Using behavioural science to increase consumer adoption of time of use electricity tariffs: evidence from survey and field experiments

by

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Declaration

I, Moira Lindsey Nicolson, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Signed:

(February 2018)

Abstract

A challenge for realising the benefits of smart meters, promoting energy security and decarbonising electricity is encouraging domestic consumers to switch from flat-rate electricity tariffs to a new generation of time of use (TOU) tariffs. However, a greater challenge is how to ensure that the right consumers sign up and that consent is informed: not all consumers will save money on a TOU tariff and evidence shows that a sizeable minority could be financially worse off.

In a marked departure from the existing literature, this thesis argues that opt-out enrolment (a type of 'nudge') is unlikely to be a suitable method of recruiting consumers onto TOU tariffs, even though it could achieve almost universal enrolment. The first study shows that half of British energy consumers are unable to make informed choices about the cost-effective tariff for them, particularly those in low socio-economic grades. Consumers are therefore unlikely to opt-out of being switched onto a TOU tariff, even when unsuitable.

Results from three further studies covering a collective sample size of 16,000 participants, show that tailoring the marketing of TOU tariffs towards electric vehicle (EV) owners could increase demand for TOUs amongst EV owners whilst reducing demand amongst non-EV owners, who pose less of a burden to the electricity network and are less likely to save money from switching. Unlike opt-out enrolment, tailored marketing is an 'effective and selective' nudge (Johnson, 2016). Unlike personalised defaults, tailored marketing can achieve informed consent.

The results have implications for multiple 'smart' energy programmes, from signing up to TOU tariffs or direct load control contracts to participating in vehicle-to-grid services. In each case, a decision will need to be made about whether

consumers will be left to opt-in or opt-out of such services, and to what extent it matters that consent is informed.

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I dedicate this thesis to my mum Sandra Nicolson, the hardest working person that I know and whose work ethic has no doubt made it possible for me to reach the final stage of this PhD.

Published work

This thesis draws on work from several of my previous publications, outlined below.

Peer-reviewed journal publications

Nicolson, M., Huebner, G.M., Shipworth, D. and Elam, S. (2017). “Tailored emails prompt electric vehicle owners to engage with tariff switching information”. *Nature Energy*, 2, 17073, 1-6.

- ➔ I authored the text for this paper in full, revising it based on comments from G.M. Huebner in particular but also from D. Shipworth and three anonymous peer reviewers. Chapter 7 of this thesis draws heavily on this article, occasionally verbatim.

Nicolson, M., Huebner, G.M. and Shipworth, D. (2017). “Are consumers willing to switch to smart time of use electricity tariffs? The importance of loss-aversion and electric vehicle ownership.” *Energy Research & Social Science*, 23: 82-96.

- ➔ I authored the text for this paper in full, revising it on the basis of comments from G.M. Huebner, D. Shipworth and three anonymous peer reviewers. Chapters 2 and 3 of this thesis draw on content from this article.

Peer-reviewed conference papers

Nicolson, M., Huebner, G.M. and Shipworth, D. (2016). “Applying behavioural economics to boost uptake to ‘smart’ time of use tariffs – a pre-analysis plan for a randomised control trial”. Behave 2016 4th European Conference on Behaviour and Energy Efficiency, 8-9 September 2016.

- ➔ I wrote the text for this article, revising it based on comments to the conference presentation received from my co-authors. The Pre-Analysis

Plan section of this paper is reproduced, although not necessarily verbatim, in Method section for study 2(a) in Chapter 6.

Policy reports

Hledik, R., Gorman, W., Irwin, N., Fell, M., **Nicolson, M.**, Huebner, G.M. “The value of TOU tariffs in Great Britain: Insights for decision-makers”. Report prepared for Citizens Advice. London, UK: Brattle Group and UCL Energy Institute, July 2017.

- ➔ This was a collaborative project between the Brattle Group and collaborators at the UCL Energy Institute, for which UCL was responsible for undertaking a systematised review of the literature on demand for TOU tariffs and a survey of 3,000 British energy bill payers, both of which are used in this thesis as follows:
    - The systematised review forms the basis of the review described in Chapter 2. The trial protocol for the review was drafted by M.J. Fell with feedback from myself and G.M Huebner; the literature searching and screening was conducted by M.J. Fell and G.M. Huebner; the data extraction from the screened documents was conducted solely by me; the meta-analysis is exclusively my work; and the interpretation of the results is also mine but benefitted from feedback from M.J. Fell, G.M. Huebner and R. Hledik. For clarity, the tasks undertaken by G.M. Huebner and M.J. Fell are also marked in the chapter itself by adding their initials in parentheses after the relevant task; when unmarked, the tasks are undertaken exclusively by me.

- Part of the primary research conducted for this project – an online survey of 3,000 British energy bill payers – forms the basis of the results for Study 2(b). The idea to include a question on tailoring the marketing of a TOU tariff was mine and the questions used to generate the data used in this thesis were designed solely by me. No other content from this survey is used in this thesis.

➔ The final report was written collaboratively between all authors, however I was only responsible for authoring specific sections on the 'Consumer attractiveness of TOU tariffs' (p.35-38) and the Marketing results of the 'Primary Market Research' section (p.46-48). It is only the written sections of this report that were written by me and dealt specifically with my research that are used (in a very limited basis) in this thesis.

Nicolson, M., Huebner, G.M., Shipworth, D., Elam, S. (2016). "Do you want a time of use tariff with that? Prompting electric vehicle owners to switch tariff shortly after purchasing their vehicle". Report to the UK Office for Low Emission Vehicles. London, UK: UCL Energy Institute, November 2016.

➔ This unpublished report was written by me and revised based on comments from G.M. Huebner, D. Shipworth and also Nick Brooks at the Office for Low Emission Vehicles. I draw on content from this report in Chapter 7.

Journal publications under review

Nicolson, M., Fell, M.J., Huebner, G.M. "Consumer demand for time of use electricity tariffs: a systematised review of the empirical evidence". *Under review at the Journal of Renewable and Sustainable Energy Reviews*.

➔ I wrote the text for this article and revised it based on comments from G.M. Huebner and M.J. Fell. This is the article which is based on data collected for Citizens Advice (referred to in the policy report above). The review in Chapter 2 draws heavily on this article, often verbatim.

List of acronyms

BEIS	Department of Business, Energy and Industrial Strategy
CMA	Competitions and Markets Authority
DECC	Department of Energy and Climate Change
DLC	Direct load control
DSR	Demand side response
EUT	Expected utility theory
EV	Electric vehicle
GB	Great Britain
Ofgem	Office of Gas and Electricity Markets
OLEV	Office for Low Emission Vehicles
ONS	Office of National Statistics
TOU	Time of use tariff

Chapter 1

Introduction:

Opt-ins, opt-outs and effective and selective nudges – injecting energy into an old debate

1 The changing electricity system

1.1 Domestic demand-side response

The UK energy system is changing. Renewable electricity now accounts for 25% of total UK electricity generation compared to less than 5% in 2004 (DUKES, 2017). The way we heat our homes and the type of vehicles we drive are changing too. In 2010, one year prior to the introduction of the UK Government's electric vehicle (EV) grant, there were just 24 plug-in EVs on the road; today there are just over 100,000 (SMMT, 2011, 2017a). Ownership of heat pumps, the Government's favoured alternative to gas boilers in homes (DECC, 2012b), is also rising (DUKES, 2017).

Whilst necessary for meeting UK carbon emission targets (DECC, 2008), these changes present a range of challenges for the electricity system and the affordability of energy. Unlike fossil-fuelled power plants, renewable generation cannot be ramped up or ramped down to match the daily or seasonal variations in electricity demand (Parliamentary Office of Science and Technology, 2014). Another concern is the strain that EVs and the greater penetration of electric heating will place on the UK electricity network, particularly at times of peak electricity demand (DECC, 2012a; Frontier Economics and Sustainability First, 2015; National Grid, 2017; Ofgem & BEIS, 2017).

Domestic demand for heating and transport presents a particular challenge because, whilst household customers only consume one third of energy by volume (Ward et al., 2015), they are estimated to consume 50 percent of the electricity used in the peak evening hours (Hesmondhalgh, 2012).

The conventional solution to managing increased electricity demand is to reinforce local electricity networks, which could be funded through taxes on consumer energy bills (Frontier Economics and Sustainability First, 2012). Energy storage and interconnectors could help to address the challenges of having an increasingly intermittent renewable electricity supply. However, storage technologies are still costly and interconnectors require cross-country cooperation and large infrastructure investments, adding to the upfront costs of moving to a low-carbon economy (Trainer, 2013).

An approach that could potentially lower the cost of the energy transition is to incentivise consumers, including domestic consumers, to charge their vehicles or run their heating at times of low electricity demand or when renewable sources of electricity are more abundant.[1] This is called demand-side response (DSR) and the most recent UK Government estimates suggest that DSR could save consumers up to £40 billion in the coming decades through reductions in energy bills (Sanders et al., 2016; Ofgem & BEIS, 2017).

One way in which it is expected that domestic consumers will be incentivised to participate in DSR is through price signals delivered via time of use electricity tariffs (TOUs), in which the price of electricity varies depending on factors such as electricity network constraints and the wholesale price of electricity. Following the UK smart meter roll-out, it will be much easier for energy companies to charge consumers according to the time of day they use electricity (Accenture, 2013; US Department of Energy, 2013b; DECC, 2012a) and therefore to offer TOUs because smart meters automatically send electricity meter readings to energy suppliers in near real time and are capable of doing so at half-hourly intervals (Smart Energy Code Company, 2017).

[1] Storage technologies and demand-side response are mutually complementary but it is also important to distinguish between energy storage and demand-side response because they both involve different financial costs and potentially different types of consumer behaviour change.

