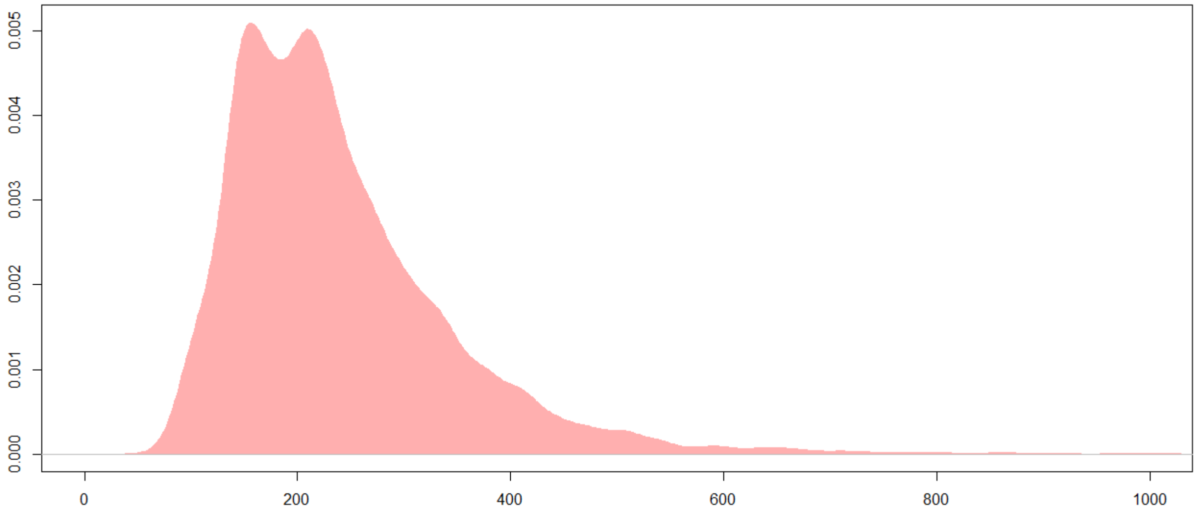


Figure 3. Individual switching probabilities including billing and network effect (20th quarter)



The next set of results relate to the distribution of billing amounts, based on the simulated equation results in Table 2. The average bill size is equal to approximately $238 a quarter. This amount is slightly lower than the actual 2019 data, which was $323 and $283 per quarter respectively for NSW and Victorian households (AEMC, 2020c). Although this result may on average underestimate the size of electricity bills, acknowledging that the sample did not include renters, the distribution of bills shown in figure 4 is consistent with past studies identifying a familiar lognormal distribution when analysing utility bills (Fan et al., 2015; Roberts et al., 2019). Larger, wealthier households are likely to consume a large amount of electricity relative to average households.

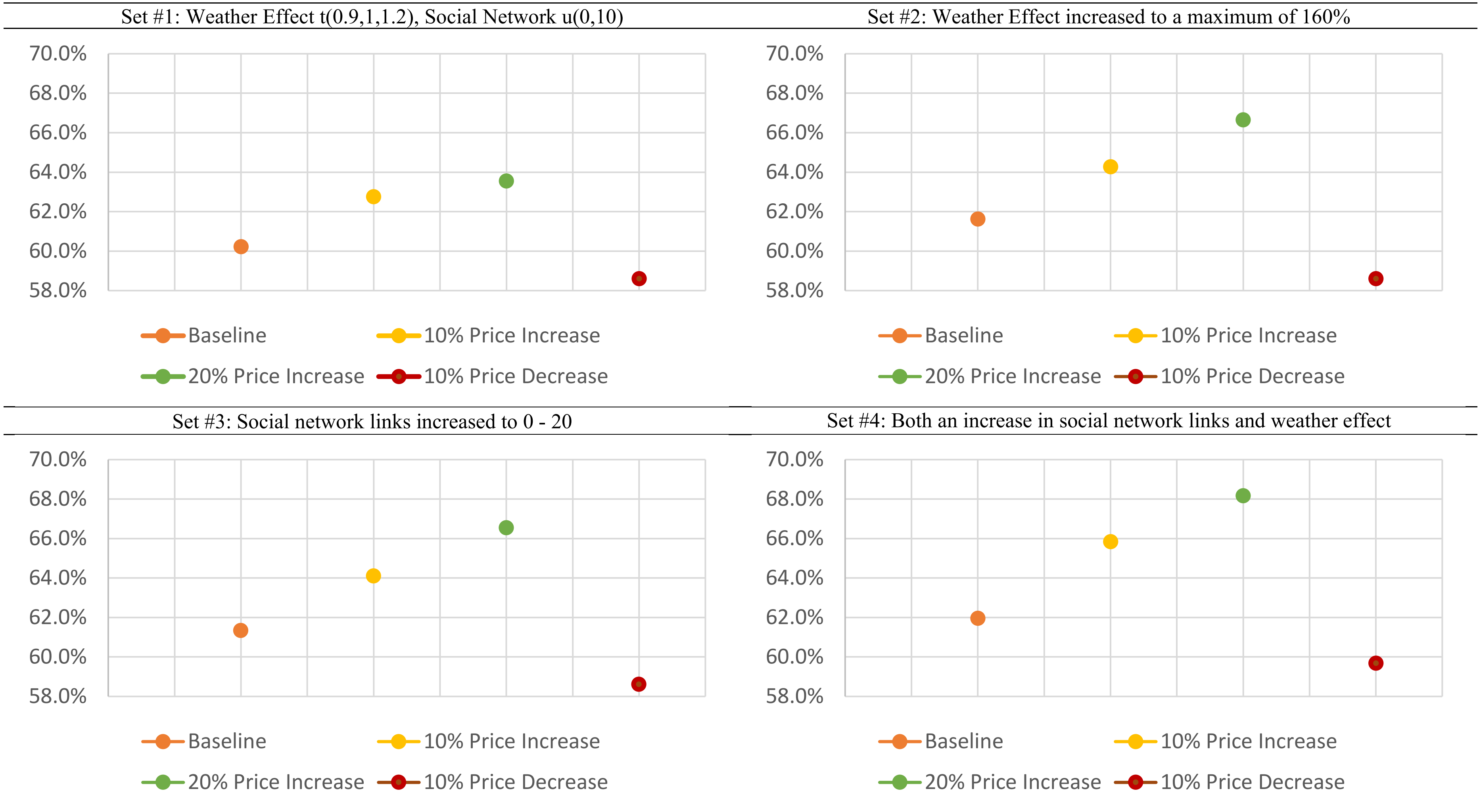
Figure 4. Distribution of household bill amounts



5.4.2 Aggregate switching rate

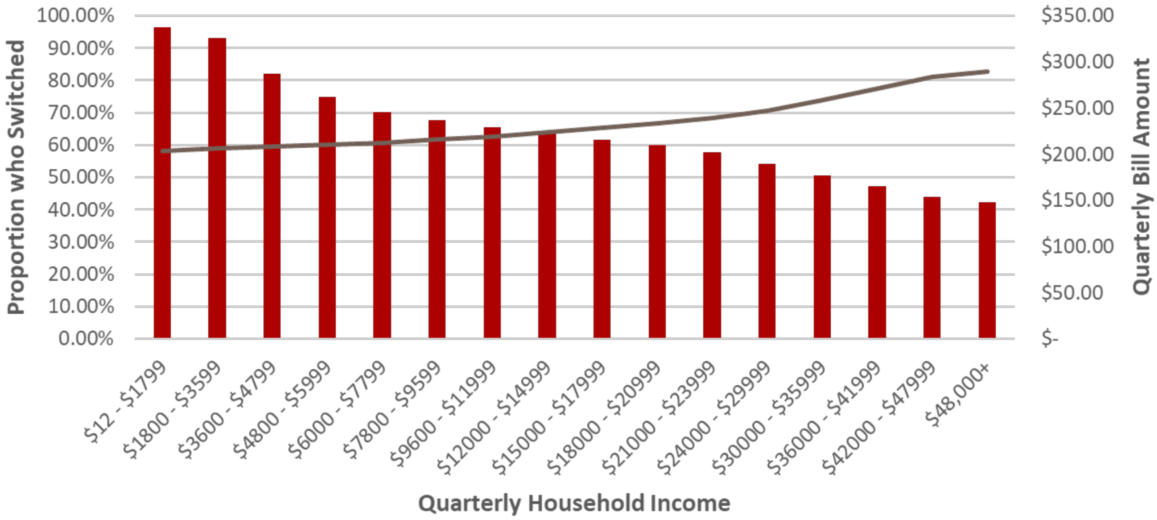
The results in Figure 5 present the aggregate switching rates for several sets of the model. In the main set, the small-world social network is assumed with between 0 and 10 links allowed. The weather variance is between 80% and 120% and price changes range from no change, a 10% increase, a 20% increase, and a 10% decrease. Subsequent model sets will be reported as part of the sensitivity analysis. The model results show that the annual average switching rate is equal to 60.04%. Varying the size of the annual price increases led to statistically significant changes in the aggregate switching rate. A 1% change in the annual price of electricity bills leads to an average of 0.19% change in the switching rate after five years. This result is consistent with prior studies identifying a low propensity to switch due to changes in tariffs (Andruszkiewicz et al. 2020; Conway and Prentice, 2020). The two modes identified in the distribution for the likelihood of switching (see Figure 2), make this analysis unique. Most of the respondents who had switched by the end of the simulation had a likelihood of switching between 8% and 10% at the start of the simulation. The households who have not switched are most likely to be those households with switching rates below 3%.

Figure 3. Aggregate Switching Rate by Set (Small-World Social Network)



When looking at the cohorts of households who switch, there is evidence to suggest that there are clusters of households switching. Figure 6 presents a clear negative relationship between the proportion of households who switched and their household income. Over 60% of households with incomes less than $1,250 a week had switched after five years, with this proportion reaching 83% for those households earning less than $149 a week.

Figure 4. Switching rates, household income, and quarterly bill amounts



This result highlights that low-income households are most likely to switch, therefore most likely to evaluate the trade-off between the demand charge and consumption restrictions. The cohort of households with weekly incomes of less than $1,250 per week represents 41.7% of all households. This finding is further reinforced by the fact that the design of the algorithm that matches households as neighbours is a function of income and age. Most households have neighbours with similar incomes and age, leading to clusters of households with different switching rates. Consequently, the social network effect predominantly affects low-income households, representing less than 50% of the population. This result does mean that social network effects have no effect on high-income households. Rather, it is the case that high-income households are more likely to be neighbours and have a low likelihood of switching. The DCE proportions suggest that the feedback effect will be negative on average a third of the time, however, this does vary with socio-demographic factors such as age, where older respondents are more likely to select the status quo contract. This result, coupled with the switching logit result suggest that older respondents with high incomes are less likely to switch. The implication of this model suggests that after five-years, 60% of households will change to a new electricity contract. It will predominantly affect lower-income households, allowing them to trade-off consumption restrictions against higher fixed costs.

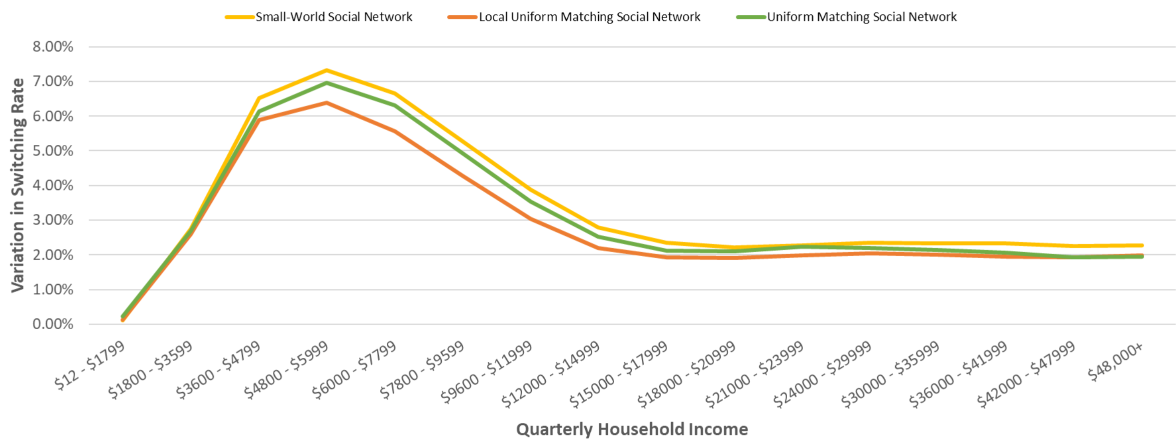
5.4.3 Sensitivity Analysis

The previous results only represent 10% of the total models run. Moving on to alternative versions where the small-world social network is assumed set two increases the size of the weather shock so that it is possible for bills to exceed a household's expected bill amount by up to 60%. The average difference between the aggregate switching rate between each set is equal to 1.83%. This result suggests that more extreme variations in temperature, which lead to a higher likelihood of bills exceeding expectations, will have a small effect on the aggregate switching rate. The low effect is partly the result of how the bill shock works in the model. Those households who have high bill to income ratios are going to be more likely to switch in most periods. For other households where the ratio is approaching zero, the bill shock is negative, leading to a lower likelihood of switching. For both these groups, the weather affects those households on the margin with respect to the thresholds specified. The price changes in each run affect the proportion of households that are influenced by the billing effect. Those households who had not switched by the end of the simulation were likely to already have a low likelihood of switching, which was lowered further by the negative billing effect.

Set three increases the size of the social network effect from a maximum of ten links to twenty. Increasing network size increases the aggregate switching rate marginally with an average change equal to 1.34%. Networks with higher income households may already have lower intentions of switching in part due to the bill shock effect. Less instances of higher income households intending to switch means less chances for the social network effect to occur. This result does change when considering both the increase in weather variation and social network size as reported in set 4. The change in the proportion for every 1% increase in price leads to a 0.31% change in the switching rate. As the proportion of households affected by the bill shock effect increases, it provides more opportunity for the social network effect to diffuse. The majority of households on average select a regulated contract based on the average probabilities reported in Table 1. This result, however, is conditional on the contract attributes included.

The last set of sensitivity analysis reported relates to differences in the social network assumed. The findings related to income differences and switching behaviours are robust to the social network assumptions. Figure 7 reports the average variation in switching rates across each of the three social networks modelled.

Figure 7. Differences in Switching Rate by Income and Social Network



The bill shock effect is strongest when considering households with an income between $3,600 and $7,800. After this range, the variation falls to 2% for higher income ranges. The highest variation is for the small-world social network and the lowest for the local uniform matching network. The difference may be due to the social network effect clustering within low-income networks. With local uniform matching networks, the connections are random, potentially reducing the instances that connected neighbours experience network effects. For the global matching network, on average, households are more likely to select away from the status quo regulated contract. Over time, this results in the highest aggregate switching rates across the different models when compared by the social network assumed. The switching rates range between 60.20% and 68.95%, with anaverage rate of 64.12%, and 1% price changes lead to 0.23% changes in the switching rate.

5.5 Conclusion and Limitations

In this study we have combined an ABM with a DCE to evaluate a demand response policy that has households trade off consumption restrictions in the peak period versus higher fixed costs. The design of this policy meant that households did not have to make this trade-off unless they switched from their existing contract. Based on the real-world data, simulated household characteristics, as well as modelled price changes, weather shocks, and social network effects, the aggregate switching rate after five years was approximately 60%. Increases in the size of the weather shock and the size of social networks lead to small changes in the switching rate over time. In terms of who switches, most households that switch have lower incomes. Clusters of these households are influenced by others switching in their network. This effect, however, is not as strong for high-income households. Under these sets of assumptions, a demand response policy approach only provides flexibility to low-income households and results in low-income households switching. Shifting behaviour of high-income households would require other approaches. The benefits of combining both modelling approaches have been highlighted, but there are some limitations that need to be acknowledged. One major limitation of this study is that the bill shock provides only a partial limitation of switching rates across income groups. The results are sensible for high-income, but not low-income households. Based on the modelled bill shock the lower income households are most likely to switch based on positive bill shocks. This result is in contrast with what has been published in previous studies. It appears that there is an omitted variable that, if past empirical results are valid, would completely offset the bill shock effect for this cohort of households. However, it may also be the case that past studies may have under sampled low-income households. For the survey data collected in this study, that was certainly the case. Either way, improvements to the switching model developed as well as improved sampling of this cohort is one area for future research.

Following the previous limitation, the switching model could be improved in terms of its predictive power. This could be one area for future research, identifying additional determinants of switching which could be used to further identify how different groups would be affected by the proposed scenario. The model does make several assumptions that include parameters that are currently not externally validated. Although this was partially mitigated through calibration to real-world data, this does highlight an opportunity for future research utilising other methods to determine whether weather shocks and social network effects influence the likelihood of a household engaging in active contract switching.

5.6 Appendix

1.0 Variable Sources

Variable:	Source:
Age (Continuous)	2016 ABS Census
Annual Household Income (Categorical)	2016 ABS Census
Daily Computer Use (1 = Yes)	Survey
Daily Television Use (1 = Yes)	Survey
Number of Adults (Continuous)	2016 ABS Census
Number of Children (Continuous)	2016 ABS Census
Own Solar Panels (1 = Yes)	Survey
Reviewed Bill Recently (1 = Yes)	Survey
Turnoff Appliances (1 = Yes)	Survey
Time-of-Use Tariff (1 = Yes)	Survey

2.0 DCE Model Results:

Variable	Mean Parameters		Standard Deviation Parameters		Status Quo Interactions		
	Mixed Multinomial Logit Coef. (Robust Std. Error)						
Daily Reminders	-0.757	(0.464)	5.018***	(0.192)	Age	0.319***	(0.013)
Real-Time Reminders	4.371***	(0.197)	8.515***	(0.309)	Gender	-0.678	(0.452)
One Consumption Restriction	5.855***	(0.407)	14.313***	(0.413)	Diploma	16.041***	(0.480)
No Consumption Restrictions	10.422***	(0.404)	18.877***	(0.182)	Undergraduate	-15.222***	(0.757)
Renewable Generation	0.342***	(0.011)	0.656***	(0.008)	Postgraduate	-1.169	(0.715)
Storage	0.127***	(0.014)	0.356***	(0.006)			
Household Cost ($/year)	-2.249***	(0.321)	1.944***	(0.502)			
ASC (Status Quo)	-44.978***	(1.133)					
ASC (Option C)	-3.323***	(0.354)					
Error Component			64.082***	(1.690)			
Diagnostics							
No. of Observations	2,400						
Log-Likelihood	1,832.26						
AIC	3,708.526						
BIC	3,790.009						
McFadden Pseudo R^2	0.305						

*** 1% significance ** 5% significance * 10% significance.

3.0 Frequencies for Switching Responses

Reasons for not Switching (% of respondents selecting this reason)	
It is too much trouble to switch	31.90%
I found it difficult comparing other offers	25.15%
My bill is too small for me to care	11.04%
My feed-in tariff is very generous	9.82%
My current contract promotes renewable energy use	7.36%
It costs too much to switch	6.75%
I feel locked in with my current retailer	7.98%

Reasons for Switching (% of respondents selecting this reason)	
I wanted a lower price	48.47%
It was easy to switch	22.70%
My current contract was expiring	14.72%
I wanted a fixed-price guarantee	4.29%
I am not satisfied with the quality of my current retailer	3.07%
I am not satisfied with the reliability of my current retailer	2.45%
I wanted a contract that promotes renewable energy use	2.45%
I moved to a new house	1.84%

Chapter 6: Conclusions, Limitations, and Future Research

6.1 Overview

The overall objective of this dissertation is to explore household preferences for energy contract features that represent trade-offs of the energy trilemma. A Discrete Choice Experiment (DCE) was utilised where households were asked to evaluate different electricity contracts with features which included: increased electricity generation from renewable sources, the installation of battery storage technologies, the potential for avoiding consumption restrictions, and the provision of consumption information provided by smart meters at the household level. An online survey was used to estimate household preferences for these features. During June 2019, a total of 604 and 518 households were randomly sampled from an internet panel of participants in the states of New South Wales and Victoria respectively. The main components of the survey included a financial literacy questionnaire, the discrete choice experiment, questions about household billing information, a risk preference elicitation exercise, attitudinal questions, and finally socio-demographic questions. These components were used in different combinations to answer the research questions posed in each chapter. Following data collection, a series of mixed logit models were estimated in either Willingness-to-Pay (WTP) or Willingness-to-Accept (WTA) space. Three treatments were developed and written up as separate papers to analyse three unique sources of preference heterogeneity hypothesised to influence household preferences for different contract features. The fourth and final paper further contributes to the literature through agent-based modelling, where the choice to switch contracts and select new contract features are simulated simultaneously. Another novel aspect of the final paper is in linking the estimated parameters from a DCE with an Agent-Based Model (ABM) to simulate a scenario where the decision to switch to a new contract and selection of the final contract are jointly simulated.

Across each of the DCE papers, there was a consistent finding that the average household had a willingness to pay for increased community storage and a transition to green electricity. This finding is important given that in Australia over the last decade, prices have continued to rise. The reliability of the network has been maintained, and at a national level, the proportion of renewable generation has increased to 20% of total generation. As the proportion of renewable generation continues to increase, more investment may be required to safeguard against issues related to intermittency and general network stability. In each paper, regardless of the respondent's location and whether presented as a WTP or WTA scenario, households are willing to pay more as part of their electricity bills to fund reliability of the energy network, to avoid consumption restrictions and to increase investments in renewable energy sources. They are also willing to pay for smart meters that provide real-time energy consumption information, but not for daily information. These findings suggest that energy policies emphasizing reliability and green electricity should be prioritised in the future, especially if the goal is to mitigate climate change and potentially improve economic productivity. The average preference for each feature suggests that households will be better off if the network becomes more reliable and less reliant on fossil fuels for electricity generation. They will also, on average, be better off if real-time information is provided. Finally, they are willing to pay to avoid consumption restrictions, in effect supporting the payment of a peak demand charge. These results have been noted in previous studies. Despite this, the novelty of these results relates to the fact that these preferences are for Australian households who have experienced a decade of rising prices. Households are already paying for renewable energy through their electricity bills. Investments in energy infrastructure have resulted in the Australian electricity market being one of the most reliable in the world. Yet, despite these facts, Australian households are willing to pay more for additional investment. This is especially important given that as the proportion of renewables increases, there will be new challenges arising due to the intermittency issues associated with renewable generation. In terms of the other contract features, smart meters are common in Europe and the United States, yet they have not achieved the same market penetration in Australia. Despite this, households do have a positive preference for smart meters, suggesting that a wider rollout of smart meters is not due to household preferences in the Australian states sampled. In the last decade, there has been one attempted rollout of smart meters in the state of Victoria, with the reported benefits realised by consumers well below the cost of the rollout. Finally, the demand response feature is a new contract feature relative to past studies. By grouping restrictions by activities, households have stated that they are willing to preserve the ability to perform these activities during the peak evening consumption period. In effect, this result suggests that Australian households are willing to pay a demand charge, something that is not currently included as a standard contract feature.

6.2 Preference Heterogeneity

The first paper' investigated whether the preference for each feature was in part determined by whether households had to pay for increasing levels of each feature or accept compensation for lower levels. Two versions of the status quo contract were developed, with the first described as a zero-cost contract, leading to the estimation of WTP values for additional features. The second version of the contract involved the maximum level for each contract feature including cost, with lower cost increases allowing the estimation of WTA estimates for reductions in the set of features. The difference in how the status quo was described is important since it represented two policy stances when considering the energy trilemma. The first represented a focus on paying more for improvements and the second focused on prioritising lower cost increases in exchange for delayed investments in reliability, green electricity, consumption restrictions and information.

By comparing both models, there was enough evidence to suggest that alternative descriptions for the status quo contract led to statistically different mean estimates for most of the contract features. The only exception was with respect to one of the consumption restrictions and the daily reminders feature. The WTA estimates were larger, suggesting that more compensation is required to reduce the levels for each of these features relative to the number of households that are WTP. The results of this paper are in line with the literature in that there is a disparity when comparing WTP-WTA estimates for the same good. The second contribution from this paper is that two sets of estimates are provided, which could be used in benefits transfer to support decision-support tools such as cost-effectiveness or cost-benefit analysis of proposed policies and infrastructure investment. For example, if one retailer was considering implementing features that would allow households to reduce price increases, the WTA estimates would be appropriate. If regulators were concerned about large price premiums levied by retail firms to fund renewables, the WTP estimates may be valid to compare against the proposed premiums. The WTP-WTA disparity is not unique when considering the wider literature, however, this result is novel in that it identifies the disparity for a private good representing an electricity contract. At the time of writing, only one 2021 paper was found which considered the disparity between WTP and WTA in the energy economics literature.