Trials have demonstrated that consumers adjust their consumption patterns when migrated onto a TOU tariff as part of their participation in industry trials (see Frontier Economics and Sustainability First, [2012] for a literature review of 30 trials). Nevertheless, for this vision of a smarter, more flexible energy system to become reality, energy bill payers must switch from their existing flat-rate electricity tariffs to a TOU tariff or a range of other types of DSR services in the first place. However, the evidence for whether consumers will adopt TOU tariffs, or how to increase uptake if demand is lower than required, is much less clear.

1.2 Consumer adoption: gaps in the evidence on domestic demand-side response

With the UK smart meter roll-out still in its infancy, TOU tariffs of the type required to meet the challenges of a future low-carbon electricity system are not widely commercially available (Michael J. Fell et al., 2015; M Nicolson et al., 2017). Although there are basic legacy options such as Economy 7 tariffs in the UK, designed to stimulate overnight demand for nuclear power, there is no measure of market demand for modern smart meter enabled TOU tariffs amongst GB consumers. Measures of uptake to smart TOUs amongst US consumers exist as do a range of proxies for GB consumer demand; this includes recruitment rates into industry TOU tariff trials, uptake to Economy 7 tariffs and measures of willingness to switch to future TOU tariffs from surveys (Chapter 2). However, there has been no attempt to synthesise this wide range of evidence to provide an overall estimate of the likely uptake of TOUs amongst domestic energy bill payers in GB.

This lack of evidence is concerning because over 70% of GB consumers have not switched their energy tariff, despite being able to save an average of £300 (CMA, 2016c), when the average saving from signing up to a domestic DSR programme is likely to be much lower. A collective saving of £40 billion is approximately £40 per household per year from now until 2050 (Ofgem & BEIS, 2017).

One way of guaranteeing sufficient uptake to TOU tariffs or other DSR services is to make them mandatory, as in Ireland (Commission for Energy Regulation, 2015). However, consumers do not like being told what to do and, furthermore, whilst some consumers will benefit from TOU tariffs, evidence suggests that a sizeable minority could face substantially higher electricity bills, sometimes by up to £200 per year (Star et al., 2010; Carmichael et al., 2014; Sidebotham, 2014a; Long Island Power Authority, 2015). One key concern is that these energy bill increases may disproportionately affect consumers who are most in need of reducing their energy bills (Ofgem, 2014b; Citizens Advice Bureau, 2014; Citizens Advice, 2017).

Voluntary recruitment strategies, on the other hand, will be easier to implement than mandates and may be better able to balance the need for greater energy system flexibility with policymakers' additional obligations[2] to minimise the negative distributional impacts of the smart energy transition.

Thus, on the face of it, there are two major gaps in the evidence on domestic DSR: (1) whether consumers will adopt TOU tariffs and, (2) how adoption could

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[2] Smart Energy GB, the independent body responsible for the smart meter consumer engagement campaign, is specifically tasked with helping to ensure that smart meters benefit all consumers, including vulnerable groups. The GB regulator, Ofgem, is specifically tasked with investigating and helping to minimise the negative distributional implications of TOU tariffs (see the recently commissioned report: Cambridge Economic Policy Associates, 2017).

be increased if uptake is insufficient whilst using recruitment methods that preserve freedom of choice.

Behavioural science offers a range of methods to increase uptake to TOU tariffs whilst preserving freedom of choice and hence respecting consumer heterogeneity (Sunstein, 2013b). Evidence from the behavioural science literature shows that an important choice is whether recruitment to TOU tariffs is opt-in or opt-out. To illustrate why, this thesis now briefly turns to an example from the health literature, the domain to which behavioural science has been most widely applied. This will be followed by a summary of the aims and research questions that this thesis intends to answer.

2 Behavioural science and nudge

2.1 Opting in versus opting out

The large cross-country variation in registration rates to national organ donor registers provides one of the most famous examples of the difference in enrolment rates observed across opt-out and opt-in enrolment systems. In Germany, approximately 12% of people are registered as organ donors whereas in Austria the rate is 99.9% (Johnson and Goldstein, 2003). The difference is that in Austria, all citizens are automatically enrolled onto the organ donor register unless they opt-out, whereas in Germany, consent is not presumed and citizens have to opt-in (Sunstein, 2013b). Opting out of the organ donor register in Austria is no more costly than opting into the organ donor register in Germany. This makes the difference in enrolment rates difficult to explain from a classical economic perspective – the dominant model of consumer decision making – which predicts that humans respond only, or at least primarily, to incentives.

Whilst it may be tempting to speculate that this cross-country gulf in organ donor registrations is due to differences in culture, social norms or higher levels of altruism or “extraordinarily effective educational campaigns” in Austria (Sunstein, 2013b, p.1), behavioural science offers a much more plausible explanation for the difference. In Austria, the path of least resistance is to stay on the organ donor register whereas, in Germany, the easiest course of action is also to do nothing and remain unenrolled. The tendency people have to stick with the pre-selected option is called inertia or, more formally, status-quo bias (Samuelson and Zeckhauser, 1988; Kahneman et al., 1991).

Environmental researchers have drawn three key lessons from the difference in uptake across opt-in versus opt-out organ registration enrolment systems. The first is that opt-out enrolment should be used to make people ‘green by default’ (Pichert and Katsikopoulos, 2008; Sunstein and Reisch, 2013; Faruqui et al., 2014; S. A. Fenrick et al., 2014; Broman Toft et al., 2014; Ebeling and Lotz, 2015; Egebark and Ekström, 2016).

The second lesson is that the observation that consumers respond both to incentives but also to the way in which choices are framed means decision making cannot be fully rational, as assumed by classical economics. Economics should therefore be reformed to account for these additional influences on behaviour; the fusion of psychology and economics into a discipline that assumes behaviour is influenced by incentives *and* the way choices are framed is called behavioural economics (Baddeley, 2017).[3]

The third is that governments should use these findings to help promote policy outcomes (Benartzi et al., 2017), including those affecting the environment

[3] Calls for economics to be reformed to include findings from other social sciences is not a new one, but has been argued for decades (Friedman, 1953), if not centuries (Hume, 1738).

(Pichert and Katsikopoulos, 2008; Sunstein and Reisch, 2013; Sunstein, 2013a). The branch of behavioural economics concerned with influencing consumer behaviour to achieve policy outcomes, such as increasing numbers on organ donor registers or green energy tariffs using default enrolment, is called ‘nudge’ (Thaler and Sunstein, 2008).

2.2 Nudge and the environment

Since the publication of *Nudge: improving decisions about health, wealth and happiness* (Thaler and Sunstein, 2008), governments are increasingly using insights from behavioural economics and behavioural science more broadly to supplement or replace traditional economic levers such as taxes and fines to influence citizens’ behaviour (in order) to achieve public priorities (Benartzi et al., 2017). There are two key virtues of nudge from a policymaker’s perspective, which is that they can be easier to implement than taxes and mandates which may lack public support and, compared to financial incentives like the UK Government’s Feed-in-Tariff or the Ultra-Low Emission Vehicle grant which deducts up to £5,000 from the value of eligible EVs, nudges are almost free, providing a high ‘bang for their buck’ (Benartzi et al., 2017).

Unsurprisingly, there is increasing support behind the idea of using behaviourally informed interventions to help achieve environmental outcomes too. The European Commission has published a set of guidelines for designing interventions to change energy behaviour (Dahlbom et al., 2009), all of which are non-coercive and do not rely on financial incentives, thereby fitting the definition of nudge (Thaler and Sunstein, 2008). The policy interest in nudge and behavioural interventions is also mirrored in the academic environmental literature with a range of review articles having discussed the potential application of behavioural economics to helping meet carbon emission targets (Shogren and Taylor, 2008; Hepburn et al., 2010; Pollitt and Shaorshadze, 2011; Sunstein, 2013a; Sunstein and Reisch, 2013; Gillingham and Palmer, 2014; Frederiks et al., 2015; Hobman et al., 2016; Lehner et al., 2016).

3 The limitations of the nudge agenda and anti-rationality arguments

However, the problem with each of these aforementioned lessons is that they are far too simplistic. The nudge literature fails to adequately account for: (1) possible trade-offs between environmental and social outcomes; (2) the lack of conclusive empirical evidence for the hypothesis that consumers who do not switch to the cheapest available tariff or do not invest in energy efficiency interventions that would reduce their energy bills are not acting rationally and; (3) variations in the impact of nudge across different policy domains. These are outlined below.

First, whilst opt-out enrolment is appropriate in cases where there is a single optimal course of action that most people do not take, but which can be favoured by making it the default, it is far less appropriate when the best course of action varies substantially across people (Carroll et al., 2009; Keller et al., 2011). Although, on average, trials find that TOU tariffs reduce energy bills, the impacts vary substantially across energy bill payers with a sizeable minority having been made significantly financially worse off (Long Island Power Authority, 2015; Schare et al., 2015; Star et al., 2010; Schofield et al., 2014; Sidebotham, 2014b). Further, if the effectiveness of opt-out enrolment implies that consumers are not fully rational, then people may be unable to process all of the information required to identify whether such a tariff will increase or decrease their energy bill, a pre-requisite for making an informed choice over whether to opt-out. Equally, householders may also be at risk of being inappropriately enrolled onto a TOU tariff even if they are left to opt-in.

Thus, the question is not as simple as ‘How can we increase uptake to TOU tariffs if adoption is lower than required?’ or even ‘How can we increase uptake to TOU tariffs if adoption is lower than required whilst respecting freedom of choice?’. Rather, the important question is, given that people do not exercise their freedom of choice and that freedom of choice does not necessarily guarantee good or informed choices, is it possible to identify recruitment methods that could increase uptake to TOU tariffs amongst consumers who are most likely to save money whilst not simultaneously increasing uptake amongst those for whom TOU tariffs may substantially increase their energy bills? Answering this question is therefore one of the key aims of this thesis.