The second paper explores financial literacy and the extent to which households were able to evaluate investments, with costs incurred today and benefits realised over time. It was hypothesised that there was a correlation between a household's financial literacy and how consistent they were in evaluating different contracts. This correlation led to a relatively higher stated WTP for financially literate households for each non-cost feature. Households who are not very financially literate might focus solely on the cost element. To explore this hypothesis, households in this treatment completed a financial literacy quiz with the number of correct answers providing a proxy measure of their financial literacy. Utilising a hybrid scaled-mixed logit, several linkages are estimated between the socio-demographic characteristics of the household, their measured level of financial literacy, and the choices made in the DCE.

Characteristics such as age, gender, and education were found to be correlated with the household's measured level of financial literacy. Identifying this link reinforces previous findings that improvements in financial literacy would be welfare improving and help increase the acceptance of investment policies. The novel element of this paper is that it ties together the characteristics of the household, their measured financial literacy, and their WTP for each contract feature as part of one model.

The third and final DCE paper evaluates whether the preference for different features is correlated with a household's preference for risk. In this paper, it was assumed that households could reduce future cost increases in exchange for lower levels of contract features, including the possibility that consumption restrictions would be imposed. It is hypothesised that the maximum levels for each of the features represent insurance against downside risks associated with electricity consumption as well as environmental degradation. Assuming this is the case, then a household's preference for risk is positively associated with the amount of compensation they would require for reductions in each of the features. In effect, this additional compensation required by risk-averse households would be compensation for less insurance against these perceived risks. The results of this study suggest that risk preferences in part determine the value placed on different features, especially if these features are valued for the insurance they provide against negative risks. For each of the DCE papers in this thesis, a moment-in-time set of preferences has been estimated. Participants have experienced a decade of rising electricity prices. Despite this rise, the average household still prefers green energy and reliability even though prices could continue to rise into the future. It may be that there is 'cash on the table', in the sense that households are yet to pay their maximum willingness to pay for these elements. From the average household's perspective, climate change may be more of a pressing issue, prompting a stronger preference for actions that mitigate this change, despite the higher cost. The ongoing reliability of the energy network is the status quo for the average household, therefore, if preserving this status quo is the preferred alternative, then a preference for ongoing funding seems rational.

In addition to these moment-in-time preferences, these results highlight that there are several behavioural factors that may influence the decisions households make when evaluating various electricity contracts. This has implications for contract designs and other market-based approaches that could assist in the transition to a greener energy market. The behavioural factors analysed suggest that decisions are not entirely representative of utility-maximising behaviour. This is important for the regulatory industry utilities since there has been a closer evaluation as to whether utilities are ensuring that they take account of their customers' preferences. The results of my thesis suggest that the electricity contract features analysed represent value for money, highlighting that preferences matter beyond price even for services provided by utilities. This work complements a small but growing literature that market forces alone may not result in an efficient market outcome for society and these issues matter to consumers in electricity contract design. The final paper considers the issue of contract switching by combining an ABM with the estimated parameters from a DCE and survey data on recent electricity bills, switching behaviour, and other socio-demographic characteristics of households. The ABM simulated the likelihood that a household would switch from their current contract each quarter, as a function of socio-demographic characteristics, changes in the size of their simulated electricity bills, and network effects based on their social networks. It was hypothesised that increases in the size of realised bills and the size of a household's social network would be positively associated with the aggregate switching rate.

The results of the simulation suggest that, on average, 60% of households would switch from their current contract after five years. Annual price increases, increases in bill variability due to weather effects, and the size of social networks were all found to increase the aggregate switching rate. The price-elasticity of switching was estimated to be equal to 0.19% for the baseline simulation, which is consistent with past studies showing that households are relatively price-inelastic with respect to their electricity consumption. This result is unique in that it may be the first time the level of how price inelastic switching rates for electricity contracts are. The result suggests that even if electricity bills continued to rise, contract switching rates may not be a reliable measure of how competitive a market may be.

Another contribution of the ABM paper is the finding that low-income households are more likely to switch contracts relative to high income households. This finding contrasts with what has been reported in past studies or publicly available data. This suggests that the bill shock effect as described in this paper may explain why high-income households do not switch, but it doesn't explain low switching rates for low-income households. Even for high-income households, this result is divergent from that found in the literature. High-income households have previously been identified as being more likely to switch. This may suggest that in an idealised utility maximising market switching in low-income households would be optimal, but such behaviour may not be observed. Despite these disparities, the scenarios considered in the DCE chapters provide an opportunity for low-income households to avoid price increases. From a policy perspective, this suggests that phased-in regulations which ensure that low-income households are automatically switched to the lowest cost contract could be socially optimal.

6.3 Avenues for Future Research

One limitation with the previous studies is that they do not consider the practical issues with implementing these features. This issue is not unique to this dissertation, DCEs are designed to elicit preferences and are not necessarily designed to account for the myriad issues which emerge with practical implementation. In Australia, the annual rate of switching is around 20%, which is comparable with other countries and suggests that it would take several years for most households to switch. If the benefits associated with these features are conditional on the households selecting these features, it is important to understand what factors influence the rate of switching to new contracts.

As part of my analysis post data collection, I attempted to use as much of the data collected as possible. However, even with the four papers, I still have different parts of the survey that can still be analysed. For example, I collected information about how certain households were in their choices when selecting between choice tasks. I have a set of attitudinal questions that can be employed to explore preference heterogeneity as part of a hybrid choice model. Utilising data in the development of future papers is one goal to be pursued post-completion of this thesis. There are also some variables that may explain some of the preference heterogeneity identified in the models estimated. These variables include a household's recent experience with electricity outages, their knowledge of the risks associated with climate change, and their understanding of the energy system. However, these variables are measured so they may be interesting to account for in future research.

The ORU panel included households from New South Wales and Victoria. Differences in infrastructure and policy at the state level may influence preferences for the features analysed. For example, Tasmania has over 92% of its electricity generation sourced from renewable sources, yet the state of Western Australia has less than 10%. It may be that these differences may influence the preference for more renewable generation in these states. Different states are currently pursuing different strategies with respect to emissions reductions, which may shape preferences with respect to the optimal mix of investments in reliability as well as generation technologies. For example, Victoria has previously rolled out smart meters, however, government reports from the state's Auditor General found that the cost of the rollout exceeded any savings households received from additional information. This may explain why the WTP for additional information in Victoria was less than half of the WTP in the NSW sample. Future research may wish to explore how past states policies influence changes in WTP over time.

The first paper highlights that there is a difference between the WTP and WTA estimates. The next phase of this research could better identify what other factors may explain this difference. For example, one explanation for the difference may relate to the relative importance of consumption restrictions. In treatment two, the status quo contract was the only contract which had a guaranteed level of no restrictions. The estimation results suggest this feature was the most important, as noted by its large WTP/WTA value. If households were following a heuristic that involved selecting a contract that only imposes either one or no restrictions, then this may create a situation whereby dominated alternatives were created. The experimental designs generated for all DCEs reported do not account for this. Future research could explore how this two-stage or even multi-stage choice heuristic influence the choices made as well as the estimated preference parameters. There may be temporal impacts determining these preferences. Is positive preference for renewables a consequence of the expectation of lower costs in the future or the reduction in environmental costs?

The second paper identifies a statistically significant correlation between a household's measured financial literacy and the choices made in the DCE. It was hypothesised that financial literacy is a source of scale heterogeneity, but not preference heterogeneity. In line with the literature, the current research does not aim to separate preference and scale heterogeneity. This paper also does not model the relationship between financial literacy, knowledge of climate change literacy, climate change risk, or energy system literacy. Future research may look at whether these items are independent and also explain the differences in WTP noted as part of the model results. It could be that financial literacy affects how households evaluate specific contracts, however, system literacy is more relevant for specific features. For example, smart meters or battery storage, and knowledge of climate change is a behavioural factor that could influence the WTP for more renewable electricity.

Another limitation is the correlation between financial literacy and time preferences. This paper does not control for time preferences; however, it is anticipated that accounting for a household's time preference is also correlated not only with measured financial literacy but also their preference for each contract feature. Future research could investigate the impact of context specific financial literacy and time preferences on the consistency of choices made in the DCE, whilst accounting for potential endogeneity issues. It may be the case that time preferences are context specific. This paper looked at one context, but do the findings of this study apply to others?

The third paper highlighted a correlation between the estimated WTA values and the risk preferences elicited for households. Future research could focus on obtaining more data for a wider set of risk categories, extending the analysis beyond the two groups analysed. Often DCEs include repeated choice observations, but the socio-demographic characteristics of each respondent is limited by the sample size. Future research looking at risk preferences and their relationship with WTP/WTA values might attempt to obtain a relatively larger sample size, as well as aligning the risk preference elicitation exercise directly with the risks of the goods or with its features being analysed.

As with all ABMs, assumptions have to be made for each of the key determinants of switching. Future research could better focus on the impacts of income, weather and social networks on households' switching behaviour. For example, weather and electricity consumption data could be jointly analysed to calibrate how weather changes affect consumption profiles. This information would then be used to better represent weather shocks. The regressions used to simulate the baseline likelihood of switching and bill amount would benefit from an increased sample size as well as a larger set of covariates linked to theory. This paper postulates that these effects are important, but the size of these effects are assumptions. Quantifying the effects through other methods would allow for this model to be calibrated to obtain accurate forecasts of changes in future switching rates. Another limitation which could be addressed in future research is that there may be other factors that influence the likelihood a household switches from their current electricity contract. The issue with low-income households having a higher likelihood of switching, despite what is noted in the literature is a limitation of the results in that it represents a puzzle. An omitted factor not captured in the model may be offsetting the bill shock effect, leading to the often-observed low switching rate for low-income households. This factor may be behavioural or a consequence of other market forces. Updating this model for these factors is one avenue for future research. Despite these limitations, the combined models demonstrated in this paper offer a novel way to analyse different scenarios based on estimated preferences for different goods. Further research that builds upon this approach could provide richer insights into consumer behaviour relevant for future policy and welfare analysis. There are also opportunities to utilise more of the results from this thesis to enhance the ABM. For example, the financial literacy indicators or risk preferences could be included to determine whether the results reported so far are affected by these factors. Additional contract levels could be defined and even modified based on changes in the switching rate that occur during the simulation.

Overall, the findings of this dissertation have policy implications in the context of investments in renewable generation and network reliability whilst controlling for public preference for reduced peak load costs of electricity and information provision. The results demonstrate that there may be distributional impacts from the various policy alternatives available, accounting for which may make future energy policy more acceptable to the public. The novel combination of methods across each paper contributes to the literature whilst highlighting how the knowledge of household preferences may better facilitate the design of future energy policies that have public acceptance in Australia and elsewhere. Incorporating estimates from a DCE in an ABM allows for those regulating energy policy to predict how changes in the electricity market may affect a household's likelihood of actively participating in the evaluation of alternative electricity contracts. Increasing the rate of participation may lead to improved efficiencies within the market, providing an incentive for retailers to offer cheaper contracts or those with better features that align more so to household preferences. For each of the DCE features, how responsive households are to selecting these new features may depend on how often they switch. This is especially the case if the investments associated with these features are dependent on a certain proportion of households switching. The decision support tool developed for this thesis is one such tool that could facilitate this analysis, as well as inspire the future development of more sophisticated decision support tools.

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Appendix 1: Energy Survey

Options for Reducing Household Energy Bills

UNIVERSITY of TASMANIA

What is your Post Code? ______________

What is your age? ___________________

Are you:

☐ Male ☐ Female ☐ Other

1. Do you currently have a mortgage or own the house you live in?

☐ Yes ☐ No

2. Are you responsible for paying your household's electricity bill?

☐ Yes ☐ No

3. Do you live in a detached house?

☐ Yes ☐ No

4. Are your household's bills pay as you go (PAYG - Prepaid)?

☐ Yes ☐ No

Information Sheet for Focus Group/Interview/Online

Thank you for your interest in taking part in this survey. Researchers at the University of Tasmania are exploring ways to reduce household electricity costs. Your participation in this survey will help inform energy policy in Australia.

Your Task

In this survey, you will be asked questions about:

- Australia's energy mix
- Knowledge of financial investments
- Choosing between electricity contracts

At the end of the survey, there will be some questions about your attitudes and follow-up questions about your household. The survey will take about 10 minutes of your time. The results of the study will be provided to government agencies and may be used in public policy. The results will be published in academic journals.