Second, how do we *know* that energy consumers are not at least approximately fully rational? Although research shows that consumers fail to exploit all the potential financial savings from switching tariff, this does not necessarily imply energy bill payers are not making rational choices with respect to their energy tariff or supplier because the cheapest tariff is not necessarily the optimal tariff (Wilson and Price, 2010). Just because people fail to make fully rational decisions regarding how much to save for retirement and when to retire (Lusardi and Mitchell, 2006b, 2008; van Rooij et al., 2011; Klapper et al., 2013) does not mean that it will also affect decisions over their energy tariff, a much less complex process that does not require an understanding of concepts such as compound interest, inflation, mortality tables and more (see Chapter 3). Third, if only a small proportion of consumers are not fully rational, then an opt-out policy may have very little negative impact on consumer welfare. This is known as the “as if” defence of the rationality paradigm; economists widely accept that economic theory often incorrectly characterises behaviour at the individual level, but are reluctant to build bounded rationality into their models on the assumption that the proportion of consumers who violate the principle of rational choice will be so small that the model will still be correct on average (Friedman, 1953). Finally, rationality may vary across consumer groups in ways that affect their likelihood of responding to behavioural interventions. For instance, research from international development shows that people with below average incomes have lower ‘mental bandwidth’ for processing information than people with above median incomes, because poverty places an undue burden on people’s limited mental resources (Mani et al., 2013). If this transfers to the rich and poor in developed countries, then it could be that early adopters of low carbon technologies – for example EVs and heat pumps who are key candidates for DSR (Frontier Economics and Sustainability First, 2012; Frontier Economics, 2012) – will be much less susceptible to behavioural interventions than other types of consumers. Thus, the interesting question is not whether energy bill payers are or are not rational, but rather, which bill payers are boundedly rational (Simon, 1957), with respect to what behaviours and how pervasive is it? Answering this questions is therefore another key aim of this thesis.

Third, even if consumers do struggle to make the best decisions for themselves, it does not imply that nudge is the right approach to help them make better choices for them or for society as a whole, as nudge aspires to do (Thaler and Sunstein, 2003; Camerer et al., 2003). Indeed, empirical research shows that, in some situations, making decisions based on ‘rules of thumb’ rather than based on all the information available to us can lead to better decisions (Gigerenzer and Brighton, 2009; Gigerenzer and Gaissmaier, 2011). However, most of the empirical research on nudge has been confined to the health and finance domains (Loewenstein et al., 2012; Lehner et al., 2016). There is therefore a risk that the nudge agenda could influence environmental policy on a narrow evidence base comprised mostly of the effectiveness of opt-out enrolment for increasing uptake to renewable energy tariffs (Pichert and Katsikopoulos, 2008; Broman Toft et al., 2014; Ebeling and Lotz, 2015) and social comparison energy billing feedback (Slemrod and Allcott, 2011; Harries et al., 2013; Dolan and Metcalfe, 2013; Schultz et al., 2015).[4]

Finally, the nudge approach has been criticised for its promotion of many high profile labels such as ‘behavioural insights’ and ‘behavioural biases’ which lack precise definitions and theoretical underpinnings (Spotswood, 2016). In this thesis, I have aimed to clarify as many of these terms as possible, for example, by offering precise definitions for both behavioural economics, nudge and behavioural science (and the potential differences between all three), in Chapter 3.

4 Policy getting ahead of science

Applying nudge to energy without further research presents two key risks. The first is a more general risk that the strong “conceptual” appeal of nudge (Halpern et al., 2012; Loewenstein et al., 2012) means that nudge gets employed as a way of achieving energy and environmental outcomes in the absence of empirical evidence in its support or even despite evidence to the contrary, whilst potentially displacing more traditional tools such as taxation and mandates which can be very effective (House of Lords Science and Technology Select Committee, 2011). This was also a concern amongst health practitioners who pointed to the

[4] This list is not exhaustive however the other applications of nudge in the environmental sector are relatively limited by comparison to the health and finance literature. For a comprehensive review of nudge as applied to energy and the environment see Frederiks et al. (2015) and Lehner et al. (2016).

effectiveness of the EU smoking ban after calls for greater use of softer behavioural change tools to reduce smoking and obesity rates (Loewenstein et al., 2012; Halpern et al., 2012).

The second risk is more specific to TOU tariff enrolment, which is that the success of opt-out enrolment at increasing enrolment rates to e.g. company pensions (DellaVigna, 2009), and national organ donor registers (E. Johnson and Goldstein, 2003), is used to justify a policy of automatically enrolling consumers onto TOU tariffs and other automated DSR schemes. However, TOUs are not like pensions because not everyone will benefit from TOUs. Nevertheless, a number of industry (Faruqui et al., 2014) and academic reports (US Department of Energy, 2016; Cappers et al., 2016) and journal papers (S. A. Fenrick et al., 2014) have already come out strongly in favour of a policy of opt-out enrolment for TOU tariffs.

The problem of using nudge to change behaviour in general arises from a fundamental but as yet unresolved contradiction in behavioural economic theory and nudge itself (Lunn, 2015; Goldin, 2015). Nudge intends to help consumers make "better" decisions for themselves and society on the basis that "in some cases individuals make inferior choices, choices that they would change if they had complete information, unlimited cognitive abilities and no lack of willpower" (Thaler and Sunstein, 2003, p.175). However, behavioural science shows that people make different choices depending on how the choice is presented to them, which, if true, means we can no longer infer what people want from what they do (Thaler and Sunstein, 2003; Gillingham and Palmer, 2014; Lunn, 2015), a key assumption behind economic welfare analysis (Samuelson, 1938) known as revealed preference theory (Varian, 2006). Therefore, it is extremely hard to prove that people are not doing what is in their best interest – that they are not rational – because behavioural economics removes the standard means for identifying what is in the best interest of the consumer.

Further, in the absence of an omniscient central planner who knows what is in peoples' best interests, it also means that we do not have an easy method for determining which direction to nudge people in (Goldin, 2015), even if people are failing to act in their interests.

The alternative to opt-out enrolment when policymakers do not know or cannot determine what course of action is in a person's best interests is for decision makers to be left to make an active choice either way (Keller et al., 2011; Sunstein and Reisch, 2013) which is known to come at a cost of much lower enrolment rates to TOU tariffs (US Department of Energy, 2013a). Moreover, if consumers are boundedly rational, opt-in enrolment still would not guarantee that the tariffs would disproportionately attract consumers with high flexible electricity use such as EV and heat pump owners. A new approach is needed.

5 A new approach to nudge – 'effective and selective' nudges

Despite its limitations, nudge still has two key advantages over harder tools such as mandates. The first is that people do not like being told what to do and, unlike mandates, nudges respect freedom of choice and consumer heterogeneity. The second is that nudges can be extremely cheap (Benartzi et al., 2017). Increasing customer switching in a low cost way is crucial if suppliers are not going to pass the costs of engagement onto consumers in the form of higher bills (Deller et al., 2017).

A more promising nudge than opt-out enrolment is to use tailored marketing to nudge those consumers who are most likely to save money from being on a TOU tariff onto TOU tariffs – for instance, EVs and heat pump owners – that does not simultaneously increase uptake amongst those who are less likely to save. Using strategies from behavioural science to increase opt-in enrolment rates has been used in the healthcare sector, including to increase registration rates to organ donor registers (A Spital, 1995; Spital, 1996), and is sometimes called enhanced active choice (Keller et al., 2011).

Unlike opt-outs and even personalised opt-out enrolment (Sunstein, 2013b; Sunstein and Reisch, 2013), tailored marketing has the potential to be both “effective and selective” (Johnson, 2016). For example, evidence from behavioural economics (Beatty et al., 2014) suggests that tailoring the marketing of TOU tariffs towards EV and heat pump owners could increase uptake amongst these consumers groups (effective) whilst deterring uptake amongst consumers who are less likely to save and could be made financially worse off (selective). Since consumers who have the potential to save the most are also the consumers with high consuming flexible electrical loads, using tailored to increase TOU tariff enrolment does not necessarily conflict with the electricity system’s requirements for much greater energy system flexibility – but only if tailored marketing does increase uptake amongst these high consuming electricity users.

Tailored marketing has never been successfully tested as a method of recruiting consumers onto energy tariffs. It is therefore unknown whether tailored marketing would attract EV or heat pump owners onto TOU tariffs. Indeed, there is very little robust evidence on how to increase voluntary uptake of TOU tariffs or DSR services if adoption is lower than required to realise the benefits outlined by the Government in its flexibility strategy (Ofgem & BEIS, 2017) or the business case for smart meters, which relies on a 30% adoption rate of TOU tariffs by 2030 (BEIS, 2016b). The small body of evidence that has tested methods of increasing uptake to TOUs is almost exclusively survey-based and usually performed on convenience samples of students (Verhagen et al., 2012) or participants recruited via social media (Dütschke and Paetz, 2013; Buryk et al., 2015) or online crowd sourcing platforms (Schwartz et al., 2015). Without exception, all studies test methods for increasing uptake amongst the average energy bill payer, which ignores the fact that a sizeable minority of energy bill payers, in some cases up to 40%, could be made substantially financially worse off (see Chapter 2). As suggested in section 1 of this chapter, there is not even a robust answer to the more basic question of how many consumers are likely to adopt TOU tariffs in the first place.

6 Aim and scope of research

This thesis has two overarching aims. The first is to conduct a systematic literature review to provide an average estimate of consumer demand for TOUs based on all published studies. The second is to provide evidence on how to increase British consumer demand for TOUs without making them the mandatory or default tariff. To achieve this second aim, the research intends to answer two research questions:

1. Are consumers able to identify the optimal tariff for them when given all the information required to make an informed choice? This question can also be rephrased as, is consumer decision making over electricity tariffs affected by bounded rationality?
2. If consumers are not able to choose the optimal tariff, would tailored tariff marketing towards consumers groups who are more likely to save money

on a TOU whilst reducing enrolment amongst consumers who could be made financially worse off? This question can be rephrased as, is tailored marketing an effective and selective nudge?