Participant responses are anonymous, ensuring your privacy is protected. Once the data has been analysed, data from the project will be archived. This study has been approved by the Tasmanian Social Sciences Human Research Ethics Committee. If you have concerns or complaints about the conduct of this study, please contact the Executive Officer of the HREC (Tasmania) Network on +61 3 6226 6254 or email human.ethics@utas.edu.au. Please quote ethics reference number [H0016832].

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Feedback

If you wish to receive a summary of the survey results, please provide your contact details at the end of the survey. We will provide Online Research Unit with the summary and they will forward it on to you in approximately six to nine months.

Consent

Please read the following statements, and if you agree, indicate your consent at the end by clicking on "yes".

1. I agree to take part in this research study.
2. I have read and understood the study information.
3. The nature and possible effects of the study have been explained to me.
4. I understand that the study involves completing an online survey which will take about 10 minutes.
5. I understand that participation involves no foreseeable risks.
6. I understand that all research data will be collected using an online platform, then securely stored by the researchers in password protected databases while being analysed and then archived.
7. Any questions that I have asked have been answered to my satisfaction.
8. I understand that the researchers will maintain confidentiality and that any information I supply to the researchers will be used only for the purposes of research.
9. I understand that the results of the study will be published
10. I understand that I cannot be identified as a participant.
11. I understand that my participation is voluntary and that I may withdraw at any time before completing the survey (even during survey completion) without any effect. I understand that I will not be able to withdraw my data after completing the survey, as data will have been collected anonymously.

I consent to the above statements.

☐ Yes

☐ No

Survey - Your Confidence in Money Matters *(Treatment 3)*

If the money matters questionnaire appears before choice tasks:

Before we discuss electricity contracts, we would like to ask several questions about how you might manage your money ('financial investments').

The following questions will help us understand how confident you are about financial investments:

If the money matters questionnaire appears after choice tasks:

We would now like to ask several questions about how you might manage your money ('financial investments').

The following questions will help us understand how confident you are about financial investments:

1. Normally, which of these assets exhibit the highest fluctuations in value over time?

   a) Savings accounts   b) Stocks   c) Bonds

2. Many Australians own shares in Australian companies. Which of the following is ALWAYS true when dividend payments are received?

   a) The payment would be the same dollar amount every year
   b) The payment would vary from year to year
   c) The payment would be a fixed percentage of the share price
   d) The payment only rises and falls with interest rates

3. It is usually possible to reduce the risk of investing in the share market by buying a wide range of shares.

   a) True   b) False

4. If you invest $1,000 in a managed fund (e.g. a property trust, share trust, equity trust, growth trust, imputation trust or balanced trust), is it possible to have less than $1,000 when you withdraw your money?

   a) Yes   b) No

5. Is an investment with a high return likely to be high risk?

   a) Yes   b) No

6. If a friend inherits $10,000 today and her sister inherits $10,000 three years from now, who will be richer in three years because of the inheritance?

   a) Your friend   b) Her sister   c) They will be equally rich

7. If you own shares in an Australian company, which ONE of these statements is true about the tax you will pay on dividend income?

   a) The dividend income is taxed at a fixed rate of 15%
   b) If the dividend carries franking credits, you are eligible for a tax offset for the company tax already paid
   c) If the dividend carries franking credits, you pay no tax on the dividend
   d) The dividend income is not taxed
   e) Don't know

Did you research or lookup on a search engine the answer to any of the previous questions?

It is ok to say yes, we are just curious to see how you are interacting with the survey.

Yes ☐ No ☐

Household Electricity Costs *(All Treatments)*

Household electricity costs are on the rise across Australia. In the last 10 years, household electricity bills have increased by an average of 5.6% every year (ACCC, 2017). These cost increases are due to more gas being used to meet peak demand.

Renewable generation can reduce power prices (and our carbon footprint) but it is not as reliable. Households can influence change through their selection of electricity contracts.

Electricity retailers can offer tailored electricity contracts that:

- Change the amount of power sourced from renewable generation
- Limit appliance use during the evening peak period
- Install batteries to store electricity that can be accessed by the community
- Provide you with more frequent updates about the cost of powering your home

Each of these changes will impact on the future cost of energy for households.

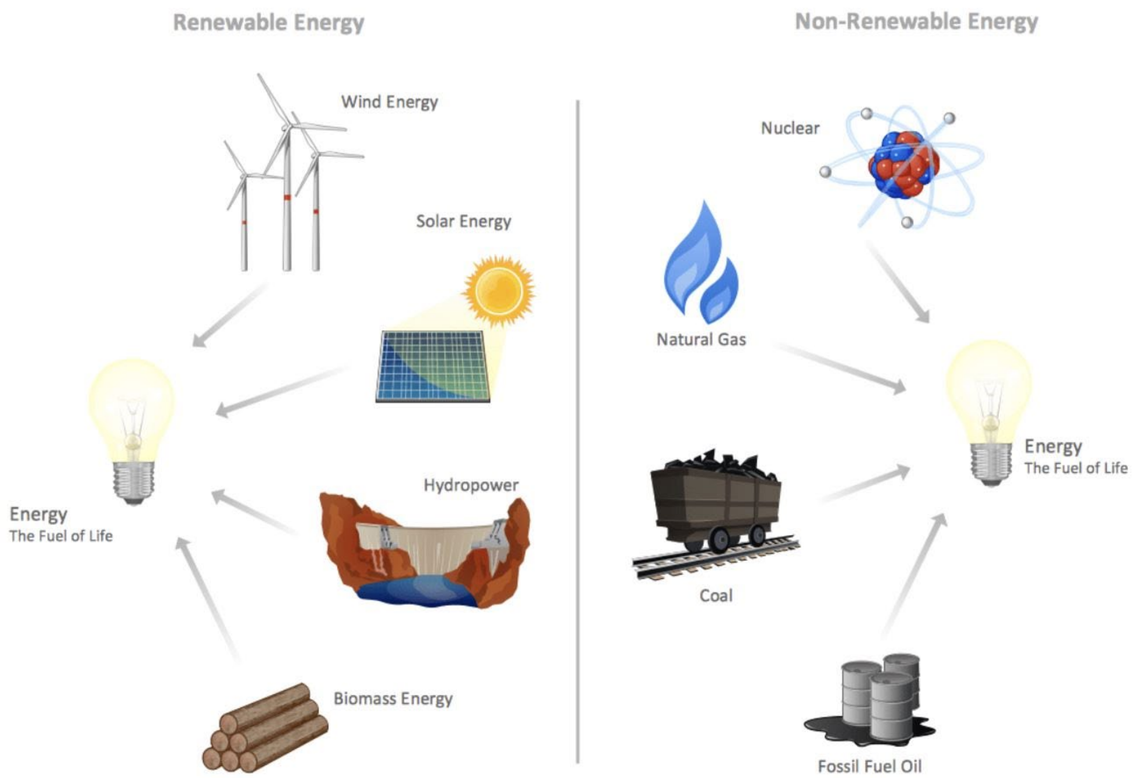
The next few pages provide information about each feature and you will be asked a simple question relating to that feature.

No one is going to contact you about your electricity contract.

Renewable Generation:

Currently 85% of all the electricity generated in Australia comes from fossil fuels such as coal and gas.

This varies across States, for example in 2016 92% of Tasmania's electricity generation was from renewable energy sources, compared to 12% for Victoria and 17% for New South Wales.



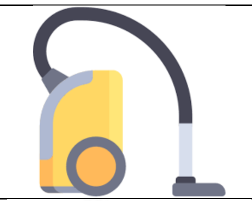
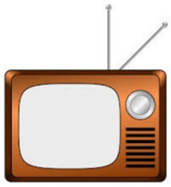
Solar and wind generate power when the weather is suitable. Storage technology, batteries, and pump storage with hydropower, can increase the reliability of solar and wind.

Consumption Limiting:

On average, households consume the most electricity in the evening (5:00pm – 8:00pm). This peak use pushes up electricity bills.

To avoid this increase in costs smart meters could **allow retailers to limit your use of certain appliances in the evening**. This is similar to water restrictions, except these limits are imposed by the retailer on all households that opt in.

Below are examples of three separate activities that retailers could limit:

Activity	Appliances Affected	
General Cleaning	Vacuum Washing Machine Dryer	
Cooking	Oven/Stove Kettle Electric Frying Pan	
Entertainment	Television Desktop Computers Chargers	

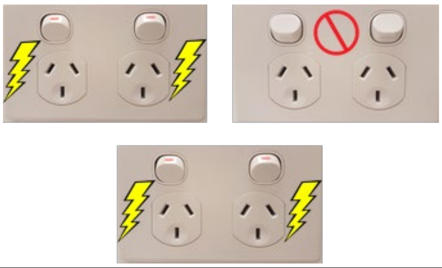
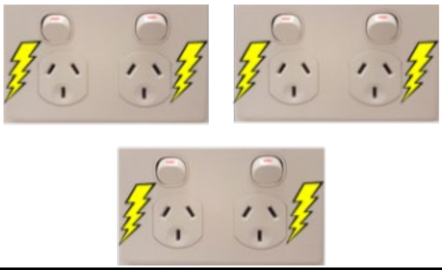
Which of the activities is the **most** important use of energy in the evening for your household?

☐ Cleaning ☐ Cooking ☐ Entertainment

The three options for limiting appliance use are:

1. High limit: Two activities are limited
2. Low limit: One activity is limited
3. No limits: No activities are limited during the peak period

The lower the limit chosen by the household, the higher the cost of electricity. For example, consider the two options below:

Option B	Option C
Low Limit	**No Limit**
	

Option B limits one activity – for example, cleaning – meaning that both cooking and entertainment activities would be available. Option C limits no activities during the peak period.

It is important to note that you choose the activities you do not want to limit during the peak period.

If you had to, which activity would you be **most willing to go without** in the evening?

☐ Cleaning ☐ Cooking ☐ Entertainment

Which activity would you be **least willing to limit** in the evening?

☐ Cleaning ☐ Cooking ☐ Entertainment

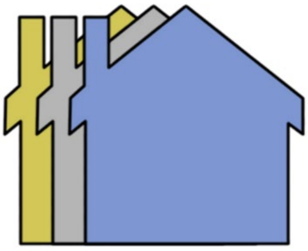
Community Storage:

- Community battery storage can store electricity as it is produced
- At peak times stored power can be used so that more expensive generation is not needed

Battery sizes are defined by **the average number of households that they can power during the peak period.**

For example, consider the two options below:

Option B	Option C
60 MWh	**20 MWh**

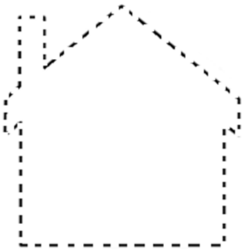


15,000 Houses

5,000 Houses

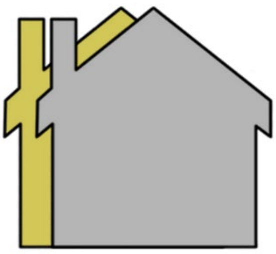
Option B represents a larger battery that can power more homes than Option C.

In this survey you will be presented with three levels of battery storage, as shown below:

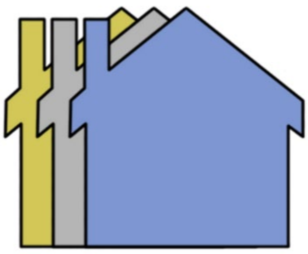


No Houses

5,000 Houses



10,000 Houses



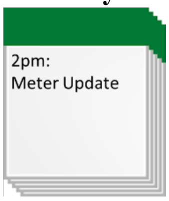
15,000 Houses

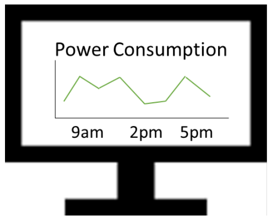
Information on electricity consumption:

Most households only know how much electricity they are consuming when they receive their bill. Old meters are only read by the electricity retailer when a bill is sent.

Electronic or "smart" meters provide frequent updates about how much power households consume to retailers.

Option B	Option C
Daily	**Real-Time**





In Option B, the household receives a daily update about their actual electricity consumption, as well as the running total so far. In Option C, the household receives these updates in real-time, either using their computer or smart phone. Note that payments still occur quarterly.

Would you use a smart phone app to check your current power consumption?

Yes ☐ No ☐

Cost to you *(Treatment 1 and 3)*

Based on current energy investments, we expect a future with the same levels of batteries, renewables, and smart meters. This will lead to less available energy during the peak period.