This research focuses exclusively on the economic motivation of domestic energy bill payers in the UK with a particular focus on EV owners and heat pump owners. These groups are chosen because they are most likely to save money on, and provide benefits to the electricity network, by switching to a TOU (for reasons laid out in Chapter 2).

The primary data collection for this thesis is confined to the UK. Some of the studies are confined to GB consumers whereas one is UK wide – the reasons for this are covered in the individual study chapters themselves. However an EU Directive 2009/72/EC mandated the implementation of smart meters in all EU Member States, with the added provision that 80% of consumers should have a smart meter by 2020 (European Commission, 2009). Therefore the method and results are relevant for countries around the world with smart meter programmes[5] which are also facing the challenge of how to decarbonise supply whilst ensuring consumers get reliable and affordable access to electricity.

7 Original contribution

This research aims to make four contributions. The first contribution is substantive. The results will have implications for all types of consumer participation in the smart grid, of which there are many examples: signing up to TOU tariffs, selling surplus solar to the grid, having the set-point on their thermostat adjusted in line with the real-time price of electricity (direct load control of heating) and giving electricity back to the grid via the battery in their EV

[7] Europe, Australia, New Zealand and the US as well as parts of Africa, Latin America and Asia.

(vehicle-to-grid). In each case, if it is agreed that consumers must give their consent to provide these services, a decision will be made about whether consumers will consent by default, unless they opt-out, or whether they have to actively decide to provide such services, and if so, whether opt-in enrolment is likely to be high enough or whether it will need to be 'enhanced'.

It makes a contribution to the evidence base used by the UK Government on how many consumers are likely to sign up to a TOU in real life (as opposed to how many say they will in surveys) and how it might be able to increase uptake to TOUs without making them mandatory, as in Ireland, or opt-out, as being advocated by some US scholars. With the increased adoption of EVs and targets for a 25% penetration rate of heat pumps by 2030 (Committee on Climate Change, 2013) and closure of the UK's coal-fired power plants, the need for high quality evidence on the likely consumer uptake of TOUs amongst domestic energy consumers – and how to increase it – is growing ever more pressing.

The second contribution is methodological. It is to demonstrate the effectiveness of alternatives to surveys for measuring demand in missing markets amongst niche populations. Like other research into future energy technologies, measuring demand for future DSR electricity tariffs has been hindered by the fact that these tariffs do not yet exist commercially on a large scale; in GB, there are currently only two modern ('smart') TOU tariffs, the British Gas' 'Free Weekends' tariff, launched in late 2016, and Green Energy's TIDE tariff, launched in 2017. Measuring demand for these tariffs amongst consumers with higher than average flexible electricity loads, such as EV owners, is particularly challenging due to their relatively low prevalence in the population. This research has used a number of innovative methods to get around both these problems, including developing a website for a virtual energy company which consumers could browse and partnering with the UK Government Office for Low Emission Vehicles (OLEV) to access a sample of over 6,000 UK EV owners for participation in a randomised control trial.

The third is a theoretical contribution to behavioural economics. That consumers do not switch tariff more frequently despite the large savings on offer (Defeuilley, 2009; CMA, 2016b) can be accounted for by multiple models of decision making, including the market failure framework from classical economics as well as bounded rationality. Answering the first research question – can consumers identify the optimal tariff when given all the information required – will help to validate the extent to which bounded rationality affects consumer decision making over energy tariffs and not just decisions regarding pensions and whether to join the organ donor register.

The fourth contribution is to broaden the empirical evidence on the effectiveness of nudge interventions, which the House of Lords Science and Technology Select Committee (2011) fears may be influencing UK policy on the back of a very narrow evidence base. So far, the literature on nudge has mostly focused on how to increase average adoption of particular financial services such as pensions (Thaler and Benartzi, 2004) using blunt instruments such as defaults that fail to account for the variation in optimal savings rates across younger and older employees or how to encourage people to save money for rainy days (Ashraf et al., 2006), quit smoking (Giné et al., 2010) or lose weight (Volpp et al., 2008) using commitment devices that may only attract the most sophisticated consumers. This research provides vital evidence on ways in which choices can be framed that could influence decision making when policymakers do not have enough information to identify which option should be made the default (Sunstein, 2013b) or when the optimal choice varies across people.

8 Structure of thesis

This thesis has 9 chapters and reports the results of four empirical studies which are summarised in Table 1. Chapter 2 outlines the role of domestic DSR in GB followed by the design and results of a systematised literature review of the available evidence on consumer demand for TOUs from OECD countries and what strategies have been tested to increase demand. The review presents and discusses the results of a meta-analysis of 66 individual measures of uptake to a TOU across 27 studies in six OECD countries to provide a consolidated estimate of uptake to TOUs, controlling for the country in which the estimate was measured and other potential correlates.

Table 1 Summary of empirical phases of this thesis

Study	Design	Sample size
Literature review, part a	Systematised review	66
Tariff Decision Making Study	Online survey with tariff vignettes	811
The Flex Trial	Fictional energy company testing price comparisons against tailored marketing on uptake to a TOU	6,446
Population-Based Survey Experiment	Online survey experiment testing impact of tailoring on EV owners relative to average bill payer	2,960
The OLEV trial	Email trial with UK Office for Low Emission Vehicles testing the	7,038

	impact of a tailored vs generic email on EV owners	

Since very few strategies have been tested to increase demand, Chapter 3 provides an overview of the leading theories used to explain and influence individual decisions, with a particular emphasis on classical economics (the most common model of individual decision-making) and behavioural economics (a leading alternative) to inform the development of strategies that will be tested to increase consumer uptake of TOUs in this thesis. This chapter justifies the choice of tailored marketing as a way of increasing uptake to TOU tariffs.

Chapter 4, the methodology section, outlines why a survey is the best method for testing the extent to which consumers are able to make optimal decisions about which tariff to switch to. It then argues why randomised control trials run in both the field (field experiments) and in the context of a population-based survey are well suited methods for testing the causal impact of the tailored marketing on consumer demand for TOUs. It outlines the approach taken to avoid some of the major criticisms of randomised control trials and the strategy used to obtain a revealed preference measure of consumer demand (a preference based on the choices people make rather than choices people say they will make) for TOUs, given that TOUs are not currently widely commercially available.

Chapters 5-7 present the design, hypotheses, analytical methods and results of each study. Chapter 5 presents the results of a survey (the “Tariff Decision Making Experiment”) used to measure the extent to which consumers are able to choose the optimal tariff from a menu of options (n=811). The results of this study showed that people struggled to select the best tariff for them. To test methods of increasing the likelihood that the tariff will be adopted by consumers most likely to benefit, to aid consumer decision making, Chapters 6 and 7 present the results of three randomised control trials in the context of an online natural field experiment targeted at EV owners and heat pump owners (the “Flex Trial”), a population-based survey experiment and an email trial in partnership with OLEV targeting just UK EV owners (the “OLEV trial”). The online natural field experiment and the population-based survey experiment are presented in the same chapter (Chapter 6) because they test the same hypotheses. The Flex Trial provides a realistic environment in which to test the hypotheses but, since participants are not informed that they are partaking in a trial, it was not possible to robustly identify which participants owned electric vehicles and heat pumps. The Population-Based Survey Experiment complements the results of the natural field experiment by collecting data on electric vehicle ownership amongst all study participants, making it possible to test whether the tailored marketing simultaneously boosts uptake amongst electric vehicle owners whilst depressing uptake amongst non electric vehicle owners using treatment-effect heterogeneity analysis. A limitation of treatment effect heterogeneity analysis is that the results cannot be interpreted causally; the OLEV trial reported in Chapter 7 was conducted on a sample of participants who were already known to own electric vehicles, making it possible to estimate the impact of tailoring using the average treatment effect, which can be given a causal interpretation. In general, each of these study-specific chapters are divided into four parts: (1) design and hypotheses; (2) analysis method; (3) main treatment effects and; (4) an interpretation of the main findings in relation to the hypotheses and research questions. Methodological strengths and limitations are also discussed with suggestions for how these could be addressed in future work.

Chapter 8 discusses the results and limitations of each of the four primary data collection studies and the meta-analysis of the 27 pre-existing studies presented in Chapter 2 in light of the wider literature and the overall aims of the thesis. Chapter 9 concludes this thesis with a summary of the main findings followed by a summary of the real-world application of the results and implications for future policy regarding the regulation of the retail electricity market in GB and the marketing of tariffs by energy suppliers. The theoretical implications of the results are also discussed, with questions for future research presented.

Chapter 2

Literature review, part (a):

The vision and the reality – a smarter electricity system and the empirical evidence on consumer demand for TOU tariffs

1 Introduction

This review chapter is structured in two parts. Section 2 outlines how and why, in the coming decades, the UK electricity system is expected to be turned on its head (BEIS, 2016c; Ofgem & BEIS, 2017; Institute of Engineering and Technology, 2017). Whereas now centralised bodies turn off and on electricity generation assets in line with the population's rhythms of electricity use and disuse, the future electricity system is one characterised by energy consumers responding to signals from their energy supplier, or potentially a range of bodies, by adapting their electricity consumption patterns in line with electricity supply.[6] I shall refer to this as "the vision".

The second part, covered in Section 3 and which I shall refer to as "the reality", outlines the widespread consumer disengagement with the energy market which suggests that domestic electricity consumers will not necessarily play the role expected of them in this vision of a smarter energy future. One of the simplest ways in which consumers are initially expected to offer greater flexibility is by signing up to TOU tariffs (BEIS, 2016b, 2016c). This section presents the design and results of a systematised review of the literature to investigate what empirical evidence there is to support the assumption of consumer participation and to provide a 'best' available estimate of overall domestic consumer demand for TOU tariffs and any early evidence of what might increase that demand. The theory behind why consumer engagement is so low, and what tools could increase

[6] DSR is not the only way in which the energy system is expected to change in future. Other changes include increasing proportions of renewable generation, energy storage and the electrification of heating and transport.

engagement to turn vision into reality is reserved for its own chapter (Chapter 3), which contains part (b) of the literature review.

2 The vision of a smarter energy future

2.1 Meeting the challenges of decarbonisation

The UK Climate Change Act sets a legally binding target for Government to cut greenhouse gas emissions by 80% of 1990 levels by 2050 (DECC, 2008). To achieve this, it needs to radically decarbonise national energy supplies, which account for 29% of the UK's greenhouse gas emissions, making energy supply the largest emitting sector just after the transport sector (BEIS, 2015). Decarbonising energy supplies whilst also ensuring consumers can access energy when they need it, at a price they can afford to pay, requires radical changes to the energy system as a whole (DECC, 2012a; European Commission, 2015; BEIS, 2016c; Ofgem & BEIS, 2017). At present, the body that operates GB's national electricity transmission system – the National Grid – ensures that electricity demand matches electricity supply by "switching on and off fossil-fuelled power plants" (Parliamentary Office of Science and Technology, 2014, p.1).

However, decarbonising energy supplies will make it increasingly desirable for more of this balancing of electricity supply and demand to be done by getting consumers (the demand-side), including domestic consumers, to alter their consumption patterns in line with supply (DECC, 2012a; European Commission, 2015; BEIS, 2016c; Ofgem & BEIS, 2017). This is called demand-side response (DSR), or demand-side flexibility, and it can be defined as a "change in electricity consumption patterns in response to a signal" (Element Energy, 2012, p.9). There are three key drivers behind DSR, all of which are themselves driven by the need to radically decarbonise energy supplies. Each of these drivers is outlined in turn.

2.1.1 Maintaining security of supply in the face of intermittent generation

As countries replace fossil fuels with renewables such as solar and wind, which provide a cleaner but less predictable supply of electricity, the ability to just turn up or turn down electricity supply when required will decline substantially in the lead up to 2050. Electricity is expensive to store (Trainer, 2013) and interconnections with other countries require cooperation and reduce energy independence, whereas incentivising consumers to defer electricity usage until its windy or sunny – or to store electricity for later use – by charging consumers less for electricity when renewable generation is high, means that supply and demand can be matched at relatively low cost (Hesmondhalgh, 2012; Element Energy, 2012; Hledik et al., 2017).

2.1.2 Maintaining security of supply at an affordable price

The UK Government is therefore relying on consumer participation in DSR to help maintain energy affordability (DECC, 2012a). Today, one third of domestic consumers' end bills are from electricity network and levy charges (Ofgem, 2017a) and, if current trends continue, this will rise to 50 percent by 2030 (Ward and Darcy, 2015). The aim is that DSR could deliver efficiency savings which could be passed onto consumers in the form of lower bills, for example, through tariffs which charge consumers less for electricity used at off-peak times or when renewable generation is more abundant (DECC, 2012a; Frontier Economics and Sustainability First, 2012; Ofgem & BEIS, 2017). These are called TOU tariffs.

2.1.3 Maintaining security of supply when electricity demand goes up – heat pumps, electric vehicles and everyone else

Without DSR, peak time electricity demand is expected to increase because, to meet carbon emission targets, the UK Government like governments elsewhere, are working to replace the vehicle fleet with EVs (Committee on Climate Change, 2013) and household gas central heating with electric heating, particularly heat pumps (DECC, 2010). However, the electrification of heat and transport will place one of the greatest burdens on the future electricity network (Frontier Economics, 2011). Domestic demand for heating and transport presents a particular challenge because, whilst household customers only consume one third of energy by volume (Ward et al., 2015), they are estimated to consume 50 percent of the electricity used in the peak evening hours (Hesmondhalgh, 2012). This thesis therefore focuses on domestic consumers, with a particular emphasis on heat pump and EV owners.

Heat pump owners were selected in particular because, across all low-carbon pathway models, heat pumps are the favoured substitute to gas boilers in individual buildings (DECC, 2010). The UK's Climate Budget is reliant on heat pumps delivering 25% of the heat demand in the domestic sector by 2030 (Committee on Climate Change, 2013). Over 60% of a household's energy demand comes from heating (Palmer and Cooper, 2012), most of which is done in the evening peak when people return from work.

EV owners were selected because evidence to date shows that EV owners have got into the habit of charging their vehicles when they get home from work (Zarnikau et al., 2015; My Electric Avenue, 2015; Capova et al., 2015), when electricity demand is at its peak and, in the UK like many other countries, the least efficient and therefore most polluting power plants are brought into operation to meet peaks in demand. As EV sales and battery capacities increase, so too do the risks to electricity networks. Estimates suggest that UK electricity networks will become overloaded when EVs reach 30%-60% market penetration(My Electric Avenue, 2015).

Conventionally, the risks posed to electricity networks from increases in electricity demand are addressed by reinforcing local electricity networks funded through 'green' taxes on consumer energy bills (My Electric Avenue, 2015). However, DSR offers a much cheaper way of managing this increased electricity demand because it does not require such large additional infrastructure investments[7] (European Commission, 2015).

2.2 The expected role of domestic consumers in a smarter energy future

There are many ways in which domestic consumers are envisioned to participate in DSR. One way is by signing up to TOU tariffs (BEIS, 2016b, 2016c) which expose consumers to price signals that indicate when it is, or is not, optimal for them to consume electricity. Following the smart meter roll-out, it is expected that

[7] Although DSR will be significantly enabled through the smart meter roll out, the UK's Smart Meter Implementation Programme is not solely being delivered to support DSR but primarily to ensure accurate billing and help deliver energy demand reduction (DECC, 2014; BEIS, 2016b).

suppliers will offer many different types of TOU tariffs, each of which can provide different levels of flexibility and require different levels of participation from consumers. The different types of TOU tariffs are described in Table 2 however, for simplicity, this thesis uses the term ‘TOU tariff’ to refer to all the possible tariff types described in Table 2.

Static TOU tariffs are the simplest form of TOU tariff that could deliver peak-load reductions in electricity demand and they would involve consumers actively changing when they use electricity. Heat pump owners on a static TOU tariff could schedule their heating system to meet a lower thermostat set-point temperature during peak times, thereby saving money and minimising the impact that their heating system will have on the electricity network (Frontier Economics, 2012; Sidebotham and Powergrid, 2015). Field trials in the UK show that TOU tariffs do effectively reduce peak demand from heat pumps (Sidebotham and Powergrid, 2015).[8]

By signing up to a static TOU tariff, and setting the timer on their EV charge point to charge their vehicle overnight, when electricity demand is low, EV owners could reduce the running costs of their EV and minimise the impact of charging their EV on the electricity network. Field trials from the US find that TOU tariffs have reduced peak time charging of EVs by 50% (Zarnikau et al., 2015). Static TOU tariffs could also play an important role in maximising the environmental benefits of EVs; when charged consistently at the most polluting times, which in the UK is during the evening peak, greenhouse gas emissions from EVs can be

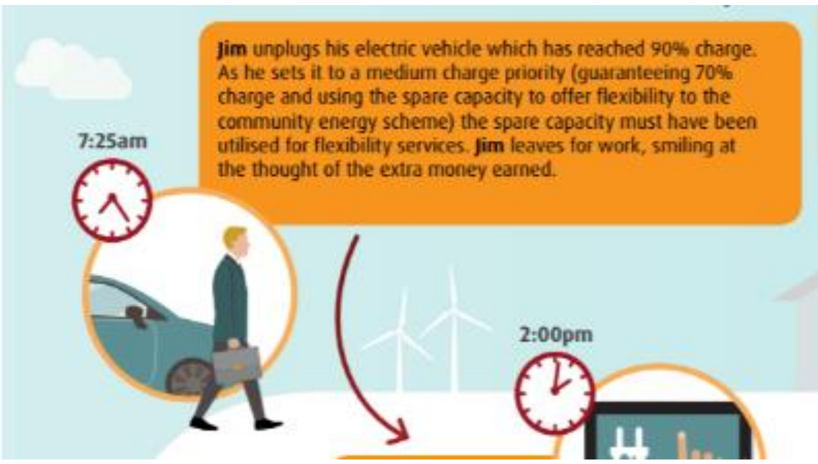
[8] Although trials also report dissatisfaction amongst some TOU trial participants with heat pumps (Bell et al., 2015; Fell, 2016).

nearly 50% higher than if charged at average electricity grid carbon intensity (Ma et al., 2012).

Another way in which domestic consumers are expected to participate in DSR, also featured in Table 2, is by signing up to services such as direct load control (DLC) contracts, in which a third party provider remotely switches appliances on/off (Ofgem, 2013a; Michael J. Fell et al., 2015).

There are also specific DLC services for EV owners. A good example of one of the roles that EV owners are expected to play in the future smarter electricity system can be found in a 'Future Smart' publication by UK Power Networks, the body responsible for managing the electricity network in London and East of England (Figure *1*).

Figure 1 The future energy consumer as imagined by UK Power Networks.



This document is describing a form of DLC called controlled charging, in which a third party remotely interrupts the current being used to charge an EV. Automated responses like DLC and controlled charging are particularly important for the less predictable tariffs, such as real-time pricing tariffs, and have been found to produce greater and more sustained reductions in peak time electricity demand than programmes in which consumers need to respond manually across TOU tariffs of many designs (Frontier Economics and Sustainability First, 2012).

However, since the only technical requirement for TOU tariffs is a smart meter, which are being installed in homes as part of the national smart meter roll-out (BEIS, 2016b), it is likely that TOU tariffs will be one of the first types of DSR offerings available to domestic consumers. Perhaps reflecting this, it is static TOU tariffs that the UK Government requires 30% of consumers to sign up to by 2030 to ensure the smart metering programme is cost-effective (BEIS, 2016b). This thesis therefore focuses mostly on TOU tariffs. However, since it is expected that consumers will need to sign up or provide their consent for any tariff or service in Table 2 (European Commission, 2015), the discussion presented in this thesis, and the results, are broadly applicable to all domestic DSR services.