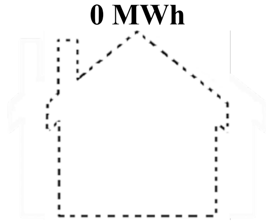
If you select “No change”:

There will be **no new generation** from renewable sources

15%

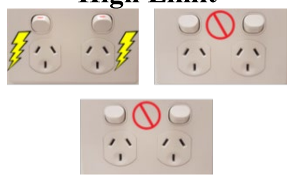
There will be **NO** new community batteries

0 MWh



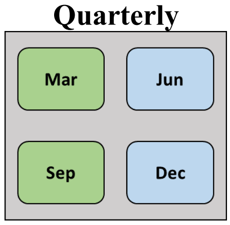
Two consumption activities will be limited during the peak period.

High Limit



There will be **NO** new smart meters
Consumption information will be **quarterly**

Quarterly



This will lead to no additional cost for households over the next five years. The other contract options will lead to the **quarterly fixed cost** of your bill increasing over the **next five years**.

$40 per quarter -----> $160 a year -----> $800 over five years

Cost to you *(Treatment 2)*

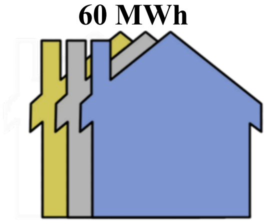
Based on current trends in energy investment we expect a future with more renewables, batteries, smart meters, and consumption during the peak period will not be affected. If you select “No change”:

60% **of total generation** will be from renewable sources

60%

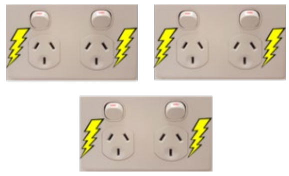
There will be a **significant investment** in community batteries

60 MWh



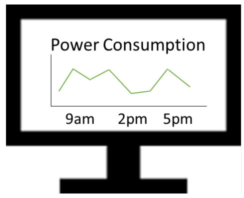
No consumption activities will be limited during the peak period.

No Limit



There will be large investment in updated smart meters
Consumption information will be **real-time**

Real-Time



This will lead to an additional cost of $120 per quarter for **the next five years**. The other contract options will also lead to less investment, however the cost increase will be smaller than the “No change” option.

$120 per quarter -----> $480 a year -----> $2400 over five years

Example *(All Treatments)*

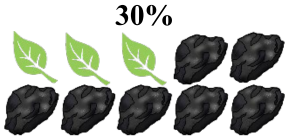
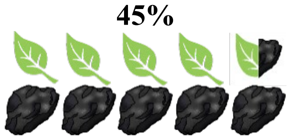
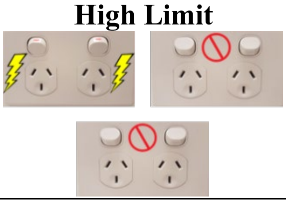
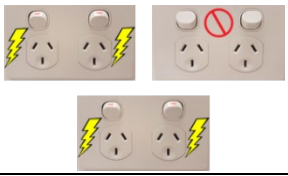
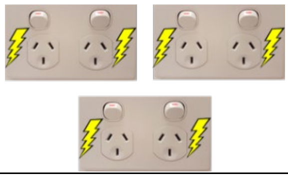
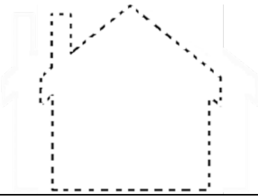
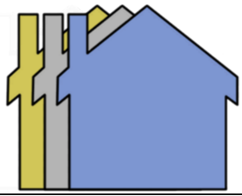
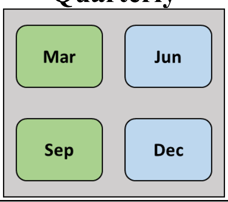
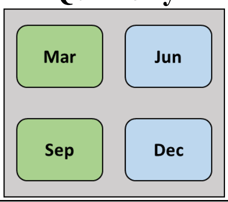
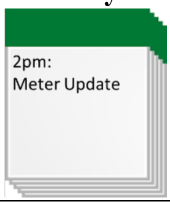
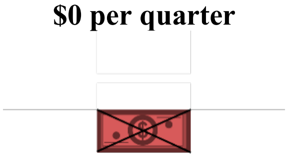
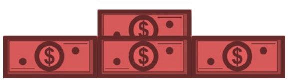
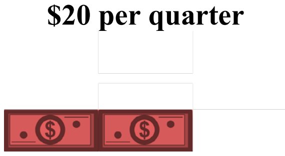
We will show you eight (8) scenarios like the example below. Each scenario describes three (3) options A, B, and C, which represent different electricity contracts.

What we want you to do is simple: tell us which contract you would select as though you had to make this choice in your real life.

Each electricity contract involves different features that provide different options for households to monitor and manage their electricity consumption.

Here’s an example where the person clicked Option A as the contract they would select. They also stated that were completely certain with their choice by clicking 10.

Example

Features	**Option A** **No change**	**Option B**	**Option C**
% of Renewable Generation	**15%** 	**30%** 	**45%** 
Consumption Limits	**High Limit** 	**Low Limit** 	**No Limit** 
Community Storage	**0 MWh** 	**60 MWh** 	**20 MWh** 
Consumption Information	**Quarterly** 	**Quarterly** 	**Daily** 
Average bill increase per quarter over the next five years	**$0 per quarter** 	**$40 per quarter** 	**$20 per quarter** 

	Option A	**Option B**	**Option C**
I would choose: *Choose one only*	☐	☐	☐

Before you start! *(All Treatments)*

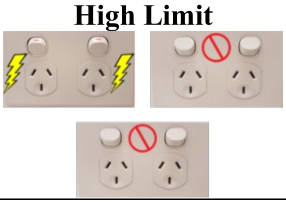
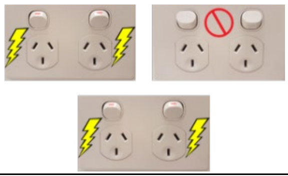
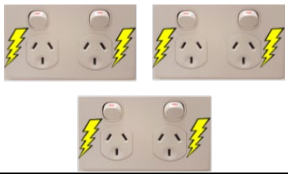
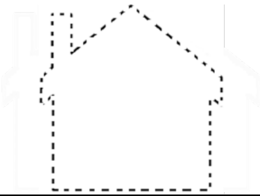
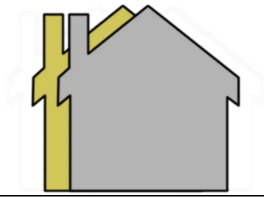
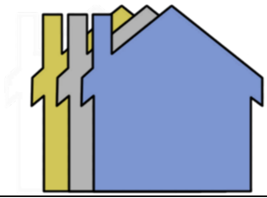
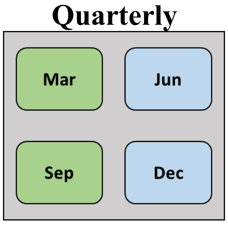
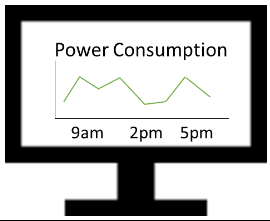
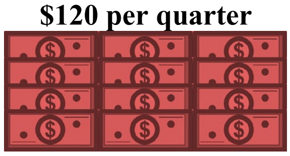
Studies have found that respondents will say that they are willing to pay a certain amount but really they wouldn’t actually reach into their pocket. Please be honest in your responses and keep in mind your actual household income and expenses. For example, **if you agree to the cost for one of the contract options, you will have less money for other things.**

It is very important that you answer the following question as if you really had to pay.

Are you ready to proceed?

Yes ☐ No ☐

Choice Task 1 *(Choice tasks 1 – 8 are for treatment 1 for illustrative purposes)*

Features	**Option A** **No change**	**Option B**	**Option C**
% of Renewable Generation	**15%** 	**45%** 	**60%** 
Consumption Limits	**High Limit** 	**Low Limit** 	**No Limit** 
Community Storage	**0 MWh** 	**40 MWh** 	**60 MWh** 
Consumption Information	**Quarterly** 	**Daily** 	**Real-Time** 
Average bill increase per quarter over the next five years	**$0 per quarter** 	**$60 per quarter** 	**$120 per quarter** 

	Option A	**Option B**	**Option C**
I would choose: *Choose one only*	☐	☐	☐

Very uncertain — **How certain were you of your choice?** *Choose one only* — **Very Certain**

1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Choice Task 2

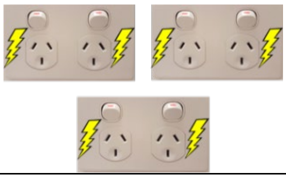
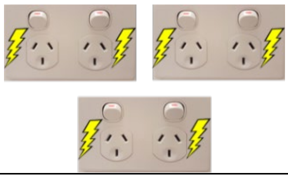
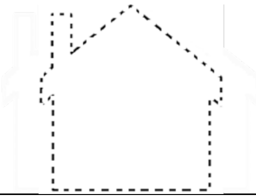
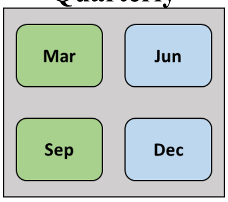
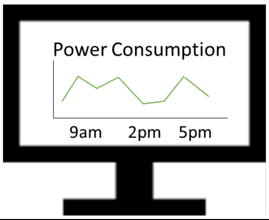
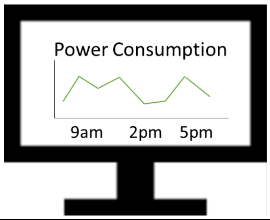
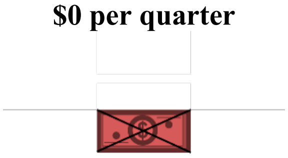
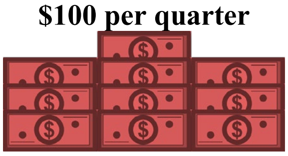
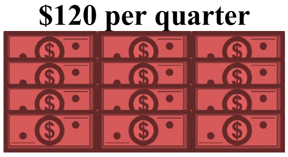
Features	Option A No change	Option B	Option C
% of Renewable Generation	15%	30%	30%
Consumption Limits	High Limit	Low Limit	No Limit
Community Storage	0 MWh	20 MWh	20 MWh
Consumption Information	Quarterly Mar Jun Sep Dec	Quarterly Mar Jun Sep Dec	Quarterly Mar Jun Sep Dec
Average bill increase per quarter over the next five years	$0 per quarter	$40 per quarter	$80 per quarter

	Option A	Option B	Option C
I would choose: *Choose one only*	☐	☐	☐

How certain were you of your choice?
Choose one only

Very uncertain									Very Certain
1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Choice Task 3

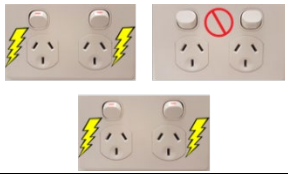
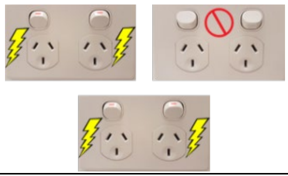
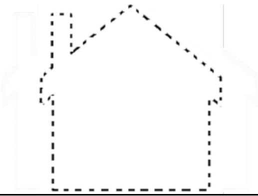
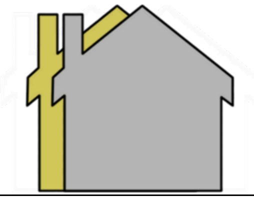
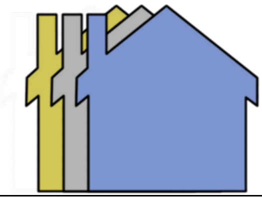
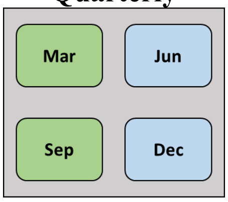
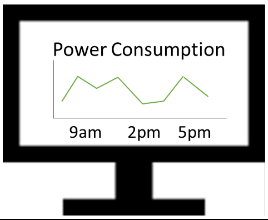
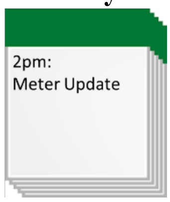
Features	Option A No change	Option B	Option C
% of Renewable Generation	**15%** 	**30%** 	**60%** 
Consumption Limits	**High Limit** 	**No Limit** 	**No Limit** 
Community Storage	**0 MWh** 	**20 MWh** 	**20 MWh** 
Consumption Information	**Quarterly** 	**Real-Time** 	**Real-Time** 
Average bill increase per quarter over the next five years	**$0 per quarter** 	**$100 per quarter** 	**$120 per quarter** 