Table 2 Different types of DSR tariffs, services and activities.

Tariff/service/activity	Incentive structure	Function
Static TOU tariff	Two or more unit rates that apply at fixed times of the day and week. A customer on a three-rate static TOU tariff is likely to be charged a higher rate for electricity on weekday evenings compared to during the day and a super off-peak rate overnight.	Useful for delivering reductions in daily peak demand, for example from heating or EVs.
Dynamic TOU tariff	Two or more unit rates that vary throughout the day or week. When these tariffs have been trialled on pilot groups of consumers, participants receive a text message notifying them of the rate that will apply the following day (e.g. High, Medium, Low).	Provide more flexibility to electricity operators than static TOU and could help to balance demand with renewable power.
Real time pricing tariff	Rate varies in near real-time in accordance with the wholesale market price of electricity, which reflects the balance of electricity supply and demand.	Provides greater potential flexibility to electricity network operators to respond to hourly or even sub-hourly changes in supply/demand and renewables.
Peak time rebate tariffs.	Financial rewards for reducing consumption at peak times of day or year.	Provides reductions at key times of the day or year, for example, the Winter peak in the UK or summer peaks due to air-conditioning use in countries with hot climates.
Direct load control service	A third party remotely switches off/on appliances in line with near real-time balance of supply and demand. When EV charge points are the device under control, this is known as	As above, with the added advantage that electricity network operators have greater assurance of a response because consumers do not have to manually respond to changes in their electricity rate

	‘controlled charging’. Could be combined with tariffs.	or even programme their appliances to respond.
Vehicle-to-grid services	EV owners are paid a fee to allow electricity grid to use EV battery as temporary storage for, or source of, electricity.	As above.
Peer-to-peer electricity trading activities	Small electricity producers and consumers (prosumers) buy and sell electricity directly from each other rather than from one of the traditional large energy suppliers. Purchasing could be automated based on algorithms set to match user preferences, for example, to automatically sell surplus solar power.	Could help to “reduce the level of energy balancing which needs to be carried out by the [National Grid]” (Energy Networks Association, 2017, p.11).

2.3 Enablers of domestic DSR

The scenarios described above, in which domestic consumers flexibly adjust their electricity consumption patterns and habits in line with the requirements of the wider electricity system, is a vision not a present reality. Until this year, when two smart meter enabled static TOU tariffs entered the market, there were no commercially available smart TOU tariffs anywhere in GB or most of Europe. There are a number of key changes that need to take place before the vision described above becomes a reality, the most challenging of which will be ensuring that consumers play the part imagined for them.

2.3.1 Energy policy

Whilst TOU electricity pricing has been an established and increasingly sophisticated part of grid management strategies involving large industrial and commercial users for many years, domestic TOU tariff programmes remain restricted to relatively basic options such as Economy 7 tariffs in GB, or the Tempo Tariff, in France, which are a legacy of these countries' historical investment in nuclear power, which is also much less flexible than fossil fuel power plants. These legacy tariffs required the installation of secondary meters which can, for example, record night-time consumption independently of day-time consumption.

Although Economy 7 tariffs played an important role in generating overnight demand for nuclear electricity when the UK invested majorly in nuclear power in the 1970s following the oil crises, they are not designed to handle the needs of an electricity system that is powered by wind or solar which varies throughout the day or to handle unexpected faults in the electricity network. There is also no incentive for British suppliers to encourage domestic consumers to alter their consumption patterns because suppliers are not exposed to the true cost of supplying domestic customers at different points in the day. However, a number of key policy enablers for domestic DSR are already underway to address these barriers.

First, the rollout of smart meters in homes across the UK and elsewhere, which record electricity use in near real-time, will make it easier for energy companies to bill consumers according to the time of day they use electricity. Second, the announcement by Ofgem of half hourly settlement for domestic electricity use in 2017, so that consumers can be billed according to their personal half-hourly variations in electricity use rather than the consumption profile of the average electricity consumer within a given profile class, “will expose the true cost of supplying that customer in any given half-hour” (Ofgem, 2016c, p.4). This will place incentives on suppliers to create TOU tariffs that will incentivise consumers to use electricity at cheaper times.

Half hourly settlement may also motivate the development of more innovative products and services from other potentially actors, such as smart thermostats which could be bundled with TOU tariffs so that, instead of having to manually respond to changes in price, consumers could allow their supplier or the third party thermostat manufacturer to automatically turns up or down in response to changes in the supply and demand of renewable electricity. Ofgem (2017b) has removed its restriction on tariff bundles to facilitate the offering of more innovative products required for realising a smarter, low carbon electricity system.

2.3.2 Energy technology

Many organisations are already trialling methods of providing smart automated responses, in which a ‘smart’ appliance can automatically respond to the price signals on a TOU tariff. For instance, a UK based home energy management company has been trialling remote control of heat pumps in which a technology is used to calculate the optimal thermostat set-point for the heat pump throughout the day, for example by storing the heat in the fabric of the home during the cheap times on a simulated TOU tariff to reduce its use during the expensive peak times (Carter, 2016). DLC is particularly useful for heat pumps because domestic heat pumps, when run most efficiently, take longer to heat up than domestic gas boilers, meaning that it may be relatively difficult for a householder to manually adjust their heating patterns in response to their tariff (Carter, 2016).

A company called Open Utility is trialling its peer-to-peer electricity trading platform called Piclo with its business customers (Ofgem & BEIS, 2017) and research has shown that it is possible to use smart meter data to disaggregate electricity use at the individual appliance level (Kelly and Knottenbelt, 2016), which could potentially be used to create appliance-specific TOU tariffs.

2.3.3 Consumer participation

Whilst the technological and policy barriers may be largely out of the way relatively soon, this vision of a more flexible electricity system in which domestic consumers respond manually or automatically to signals delivered through TOU tariffs can only be realised if consumers are willing to participate. Two types of consumer participation are required: (1) consumers to switch to a TOU tariff or other DSR programme and; (2) respond to the price signals by changing their consumption patterns.

A literature review of over 30 trials in which participants were put onto TOU tariffs to investigate its effect on electricity consumption patterns concludes that consumers are indeed sensitive to changes in the price of electricity throughout the day with the highest recorded reduction in peak demand of 22% (Frontier Economics and Sustainability First, 2012). However, the evidence on whether consumers will sign up to a TOU tariff in the first place is far less clear. Arguably this could be even more important, because, with greater automation, people would not need to respond to the price signals themselves.

2.4 A gap in the evidence on consumer participation in DSR

Aside from the United States, where more modern TOUs are now commercially available, there is no measure of current commercial consumer demand for TOUs. Alternative sources of evidence on consumer demand for TOUs include recruitment rates into TOU field trials, measures of stated demand elicited from survey participants and current market uptake of legacy tariffs such as Economy 7. However, to my knowledge, there has been no attempt to synthesise this evidence from this wide range of sources and methods to obtain an overall estimate of the likely uptake of TOU tariffs amongst domestic energy bill payers or what factors (e.g. tariff design, marketing) might increase uptake.

This lack of evidence is problematic because there are good reasons to believe that domestic consumers may not sign up to TOU tariffs or other DSR services. Since the privatisation of retail energy markets around the world almost two decades ago, half of all consumers have not left the incumbent former state supplier (Defeuilley, 2009). In its most recent inquiry, GB's Competition and Markets Authority found that over 70% of British consumers are not on the cheapest tariff for them despite potential average annual savings of almost £300 in 2015 (CMA, 2016c) and the fact that, for most people, energy bills represent the second highest item of household expenditure after housing (Office of National Statistics, 2016).

This lack of consumer engagement in the energy market presents a potential problem for uptake to TOU tariffs as well as other products such as DLC of home heating, for which the average saving is likely to be much lower; the

Government's reported estimates are that it will save consumers in the region of £40 per household per year until 2050 (Ofgem, 2017b).[9] Indeed, discouraged by what they see as overwhelming consumer disengagement in the energy market, the Smart EV Group (a stakeholder group representing the interests of electricity network operators) is in favour of a policy to mandate controlled charging of EVs (whereby a third party remotely manages the electricity supply to a customers' EV) (Cross et al., 2016). In Ireland, the regulator has taken the decision to make TOU tariffs mandatory for all domestic energy consumers (Commission for Energy Regulation, 2015). However, given that a fairly sizeable minority of people have ended up paying more on a TOU tariff relative to a flat rate tariff, such an approach is unlikely to be popular and may result in a backlash against smart meters if people perceive this as the only way to avoid TOU tariffs.

Synthesising the available evidence is important to help overcome the methodological limitations of individual measures of uptake. For example, there are also limitations in the extent to which recruitment rates into trials and stated willingness to switch to a TOU tariff from surveys can be interpreted as measures of demand for TOU tariffs, which can only be accounted for in a meta-analysis which controls for differences in uptake across measurement methods. In some cases, there are challenges in interpreting measures of commercial uptake as evidence of consumer demand. For example, approximately 13%–21% of British

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[9] Citing a recent report (Sanders et al., 2016), Ofgem's flexibility strategy reports that the maximum overall savings from greater system flexibility are estimated at £40 billion between 2016 and 2050; by the authors' own calculations, if these savings were shared across 27 million UK households (Office for National Statistics, 2016a), this amounts to £40 per household per year or £1,480 over the 34 years between 2016 and 2050. This estimate is in the same order of magnitude to the savings made by customers participating in GB field trials of TOU tariffs.

energy bill payers are on ‘legacy’ TOU tariffs introduced in the 1970s to stimulate night-time demand for nuclear power (Consumer Focus, 2012; Michael J. Fell et al., 2015; M Nicolson et al., 2017). Historical research suggests that Economy 7 meters were mainly installed by councils into local authority housing alongside electric night storage heaters in post-war Britain, in response to lobbying by the Electricity Development Association, the body financed by the electricity supply industry to develop common sales and marketing material under the Electricity Act of 1919 (Carlsson-Hyslop, 2016). Uptake to these tariffs is unlikely to reflect underlying householder preferences for off-peak pricing.