	Option A	Option B	Option C
I would choose: *Choose one only*	☐	☐	☐

Very uncertain | **How certain were you of your choice?** *Choose one only* | **Very Certain**

1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Choice Task 4

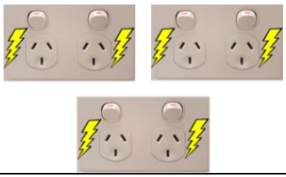
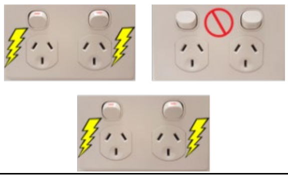
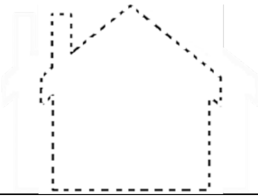
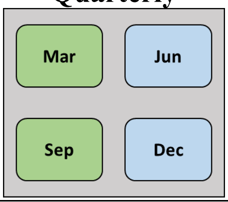
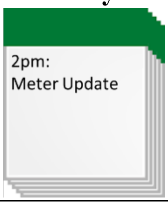
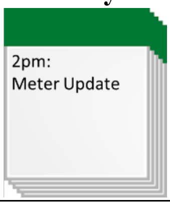
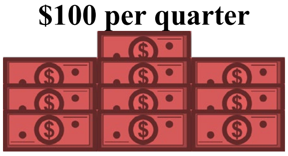
Features	Option A No change	Option B	Option C
% of Renewable Generation	**15%** 	**60%** 	**45%** 
Consumption Limits	**High Limit** 	**Low Limit** 	**Low Limit** 
Community Storage	**0 MWh** 	**40 MWh** 	**60 MWh** 
Consumption Information	**Quarterly** 	**Real-Time** 	**Daily** 
Average bill increase per quarter over the next five years	**$0 per quarter** 	**$40 per quarter** 	**$60 per quarter** 

	Option A	Option B	Option C
I would choose: *Choose one only*	☐	☐	☐

How certain were you of your choice?
Choose one only

Very uncertain									Very Certain
1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Choice Task 5

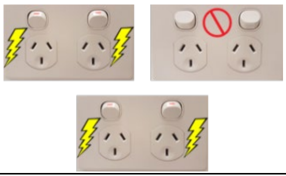
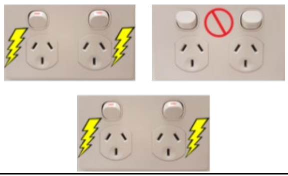
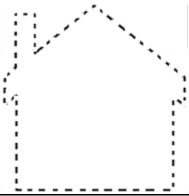
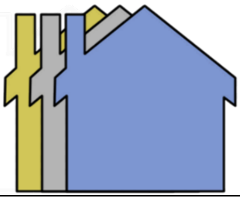
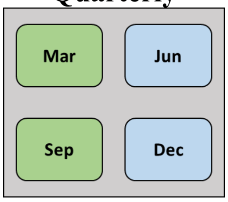
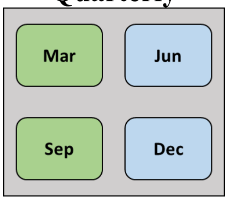
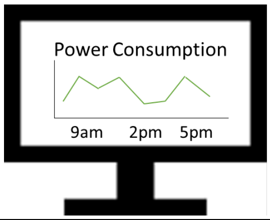
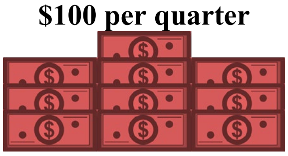
Features	Option A No change	Option B	Option C
% of Renewable Generation	15% 	30% 	30% 
Consumption Limits	High Limit 	No Limit 	Low Limit 
Community Storage	0 MWh 	20 MWh 	20 MWh 
Consumption Information	Quarterly 	Daily 	Daily 
Average bill increase per quarter over the next five years	$0 per quarter 	$100 per quarter 	$40 per quarter 

	Option A	Option B	Option C
I would choose: *Choose one only*	☐	☐	☐

Very uncertain — **How certain were you of your choice?** *Choose one only* — **Very Certain**

1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Choice Task 6

Features	Option A No change	Option B	Option C
% of Renewable Generation	15% 	30% 	60% 
Consumption Limits	High Limit 	Low Limit 	Low Limit 
Community Storage	0 MWh 	20 MWh 	60 MWh 
Consumption Information	Quarterly 	Quarterly 	Real-Time 
Average bill increase per quarter over the next five years	$0 per quarter 	$100 per quarter 	$40 per quarter 

	Option A	Option B	Option C
I would choose: *Choose one only*	☐	☐	☐

How certain were you of your choice?
Choose one only

Very uncertain									Very Certain
1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Choice Task 7

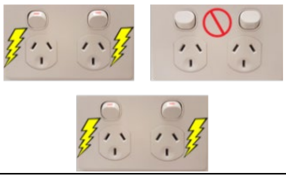
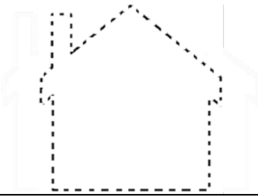
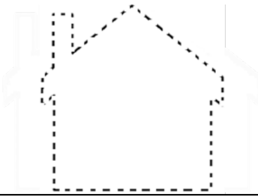
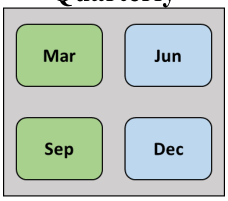
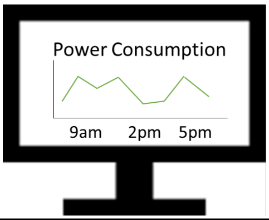
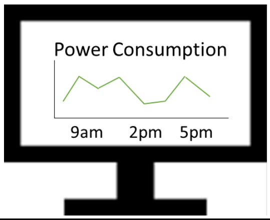
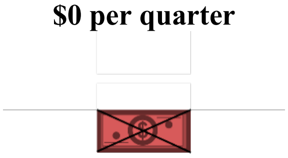
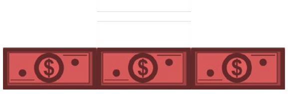
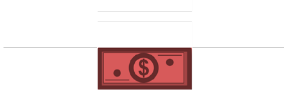
Features	Option A No change	Option B	Option C
% of Renewable Generation	15%	30%	60%
Consumption Limits	High Limit	No Limit	No Limit
Community Storage	0 MWh	60 MWh	20 MWh
Consumption Information	Quarterly Mar Jun Sep Dec	Quarterly Mar Jun Sep Dec	Quarterly Mar Jun Sep Dec
Average bill increase per quarter over the next five years	$0 per quarter	$70 per quarter	$50 per quarter

	Option A	Option B	Option C
I would choose: *Choose one only*	☐	☐	☐

Very uncertain — **How certain were you of your choice?** *Choose one only* — **Very Certain**

1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Choice Task 8

Features	Option A No change	Option B	Option C
% of Renewable Generation	15% 	15% 	15% 
Consumption Limits	High Limit 	Low Limit 	High Limit 
Community Storage	0 MWh 	20 MWh 	0 MWh 
Consumption Information	Quarterly 	Real-Time 	Real-Time 
Average bill increase per quarter over the next five years	$0 per quarter 	$30 per quarter 	$10 per quarter 

	Option A	Option B	Option C
I would choose: *Choose one only*	☐	☐	☐

How certain were you of your choice?
Choose one only

Very uncertain									Very Certain
1	2	3	4	5	6	7	8	9	10
☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Which of the following statements describes your reason for choosing Option A? *Click on one or more boxes (Treatment 1 and 3)*

- ☐ I cannot afford the cost increases
- ☐ The choices were unrealistic
- ☐ I don’t require frequent electricity consumption information
- ☐ I work during the peak period therefore consumption limits do not affect me
- ☐ Australia does not need any more renewable generation
- ☐ I do not want to pay for community batteries that others can use
- ☐ The government should be paying for these features
- ☐ I do not think climate change is an issue
- ☐ I did not know which option was best, so I stayed with the current condition
- ☐ The fixed cost of my electricity is already too high
- ☐ Some other reason, *please specify*________________________________

Which of the following statements describes your reason for choosing Option B and/or C? *Click on one or more boxes (Treatment 2)*

- ☐ I cannot afford the cost increase in option A
- ☐ I don’t require frequent electricity consumption information
- ☐ I work during the peak period, therefore consumption limits do not affect me
- ☐ Australia does not need any more renewable generation
- ☐ I do not want to pay for community batteries that others can use
- ☐ The government should be paying for these features
- ☐ I do not think climate change is an issue
- ☐ The fixed cost of my electricity is already too high
- ☐ I did not know which option was best, so I selected the cheapest
- ☐ Some other reason, *please specify*________________________________

Some Questions about your Energy Use *(All Treatments)*

1. How much, roughly, was your last electricity bill? ________________

2. Who is your current electricity retailer? ____________

3. Is your current electricity contract a standing offer contract?

   Yes ☐ No ☐ Don't Know ☐

4. In the last 24 months have you in reviewed your current electricity contract?

   Yes ☐ No ☐

5. Have you switched to another contract?

   Yes, same retailer ☐ Yes, new retailer ☐ No ☐

6. What were your reasons for (Not) switching
   Select all that apply
   Note: Only one column below appears, based on previous response

Reasons for Switching		**Reasons for (not) Switching**	
It was easy to switch	☐	It is too much trouble to switch	☐
I wanted a lower price	☐	I found it difficult comparing other offers	☐
I wanted a fixed-price guarantee	☐	My bill is too small for me to care	☐
I moved to a new house	☐	My feed-in tariff is very generous	☐
My current contract was expiring	☐	My current contract promotes renewable energy use	☐
I am not satisfied with the quality of my current retailer	☐	It costs too much to switch	☐
I am not satisfied with the reliability of my current retailer	☐	I feel locked in with my current retailer	☐
I wanted a contract that promotes renewable energy use	☐		
Other (Please Specify) __________		Other (Please Specify) __________	

7. What are your sources of heating at home?
Select all that apply

	Home	Hot Water
Reverse Cycle Air Conditioner	☐	N/A
Gas Heating	☐	☐
Electric Heating	☐	☐
Wood fire	☐	☐
Solar Panels	☐	☐
Select all the above	☐	☐
None	☐	☐

Other (Please Specify) __________

8. What are your sources of cooling at home?
Select all that apply

Open windows/doors	☐
Reverse Cycle Air Conditioning	☐
Evaporative Cooling	☐
Electric Fan(s)	☐
None	☐

Other (Please Specify) __________

9. Which of the following metering options would you prefer? *(Select one)*

Time of day pricing (Off-peak/On-peak)	☐
One constant $ per kWh price for the entire day/everyday	☐
Prices which constantly change according to the market (Ranging from $0.20 - $1.20/kWh)	☐
Appliance-specific prices (5 cents per use)	☐
Block prices ($0.20/kWh for first 50 kW, $0.50/kWh for the next 50 kW)	☐

10. If electricity prices were to spike due to unusually cold or hot weather, would you be willing to switch off all appliances for 4 hours? For example, you could turn off all appliances and go to the movies or go to a public place such as a shopping mall or recreation centre.

Yes ☐ No ☐

11. Have you installed solar panels on your house?

Yes ☐ No ☐

12. Would you trust a company, independent of energy retailers, to advise you on the best way to manage your consumption and reduce the cost of your electricity bills?
(No company will contact you based on this survey)

Yes ☐ No ☐

Trap Question Version One (All Treatments)

Recent research on decision-making shows that choices are affected by context. Differences in how people feel, their previous knowledge and experience, and their environment can affect choices. To help us understand how people make decisions, we are interested in information about you.

Specifically, we are interested in whether people in general take the time to read the directions; if not, some results may not tell very much about decision making in the real world. To show that you have read the instructions, please ignore the question below about electricity transmission and instead check only the 'none of the above' option as your answer.

On the next page, please tick who you think should be the owner of the poles and wires that transport electricity.

Trap Question Version Two (All Treatments)

Recent research on decision-making shows that choices are affected by context. We are interested in whether people in general take the time to read the directions. To show that you have read the instructions, please ignore the question below about electricity transmission and instead check only the 'none of the above' option as your answer.

On the next page, please tick who you think should be the owner of the poles and wires that transport electricity.