The challenge of even conducting such a review is amplified by the fact that tariff trials were not designed with the aim of estimating potential consumer uptake and, to my knowledge, there has been no prior attempt to extract the recruitment rates from these DSR trials or whether they are even reported in final project reports. Moreover, the evidence base is drawn from participants from all over the world and applying different tariff designs (static TOU, dynamic TOU etc.) and recruitment strategies (e.g. opt-in versus opt-out). However, this also presents an opportunity to assess the extent to which uptake varies depending on the tariff design and recruitment strategy, which could be used by decision-makers to inform the development of TOU tariffs and consumer engagement campaigns. Extracting measures of uptake from studies run in multiple countries using a range of methods, whilst controlling for the individual effects of these variations, increases the statistical power of the meta-analysis to identify potentially important influences on uptake.

The next section presents the design and results of a systematised review used to identify and screen potentially relevant evidence to produce the 'best available' estimate of consumer demand for TOU tariffs and to identify what methods might be used to stimulate consumer demand given the high levels of consumer inertia in the retail electricity market identified in the Competition and Markets Authority's most recent investigation (CMA, 2016b).

3 A systematised review of the literature on consumer demand for TOU tariffs

3.1 Aim of this review

This section presents the design and results of a systematised literature review (Grant and Booth, 2009) aimed at answering three main research questions:

1. What is domestic consumer demand for TOU tariffs in GB?
2. What methods are known to increase demand for TOU tariffs?
3. What is the variation in energy bill impacts across TOU tariff customers?

Systematised reviews use methods from systematic reviews (Grant and Booth, 2009), such as pre-specified inclusion/exclusion criteria and extraction methods, to minimise bias that can arise if researchers consciously or unconsciously select articles for review that favour particular conclusions or only those with which the researcher is already relatively familiar. Unlike a full systematic review, and like rapid evidence assessments, the completeness of searching was determined by time constraints. This review also includes a meta-analysis, "which statistically combines the results of quantitative studies to provide a more precise estimate of the results” (Grant and Booth, 2009, p.94) to answer the research questions above.

3.2 Method

3.2.1 Study selection

Included studies consist of those written in the English language that document empirical, quantitative findings on uptake to TOU tariffs amongst domestic energy consumers in OECD countries.[10] It was decided to include work from all OECD countries rather than just GB, despite this being the geographical focus for this thesis, because prior knowledge of this literature suggested that there would be too few GB studies to permit a robust meta-analysis. Studies reporting work conducted in non-OECD countries were excluded because it was judged that such countries may have different priorities and concerns related to electricity usage (e.g. in developing countries, particularly energy access) that would mean measures of uptake in these countries would be unlikely to generalise to the GB setting. Qualitative studies were not included in the review because each of the research questions that the study aims to answer requires quantitative data. Future reviews could usefully seek to find evidence to help explain the level of demand for TOU tariffs established in this study, which would require consultation of qualitative studies.

[10] Studies reporting uptake measures based only on study recruitment were initially going to be excluded, in the review protocol, however the decision was later taken to include such studies in order to provide a greater range of evidence based on studies in which people are actually able to switch to the tariff having made the decision to switch (unlike in survey research).

It was then necessary to define what data would be considered as representing ‘uptake’ to a TOU tariff. To get an idea of what uptake to TOU tariffs might look like under real world conditions, this review includes reports of switching rates to commercially available TOU tariffs. However, since these tariffs are almost all in the US - where central air conditioning rather than heating is the dominant load - it is not known whether this research can be generalised to Northern European or the GB setting where most of the demand is from heating (which is currently mostly gas). The review therefore also includes measures of uptake obtained in surveys which cover a wider range of countries, including GB. It is possible that surveys will overestimate demand for tariffs because it is easier to switch hypothetically than in real life and because there is no financial consequence of switching to the wrong tariff. The review also includes recruitment rates into TOU tariff trials as a measure of uptake. These trials were designed as efficacy trials (aiming to assess the impact of tariffs on electricity consumption patterns under high uptake of the tariffs) rather than effectiveness trials which also seek to measure effectiveness conditional on uptake. However, because two of these trials were in GB, it is the only evidence available on actual uptake to a next generation TOU amongst GB consumers. Trials may have differed substantially from what can be expected of an "average" tariff launch, particularly the use of financial incentives and bill protection. Differences in uptake across uptake method are accounted for in the analysis.

Studies that documented qualitative findings only were excluded because these types of studies could not be used to provide a quantitative measure of uptake. Studies that did not report empirical results (e.g. include only modelled uptake) were excluded because these studies would either be reliant on an empirical measure which the inclusion criteria would capture or would be based on targets or estimated optimum uptake levels, which are not equivalent to actual consumer demand. Studies that did not report research including a TOU tariff (e.g. which focused only on DLC or other non-price-based DSR) were also excluded from consideration because DLC combined with a TOU tariff is likely to be a more commercially viable offering than DLC only programmes and price-based DSR programmes are the most likely method by which consumers will be expected to engage. Studies in which a TOU tariff was offered with automation, either customer controlled automation or by a third party, would however fit the inclusion criteria. Studies focused exclusively on the non-domestic sector were excluded because they are not in the scope of this thesis. The inclusion and exclusion criteria are summarised in Table 3.

Table 3 Inclusion and exclusion criteria for review screening.

Include if source	**Exclude if source**
Is in English	Is not in English
Reports findings from empirical research or evaluation.	Does not report empirical results (e.g. includes only modelled uptake)[11].
Includes quantitative findings that can help to inform estimation of tariff uptake rates.	Reports only qualitative findings.

[11] Originally this also excluded uptake based on trial recruitment but this was later changed to increase the total pool of evidence.

Reports research designed to enable estimation of the degree of consumers' expressed or demonstrated willingness to sign up (hypothetically or in reality) to at least one TOU tariff design, and the reasons associated with this.	Does not report research including a TOU tariff (for example, focused only on DLC or other non-price-based DSR product).
Reports work conducted in an OECD country.	Reports work conducted in a non-OECD country.
Is focused on the domestic sector.	Is focused on the non-domestic sector.

3.2.2 Search methods

An initial list of five key recent publications on consumer demand for TOU tariffs were identified (Michael J Fell et al., 2015; Fell, 2016; Hobman et al., 2016; Stenner et al., 2015; Dütschke and Paetz, 2013) as a basis to generate keywords for electronic searches (Table 4). The reference lists of these publications were also checked and publications with titles that suggested they may fit the screening criteria were saved for further review. Forward citation checks were conducted using Google Scholar to identify documents referencing these publications, which were saved for later review if the titles were deemed to fit the screening criteria above. Using a 'snowballing' approach, reference lists of documents that pass screening criteria were also accessed for inclusion.

Table 4. Search terms used in conducting the search with example search string for use in Scopus.

	TOU	Uptake
Concept	TOU tariffs	Uptake
	Time-varying tariffs	Consumer
	Off peak tariffs	Acceptability/acceptance
	Dynamic pricing	Switching
	Cost-reflective tariffs	Preferences
	Critical peak pricing/rebates	
	Peak-time rebates	
	Real-time pricing	
Search term	“TOU”	uptake
	“time-of-use”	consumer*
	“time-varying”	accept*
	“off peak”	switch*
	dynamic W/2 pric* OR tariff*	preference*
	“cost-reflective”	
	“critical peak”	
	“peak-time”/peaktime	
	“real-time pric*”/realtime	
Scopus example	TITLE-ABS-KEY("TOU" OR "time-of-use" OR "time-varying" OR "off peak" OR (dynamic W/2 pric* OR tariff*) OR "cost-reflective" OR "critical peak" OR "peak-time" OR peaktime OR "real-time pric*" OR "realtime pric*") AND TITLE-ABS-KEY(uptake OR consumer* OR accept* OR switch* OR preference*) AND ALL(tariff OR pric*) AND ALL (energy OR electr*)	

The following bibliographic databases were searched:

- Scopus
- Web of Science (all databases)

- ScienceDirect
- Searches were also developed based on the above search terms for the websites of the following organisations:
- Department for Business, Energy & Industrial Strategy
- Ofgem
- Citizens Advice
- Sustainability First
- Distribution Network Operators
- National Grid
- Cambridge Energy Policy Research Group working papers
- UK Energy Research Centre
- European Commission Research and Innovation (Energy)
- US Department of Energy (including SciTech Connect)
- Websites of UK and US academic institutions (URLs including ".ac.uk" and ".edu")

Searches were recorded and reported to aid replicability, with potential sources saved in the reference management software Mendeley.

3.2.3 Study selection

Search results were screened according to the inclusion and exclusion criteria outlined in Table 3. Screening was initially conducted in parallel by two screeners[12] until high levels of agreement were reached in the EPPI-Reviewer

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[12] As outlined at the outset of this thesis, under the title 'Published work', this review was conducted as part of a project for Citizens Advice. The search strategy and screening was conducted by colleagues at the UCL Energy Institute Michael Fell and Gesche Huebner. I inputted

software (review author initials: MF, GMH). Subsequent screening on title/abstract was performed by a single screener (review author initials: MF). Included items were then screened again on the full document. The list of final documents for inclusion were reviewed following screening. Publications known to be relevant but which were not present in the initial documents for screening were later included if they passed the screening criteria.