Trap Question Version Three (All Treatments)

To show that you have read the instructions, please ignore the question below about electricity transmission and instead check only the 'none of the above' option as your answer.

On the next page, please tick who you think should be the owner of the poles and wires that transport electricity.

Who should own the poles and wires that transport electricity?

Please tick your preferred choice.

- Government ☐
- Private Companies ☐
- Foreign Companies ☐
- Individuals ☐
- Public Companies ☐
- Public-Private Partnership ☐
- None of the above ☐

Make a Choice! *(Treatment 1 and 2)*

Each investment has two possible results (X or Y). Alongside each result is the payoff you could earn as well as the probability of that result occurring. You can earn additional credits for completing the survey based on:

- which investment you select and
- which of the two results occur

As an example, if you select Investment E2 and X occurs, you would be paid 24 points, if Y occurs you would be paid 36 points.

Select the investment you prefer below:

	Result	Payoff	Chance	Your Selection *tick one box*
Investment 1	X	28	50%	☐
	Y	28	50%	
Investment 2	X	24	50%	☐
	Y	36	50%	
Investment 3	X	20	50%	☐
	Y	44	50%	
Investment 4	X	16	50%	☐
	Y	52	50%	
Investment 5	X	12	50%	☐
	Y	60	50%	
Investment 6	X	2	50%	☐
	Y	70	50%	

How often do you play cards?

Often ☐ Sometimes ☐ Rarely ☐ Never ☐

How well do you understand the odds provided in horse-racing such as the Melbourne Cup?

Not very well ☐ Somewhat ☐ Very well ☐

Your Thoughts on Values *(All Treatments)*

In the next set of questions we are interested in your opinion on a variety of statements. To answer these, simply circle the number that best corresponds to how much you agree or disagree with the statement – see the example below.

EXAMPLE QUESTION

Winter this year has been warmer than previous winters

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

Creativity is an important trait

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

It is important to form your own opinions and have original ideas

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

Learning things and improving your own abilities is important

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

It is important to make your own decisions about life

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

Doing everything independently is important

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

Freedom to choose what you want to do is important

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

You are always looking for different kinds of things to do

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

Excitement in life is important to you

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

It is important to have all sorts of new experiences

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

It is important to maintain traditional values or beliefs

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

Following family traditions is important

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

You strongly value the traditional practices of your culture

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

You should always do what people in authority say

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

It is important to follow rules even when no one is watching

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

Obeying all the laws is important

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

It is important to avoid upsetting other people

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

It is important never to be annoying to anyone

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

You should always try to be tactful and avoid irritating people

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	**2**	**3**	**4**	**5**

Finally, a few questions to make sure that the people we are surveying are from a wide range of backgrounds and interests

(All Treatments)

Do you try to find ways to reduce your household's energy bill?

☐ Often ☐ Sometimes ☐ Never

Do you turn off appliances at the power point?

☐ Often ☐ Sometimes ☐ Never

Have you purchased a new fridge and/or dryer in the last 5 years?

☐ Yes ☐ No

If so, how recently? ____________ (months, days)

Was energy efficiency an important factor when replacing your fridge and/or dryer?

☐ Yes ☐ No

How many people are there in your household? ________ people

How many of the children are 15 years of age or younger? ________ children

What is the highest level of education you have obtained? *Please tick one*

- ☐ Year 9 or below
- ☐ Year 10
- ☐ Year 12
- ☐ Certificate or equivalent (for example, Certificate I, II, III or IV)
- ☐ Advanced diploma and diploma from a university/TAFE or equivalent
- ☐ Bachelor's degree or equivalent
- ☐ Graduate diploma or graduate certificate from university or equivalent
- ☐ Postgraduate degree or equivalent

What is the number of bedrooms in your house? ___________

What is the number of bathrooms in your house? ___________

How often do you use your clothes dryer?

- [ ] Daily
- [ ] Weekly
- [ ] Once in a while
- [ ] 2-3 times a week
- [ ] Almost never
- [ ] Do not own a clothes dryer

How often do you use your television?

- [ ] Daily
- [ ] Weekly
- [ ] Once in a while
- [ ] 2-3 times a week
- [ ] Almost never
- [ ] Do not own a television

How often do you use your computer/laptop?

- [ ] Daily
- [ ] Weekly
- [ ] Once in a while
- [ ] 2-3 times a week
- [ ] Almost never

Do you have a home office?

- [ ] Yes
- [ ] No

If yes, do you work/study at home for more than 3 hours (in a day, on average)?

- [ ] Yes
- [ ] No

To the best of your knowledge, please indicate your total household income before tax. If you have shared household responsibilities with a spouse or partner, please indicate the total combined income for both you and your partner/roommate. *Please tick one box.*

This last question is very important because studies suggest that income influences people's choices.

	Annual income	Weekly income
☐	$1 to $7,799	$1 to $149 a week
☐	$7,800 to $15,599	$150 to $299 a week
☐	$15,600 to $20,799	$300 to $399 a week
☐	$20,800 to $25,999	$400 to $499 a week
☐	$26,000 to $33,799	$500 to $649 a week
☐	$33,800 to $41,599	$650 to $799 a week
☐	$41,600 to $51,999	$800 to $999 a week
☐	$52,000 to $64,999	$1,000 to $1,249 a week
☐	$65,000 to $77,999	$1,250 to $1,499 a week
☐	$78,000 to $90,999	$1,500 to $1,749 a week
☐	$91,000 to $103,999	$1,750 to $1,999 a week
☐	$104,000 to $155,999	$2,000 to $2,999 a week
☐	$156,000 or more	$3,000 or more per week

Appendix 2: GAMS Code for Chapter 5

```
*Author: Mark Steven Tocock
*Social Network Model


sets
        households /h1*h10000/
        neighbour /n1*n10/
        simulate /s1*s200/
        ;

parameters

        Number_Connections_Row(households, simulate)
        Number_Connections_Row_Test(households, simulate)
        Row_Number(households)
        Age(households, simulate)
        Income(households, simulate)

        Col_Check(households, neighbour)
        Rand_check1(households)

        Col_Number(neighbour)
        / n1 = 1
          n2 = 2
          n3 = 3
          n4 = 4
          n5 = 5
          n6 = 6
          n7 = 7
          n8 = 8
          n9 = 9
          n10 = 10
        /

        Rand_Num(households, neighbour, simulate)
        Rand_Num_Match(households, simulate)

        Mapping(households, neighbour, simulate)
        Test(households, simulate)
        Sum_Check(households, simulate)
        ;

$CALL GDXXRW C:\Users\MarkT\Documents\gamsdir\projdir\ABM_INPUT_NETWORKV20.xlsx index=GAMS!A1:E6
$GDXIN ABM_INPUT_NETWORKV20.gdx
$LOAD Row_Number
$LOAD Age
$LOAD Income

Number_Connections_Row(households, simulate) =  uniformint(0,10);

loop((households, neighbour),

Rand_Num(households, neighbour, simulate) = uniformint(0,1000) - Row_Number(households);

Rand_Num_Match(households, simulate) = Uniform(0,1);
);

loop((households, neighbour, simulate),
        if(Col_Number(neighbour) <= Number_Connections_Row(households, simulate),
              Mapping(households, neighbour, simulate) = 0;
        );
);

loop(simulate,
```

```
loop(neighbour,
    loop(households,
        if(Row_Number(households) <>  Row_Number(households + Rand_Num(households, neighbour, simulate)) and
Number_Connections_Row(households, simulate) <> 0 and Number_Connections_Row(households +
Rand_Num(households, neighbour, simulate), simulate) <> 0 and Age(households  + Rand_Num(households, neighbour,
simulate), simulate) - 10 <= Age(households, simulate) and Age(households, simulate) <= Age(households  +
Rand_Num(households, neighbour, simulate), simulate) + 10 and Income(households, simulate) <= Income(households  +
Rand_Num(households, neighbour, simulate), simulate) + 2 and Income(households  + Rand_Num(households, neighbour,
simulate), simulate) - 2 <= Income(households, simulate) and Col_Number(neighbour) <=
Number_Connections_Row(households, simulate) and Col_Number(neighbour) <= Number_Connections_Row(households
+ Rand_Num(households, neighbour, simulate), simulate),
                        if(Mapping(households, neighbour, simulate) = 0 and Mapping(households + Rand_Num(households,
neighbour, simulate), neighbour, simulate) = 0,
                              Mapping(households, neighbour, simulate) = Row_Number(households + Rand_Num(households,
neighbour, simulate));
                              Mapping(households + Rand_Num(households, neighbour, simulate), neighbour, simulate) =
Row_Number(households);
                        );
        elseif (Row_Number(households) <>  Row_Number(households + Rand_Num(households, neighbour, simulate)) and
Number_Connections_Row(households, simulate) <> 0 and Number_Connections_Row(households +
Rand_Num(households, neighbour, simulate), simulate) <> 0 and Age(households  + Rand_Num(households, neighbour,
simulate), simulate) - 10 <= Age(households, simulate) and Age(households, simulate) <= Age(households  +
Rand_Num(households, neighbour, simulate), simulate) + 10 and Col_Number(neighbour) <=
Number_Connections_Row(households, simulate) and Rand_Num_Match(households, simulate) <= 0.5) and
Col_Number(neighbour) <= Number_Connections_Row(households + Rand_Num(households, neighbour, simulate),
simulate),
                        if(Mapping(households, neighbour, simulate) = 0 and Mapping(households + Rand_Num(households,
neighbour, simulate), neighbour, simulate) = 0,
                              Mapping(households, neighbour, simulate) = Row_Number(households + Rand_Num(households,
neighbour, simulate));
                              Mapping(households + Rand_Num(households, neighbour, simulate), neighbour, simulate) =
Row_Number(households);
                        );
        elseif (Row_Number(households) <>  Row_Number(households + Rand_Num(households, neighbour, simulate)) and
Number_Connections_Row(households, simulate) <> 0 and Number_Connections_Row(households +
Rand_Num(households, neighbour, simulate), simulate) <> 0 and Income(households, simulate) <= Income(households  +
Rand_Num(households, neighbour, simulate), simulate) + 2 and Income(households  + Rand_Num(households, neighbour,
simulate), simulate) - 2 <= Income(households, simulate) and Col_Number(neighbour) <=
Number_Connections_Row(households, simulate) and Rand_Num_Match(households, simulate) <= 0.5) and
Col_Number(neighbour) <= Number_Connections_Row(households + Rand_Num(households, neighbour, simulate),
simulate),
                        if(Mapping(households, neighbour, simulate) = 0 and Mapping(households + Rand_Num(households,
neighbour, simulate), neighbour, simulate) = 0,
                              Mapping(households, neighbour, simulate) = Row_Number(households + Rand_Num(households,
neighbour, simulate));
                              Mapping(households + Rand_Num(households, neighbour, simulate), neighbour, simulate) =
Row_Number(households);
                        );
        );
    );
);

);

Test(households, simulate) = sum(neighbour$(Mapping(households, neighbour, simulate)>0),1);
Sum_Check(households, simulate) = Number_Connections_Row(households, simulate) - Test(households, simulate);


Display Mapping, Number_Connections_Row, Sum_Check;

execute_unload "ABM_OUTPUT_NetworkV3.gdx" Mapping, Number_Connections_Row, Sum_Check;
execute 'gdxxrw.exe ABM_OUTPUT_NetworkV3.gdx o=Number_connections.xlsx par=Number_Connections_Row'
execute 'gdxxrw.exe ABM_OUTPUT_NetworkV3.gdx o=Sum_Check.xlsx par=Sum_Check'
```

```
*Author: Mark Steven Tocock

*Switching Model


execseed = 1;

sets

$onInLine
        households /h1*h10000/                    /* Households are the agents */
        neighbour /n1*n10/
        quarter /q1*q20/                    /* Time variable, each iteration represents three months */
        simulate /s1*s200/
        ;

$offInline

Parameters

        rows(households) /h1*h10000 = 0/

        Alternative_1(households, simulate)
        Alternative_2(households, simulate)
        Alternative_3(households, simulate)

        Prob_Alt1(households, simulate)
        Prob_Alt2(households, simulate)
        Prob_Alt3(households, simulate)

        Age(households, simulate)
        Gender(households, simulate)
        Diploma(households, simulate)
        Under(households, simulate)
        Post(households, simulate)


        Switching_History(households, quarter, simulate)
        /h1*h10000 .q1*q20 .s1*s200 = 0/

        Record_Switch(households, quarter)
        Class_Assign(households)
        Initial_Switch_Probabilities(households, simulate)
        Individual_Switch_Probabilities(households, quarter, simulate)
        Total_Switch(quarter)                    Records the total number of households that switch each quarter
        Bill_Exp_Initial(households, simulate)
        Bill_Exp_Total(households, quarter, simulate)
        Income_Convert(households, simulate)
        Switch_Prob(households, quarter, simulate)

        Weather_Effect(quarter, simulate)

        Mapping(households, neighbour, simulate)
        Neighbour_Switch(households, neighbour, quarter, simulate)
        Network_Positive(households)
        Network_Negative(households)
        Network_NET(households, quarter, simulate)
        /h1*h10000 .q1 .s1*s200 = 0/
        Network_Effect(households, quarter, simulate)
        /h1*h10000 .q1 .s1*s200 = 0/

        Price_Increase_Bill(quarter)
        / q1 1
          q2 1
          q3 1
          q4 1
          q5 1
```

```
 q6 1
 q7 1
 q8 1
 q9 1
 q10 1
 q11 1
 q12 1
 q13 1
 q14 1
 q15 1
 q16 1
 q17 1
 q18 1
 q19 1
 q20 1
/

Bill_Growth(households, quarter, simulate)


*Original proportions = 07, 0.15, 0.15

Aggregate_Switch(simulate, quarter)
Individual_weighting(simulate)
/ s1*s200 = 1
/
Bill_weighting(simulate)
/ s1*s200 = 1
/
Network_weighting(simulate)
/ s1*s200 = 1
/



*The probability of switching is set to zero for the first quarter
Bill_Switch_Probabilities(households, quarter, simulate)
/h1*h10000 .q1 .s1*s200 = 0 /


*        Change_Switch(quarter)
Num2(households, simulate)
Num3(households, simulate)
Att1(households, simulate)
Att2(households, simulate)
Att3(households, simulate)
Att4(households, simulate)
Att5(households, simulate)
Att6(households, simulate)
Att7(households, simulate)


Bill_Var(households, quarter, simulate)

Rand_Num_Switch(households, quarter, simulate)
;

* The code below imports the parameter data. Currently the data imported is focussed on importing random number from a
[0,1] Uniform Distribution

$CALL GDXXRW C:\Users\MarkT\Documents\gamsdir\projdir\ABM_INPUT.xlsx index=GAMS!A1:E13
$GDXIN ABM_INPUT.gdx
$LOAD Initial_Switch_Probabilities
$LOAD Bill_Exp_Initial
$LOAD Income_Convert
$LOAD Network_Positive
$LOAD Network_Negative
```

```
$LOAD Weather_Effect

$LOAD Gender
$LOAD Diploma
$LOAD Under
$LOAD Post

$GDXOUT

$call gams C:\Users\MarkT\Documents\gamsdir\projdir\Social_Network_V14.gms


$GDXIN ABM_OUTPUT_NetworkV3.gdx
$LOAD Mapping

$GDXIN ABM_INPUT_NETWORKV20.gdx
$LOAD Age

$GDXOUT;


Num2(households, simulate) = Uniform(0,1);
Num3(households, simulate) = Uniform(0,1);

Att1(households, simulate) = Normal(0,1);
Att2(households, simulate) = Normal(0,1);
Att3(households, simulate) = Normal(0,1);
Att4(households, simulate) = Normal(0,1);
Att5(households, simulate) = Normal(0,1);
Att6(households, simulate) = Normal(0,1);

Att7(households, simulate) = Normal(0,1);
Alternative_1(households, simulate) = exp(-2.24889+1.94413*Att6(households, simulate))*((-0.756798-
5.01842*Att1(households, simulate))*(-1) + (4.37083-8.51489*Att2(households, simulate))*(-1) +
(5.85533+14.3126*Att3(households, simulate))*(-1) + (10.4218+18.877*Att3(households, simulate))*(-1) + (0.341603-
0.656211*Att4(households, simulate))*0  + (0.127399+0.355859*Att5(households, simulate))*0+
0.318805*Age(households, simulate) - 0.678348*Gender(households, simulate) + 16.0407*Diploma(households, simulate) -
15.2216*Under(households, simulate) - 1.16892*Post(households, simulate) - 44.9772) - EXP(-
2.24889+1.94413*Att6(households, simulate))*0 ;
Alternative_2(households, simulate) = exp(-2.24889+1.94413*Att6(households, simulate))*((-0.756798-
5.01842*Att1(households, simulate))*(-1) + (4.37083-8.51489*Att2(households, simulate))*(-1) +
(5.85533+14.3126*Att3(households, simulate))*(1) + (10.4218+18.877*Att3(households, simulate))*(0) + (0.341603-
0.656211*Att4(households, simulate))*0 + (0.127399+0.355859*Att5(households, simulate))*0 +
64.0823*Att7(households, simulate)) - EXP(-2.24889+1.94413*Att6(households, simulate))*40;
Alternative_3(households, simulate) = exp(-2.24889+1.94413*Att6(households, simulate))*((-0.756798-
5.01842*Att1(households, simulate))*(-1) + (4.37083-8.51489*Att2(households, simulate))*(-1) +
(5.85533+14.3126*Att3(households, simulate))*(0) + (10.4218+18.877*Att3(households, simulate))*(1) + (0.341603-
0.6562111*Att4(households, simulate))*0  + (0.127399+0.355859*Att5(households, simulate))*0  +
64.0823*Att7(households, simulate) - 3.32333) - EXP(-2.24889+1.94413*Att6(households, simulate))*80;

loop((households, simulate),

if(exp(Alternative_1(households, simulate)) = 0 and exp(Alternative_2(households, simulate)) = 0 and
exp(Alternative_3(households, simulate)) = 0,
      Prob_Alt1(households, simulate) = 0.3333333333333;
      Prob_Alt2(households, simulate) = 0.3333333333333;
      Prob_Alt3(households, simulate) = 0.3333333333334;
  else
      Prob_Alt1(households, simulate) = exp(Alternative_1(households, simulate))/(exp(Alternative_1(households,
simulate)) + exp(Alternative_2(households, simulate)) + exp(Alternative_3(households, simulate)));
      Prob_Alt2(households, simulate) = exp(Alternative_2(households, simulate))/(exp(Alternative_1(households,
simulate)) + exp(Alternative_2(households, simulate)) + exp(Alternative_3(households, simulate)));
      Prob_Alt3(households, simulate) = exp(Alternative_3(households, simulate))/(exp(Alternative_1(households,
simulate)) + exp(Alternative_2(households, simulate)) + exp(Alternative_3(households, simulate)));
);
);
```

```
Rand_Num_Switch(households, quarter, simulate) = Uniform(0,1);

Binary Variables

        Switch(households, quarter, simulate)            Record 1 for yes switching occurs or 0 if not switching.

variables

        Contract_Selected(households, simulate)
        ;

Contract_Selected.l(households, simulate)$(Num3(households, simulate) <= Prob_Alt1(households, simulate)) = 1;
Contract_Selected.l(households, simulate)$(Num3(households, simulate) >  Prob_Alt1(households, simulate) and
Num3(households, simulate) <= (Prob_Alt1(households, simulate) + Prob_Alt2(households, simulate))) = 2;
Contract_Selected.l(households, simulate)$(Num3(households, simulate) >  (Prob_Alt1(households, simulate) +
Prob_Alt2(households, simulate)) and Num3(households, simulate) <= (Prob_Alt1(households, simulate) +
Prob_Alt2(households, simulate) + Prob_Alt3(households, simulate))) = 3;


rows("h1") = 1;

loop(households,
        rows(households) = rows(households-1) + 1;
);

loop(simulate,


loop(quarter,

*Bill equation

        Bill_Growth(households, "q1", simulate) = Bill_Exp_Initial(households, simulate);
        Bill_Growth(households, quarter, simulate) = Price_Increase_Bill(quarter)*Bill_Growth(households, quarter-1,
simulate);


        Bill_Var(households, quarter, simulate) =(Bill_Growth(households, quarter, simulate)*Weather_Effect(quarter,
simulate) - Bill_Growth(households, quarter, simulate)) + Bill_Growth(households, quarter, simulate);


        Bill_Exp_Total(households, quarter, simulate) = Bill_Var(households, quarter, simulate);

        Bill_Switch_Probabilities(households, quarter, simulate)$(Bill_Exp_Total(households, quarter,
simulate)/Income_Convert(households, simulate)*100 > 5) = 0.10;
        Bill_Switch_Probabilities(households, quarter, simulate)$(Bill_Exp_Total(households, quarter,
simulate)/Income_Convert(households, simulate)*100 < 1) = -0.01;

      Individual_Switch_Probabilities(households, quarter, simulate) = exp(Initial_Switch_Probabilities(households,
simulate))/(1+exp(Individual_weighting(simulate)*Initial_Switch_Probabilities(households, simulate))) +
Bill_Switch_Probabilities(households, quarter, simulate) + Network_NET(households, quarter-1, simulate)/10;
      Switch_Prob(households, quarter, simulate) = Individual_Switch_Probabilities(households, quarter, simulate);

* For the next line if a household has already switched then it fixes the probability to equal one.

     Individual_Switch_Probabilities(households,quarter, simulate)$(Switching_History(households, quarter-1, simulate) = 1)
= 1;

     Switch.l(households, quarter, simulate)$(Individual_Switch_Probabilities(households, quarter, simulate) <
Rand_Num_Switch(households, quarter, simulate)) = 0;
     Switch.l(households, quarter, simulate)$(Individual_Switch_Probabilities(households, quarter, simulate) >=
Rand_Num_Switch(households, quarter, simulate)) = 1;

*The next line records for each quarter if the households switched
```

```
    Switching_History(households, quarter, simulate) = Switch.l(households, quarter, simulate);


*Network Effect

*The next line records a one for every household's neighbour which has switched in the current quarter

    Neighbour_Switch(households, neighbour, quarter, simulate) = Switch.l(households + (Mapping(households, neighbour, simulate) - rows(households)), quarter, simulate);
    Network_NET(households, quarter, simulate) = sum(neighbour$(Neighbour_Switch(households, neighbour, quarter, simulate)*Contract_Selected.l(households + (Mapping(households, neighbour, simulate) - rows(households)), simulate) = 1), Network_Negative(households)) + sum(neighbour$(Neighbour_Switch(households, neighbour, quarter, simulate)*Contract_Selected.l(households + (Mapping(households, neighbour, simulate) - rows(households)), simulate) > 1), Network_Positive(households));

);

        Aggregate_Switch(simulate, quarter) = sum(households, Switch.l(households, quarter, simulate));

);



*Display Neighbour_Switch, switch.l, mapping, Network_NET, Network_Effect, Aggregate_Switch, Bill_Switch_Probabilities;

execute_unload "ABM_OUTPUT.gdx" Aggregate_Switch, Individual_Switch_Probabilities, Switch, Bill_Switch_Probabilities, Contract_Selected, Network_NET, Mapping;
execute 'gdxxrw.exe ABM_OUTPUT.gdx o=results_Aggregate_Switch.xlsx par=Aggregate_Switch'
execute 'gdxxrw.exe ABM_OUTPUT.gdx o=results_prob.xlsx par=Individual_Switch_Probabilities'
execute 'gdxxrw.exe ABM_OUTPUT.gdx o=results_billprob.xlsx par=Bill_Switch_Probabilities'
execute 'gdxxrw.exe ABM_OUTPUT.gdx o=results_Switch.xlsx var=Switch'

Display Bill_Exp_Total, Weather_Effect, Contract_Selected.l

*Display  switch.l, Neighbour_Switch.l, Network_Effect, Switch_Neighbour, Network_Prob_Effect, Individual_Switch_Probabilities, Bill_Switch_Probabilities, Total_Switch, contract_selected.l, Contract_Selected.l;

*execute_unload "ABM_OUTPUT.gdx" Switch, Connections, Bill_Exp_Total, Switch_Neighbour, Individual_Switch_Probabilities, Bill_Switch_Probabilities;
*execute 'gdxxrw.exe ABM_OUTPUT.gdx o=results_connections.xlsx par=Connections_sort'
*execute 'gdxxrw.exe ABM_OUTPUT.gdx o=results_connections_time.xlsx par=Connections_time'

*execute 'gdxxrw.exe ABM_OUTPUT.gdx o=results_Network_Test.xlsx par=Switch_Neighbour'
*execute 'gdxxrw.exe ABM_OUTPUT.gdx o=results_Network_Effect.xlsx par=Network_Effect'
```