3.2.4 Data extraction

All sources included were coded in EPPI-Reviewer for the following key characteristics:

- Geographical location of study
- Whether air conditioning was a significant load
- Study start year
- Method of assessing uptake (survey, commercial product, trial recruitment, other)
- Experimental design
- Type(s) of TOU tariff(s) tested and their characteristics
- Organization(s) administering the study
- Organization(s) offering (or framed as offering) the TOU tariff(s)
- Characteristics of sample receiving the TOU intervention
- Size

on the search strategy and undertook all of the data extraction from the documents and all the analysis.

- Sampling method – participant characteristics, recruitment method (opt-in, opt-out/framing)
- Whether an incentive was given to participants
- Whether bill protection was included
- Type(s) of outcome(s) measured by the intervention (including measure/proxy of uptake/responsiveness and customer satisfaction)
- Role of automating technology
- Whether an ongoing satisfaction assessment was conducted
- Reported outcome(s), key interpretations and main conclusions

Extraction was conducted by a single reviewer in EPPI-Reviewer (review author initials: MLN). Not all studies reported uptake and so this had to be computed, where possible, from the information provided.[13] Nine studies included at the screening stage (Train et al., 1987; Goett and Keane, 1988; Raw and Ross, 2011; Wakefield et al., 2011; Gamble et al., 2009; Faruqui et al., 2013; Ohio Power Company, 2013; Long Island Power Authority, 2015; Harding and Lamarche, 2016) did not include information to compute or obtain a measure of uptake so were excluded at this point. Report tables were compiled using EPPI-Reviewer in MS Word format from which a second extraction was undertaken to transpose key characteristics required for numerical analysis into MS Excel, for later importing into the statistical software package Stata for meta-analysis.

[13] For example, a tariff trial might report the total number of participants solicited for participation and the total number of enrolled participants. Alternatively, a study might report the total number of customers enrolled on a commercially available tariff on offer to all French consumers, in which case the recruitment rate can be approximated based on the population of France.

3.2.5 Data synthesis – meta-analysis

Meta-analysis is most commonly used to aggregate results of clinical trials and the standard definition of meta-analysis reflects this: "meta-analysis is a statistical methodology that integrates the results of several independent clinical trials that are considered by the analyst to be "combinable"" (Huque [1988] cited in Kontapantelis and Reeves, 2010; 201). Meta-analysis is a two-stage process, the first of which involves providing an appropriate summary statistic for each study and the second in which the statistics are combined to obtain an overall average effect (Kontapantelis and Reeves, 2010; Kelley and Kelley, 2012).

For the first stage, I create a normalised measure of uptake to a TOU tariff across all studies. Unlike the measures of uptake from trials and those for commercially available tariffs, which are expressed as proportions, most surveys measure willingness to switch along Likert scales. For comparability, I convert these outcomes into the proportion of participants who selected any point above the mid-point as switchers.[14] I note that this does not constitute making an assumption that people who expressed a strong willingness to switch would switch in reality; this is just a method of obtaining a normalised outcome measure and the discussion of the results gives a strong consideration to the extent to which behavioural intentions predict future behavioural action, consistent with the empirical literature (Whitehead and Blomquist, 2006; Morwitz et al., 2007).

[14] For example, on a 5-point Likert scale in which 1 is not willing to switch and 5 is strongly willing to switch, the proportion of participants who selected 4 or 5 was recorded and used as the outcome measure.

For the second stage, to obtain an aggregated measure of uptake to TOU tariffs I compute the upper and lower 95% confidence intervals for mean uptake to a TOU tariff disaggregated by the method by which uptake was measured (commercial uptake, trial recruitment, stated preference) for reasons that will become apparent in the discussion of the results. In clinical meta-analyses, this average is usually weighted by the sample size in each study, as recommended in (Kontapantelis and Reeves, 2010).

The intuition behind such weighting in clinical trials is that studies with larger sample sizes will have more precise estimates of the effect size. However, since the outcome measure in each study is a single observation in itself rather than an average of multiple observations, it is not possible and, in any case would not make sense, to compute the standard error around uptake for each study; instead, variation in average uptake across all studies is illustrated by presenting the confidence intervals.[15]

To estimate the correlation between uptake to a TOU tariff and observable differences in the tariff design, recruitment method and, importantly for this thesis, the way in which the tariff was framed to consumers, the following equation was used to describe the uptake in study i in a study s:

Equation 1 $$\gamma_{is} = \alpha_{is} + \beta_{is}\theta_s + \beta_{is}\mu_{is} + \beta_{is}\chi_{is} + \delta_s + \varepsilon_{is}$$

[15] For many TOU trials, the final reports only reported the proportion who agreed to participate but not the number of participants who were solicited to take part so it would not be possible to account for the sample size per group. Moreover, the number of participants who complete a survey is not comparable to the number of people who are solicited to take part in a tariff trial or who are eligible for signing up to a commercially available tariff.

where γ_{is} is a proportion ranging from 0.0 to 1.00 for each uptake measure *i* in study s. The constant, α_{is}, equals the average uptake to a TOU tariff across each measure *i* and study *s* conditional on the covariates θ_s, μ_{is} and χ_{is}. The covariate θ_s is a dummy variable in which the value 1 is assigned to an uptake measure *i* from a study *s* that reports willingness to switch to a TOU tariff from a survey experiment and the value zero if the uptake measure is from a study that reports the participant recruitment rate into a TOU tariff trial or uptake to a commercially available tariff. This is included in all specifications because it is assumed that the method of measuring uptake will affect the size of uptake *y*. μ_{is} is a dummy variable in which the value 1 is assigned to an uptake measure i from a study s in which enrolment was opt-out and 0 if it was opt-in. This is included in all specifications because the research on opt-in versus opt-out enrolment suggests that opt-out enrolment rates are substantially different to opt-in rates.

To estimate the relative contribution that each covariate makes to explaining the variation in γ, each covariate represented by χ_{is} in the equation above is introduced separately, in independent regression analyses in which χ_{is} is respectively: a dummy variable or a series of dummy variables indicating whether the uptake measure *i* from a study *s* run in GB, the Netherlands, Australia, Norway or France, in which the United States is the omitted dummy and therefore the reference category; a series of dummy variables indicating whether the uptake measure *i* from study *s* relates to a capacity pricing tariff, a critical peak rebate tariff, a dynamic TOU tariff, real-time pricing tariff, static TOU tariff combined with critical peak pricing, a static tariff combined with real time pricing, an inverse static TOU tariff (in which the peak rate is overnight rather than during the day), a static TOU tariff plus a static TOU tariff combined with critical peak pricing and a static TOU tariff plus a static TOU combined with critical peak pricing and a critical peak rebate[16], in which a static TOU tariff (in which the peak rate is during the day rather than overnight) is the omitted dummy variable and therefore the reference category against which the coefficient β on each covariate should be compared; a dummy variable indicating whether the uptake measure *i* was from a study *s* in which the tariff was framed to potential consumers as being able to save them money (a money frame), and zero otherwise, excluding studies in which it was not possible to identify what framing was used; a dummy variable indicating whether the uptake measure *i* was from a study *s* in which the tariff was framed to potential consumers as being able to save them money and help the environment (an environmental frame), and zero otherwise, excluding studies in which it was not possible to identify what framing was used; a dummy variable in which the value 1 is assigned to a measure of uptake *i* in study *s* in which the tariff was accompanied by bill protection and zero otherwise; a dummy variable in which the value 1 is assigned to a measure of uptake *i* in study *s* in which participants were offered an upfront cash payment and zero otherwise, excluding uptake measures from all survey experiments[17]; a dummy variable in which the

[16] The penultimate two categories contain multiple tariffs because the study from which the measure of uptake was drawn enrolled participants into a trial in which they would have been randomly assigned to different types of tariffs. As such, the measure of uptake cannot be disaggregated by tariff type but instead arguably reflects a persons' willingness to participate in a trial in which they could be enrolled on any of the tariffs.

[17] Cash incentives are usually provided to compensate people for the inconvenience of participating in a trial or to attract consumers to participate in a trial or to sign up to a tariff; in

value 1 is assigned to a measure of uptake *i* in study *s* in which the tariff was accompanied by an automation device that allows consumers to remotely adjust their electrical devices in response to the price or which allows a third party, usually the supplier, to do so on their behalf. The term δ_s is a fixed effect for each study *s* from which the measure of uptake *i* was taken, implemented as a series of dummy variables for each study.

The equation will be estimated using Ordinary Least Squares regression.[18] Ordinary Least Squares regression assumes that uptake measures are identically and independently distributed across studies. However, this is unlikely to be true because many uptake measures are recorded from the same studies, for example, because some studies tested multiple tariff types and recorded uptake measures independently for each tariff type. Uptake measures from the same study are likely to be correlated because they are based on the same sample population, tariffs, study design and so on. Some of these potential drivers are observed and included in the model, for example, tariff type and whether the study was a survey; however, others, such as recruitment method, are not included either because it was not recorded in the original reports or because the methods vary too much to create meaningful sub-groups. Equation 1 therefore includes fixed effects for each study, which adjusts standard error

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surveys, cash is used as payment for undertaking the survey so it does not serve the same purpose and would not be appropriate to consider it as such.

[18] Meta-analyses often make use of bespoke meta-analyses function in software packages, such as the meta or metaan command in Stata. However, these commands have been designed with clinical trials in mind, in which the outcome from each study (the standardised effect size from a treatment administered in a randomised control trial) can be associated with a respective standard error, which provides an estimate of the variation in response to the treatment within the population. As noted above, the measure of uptake in each study is an observation not an average of several observations so a standard error estimate cannot be computed.

estimates for specific intra-cluster correlation that cannot be explained by the covariates. Study fixed effects will also penalise results that are strongly dependent on results from a single or very few studies and which may therefore be less reliable than results from multiple studies (however, conversely, the fixed effects could also mask effects that are constant across studies, which may therefore be reliable results, which is why we use and interpret results which include these effects carefully). [19]

Studies did not report uptake by different population sub-groups to enable meaningful analysis of heterogeneity across factors such as age, income, appliance type (EV, heat pump) and so on.

3.3 Results

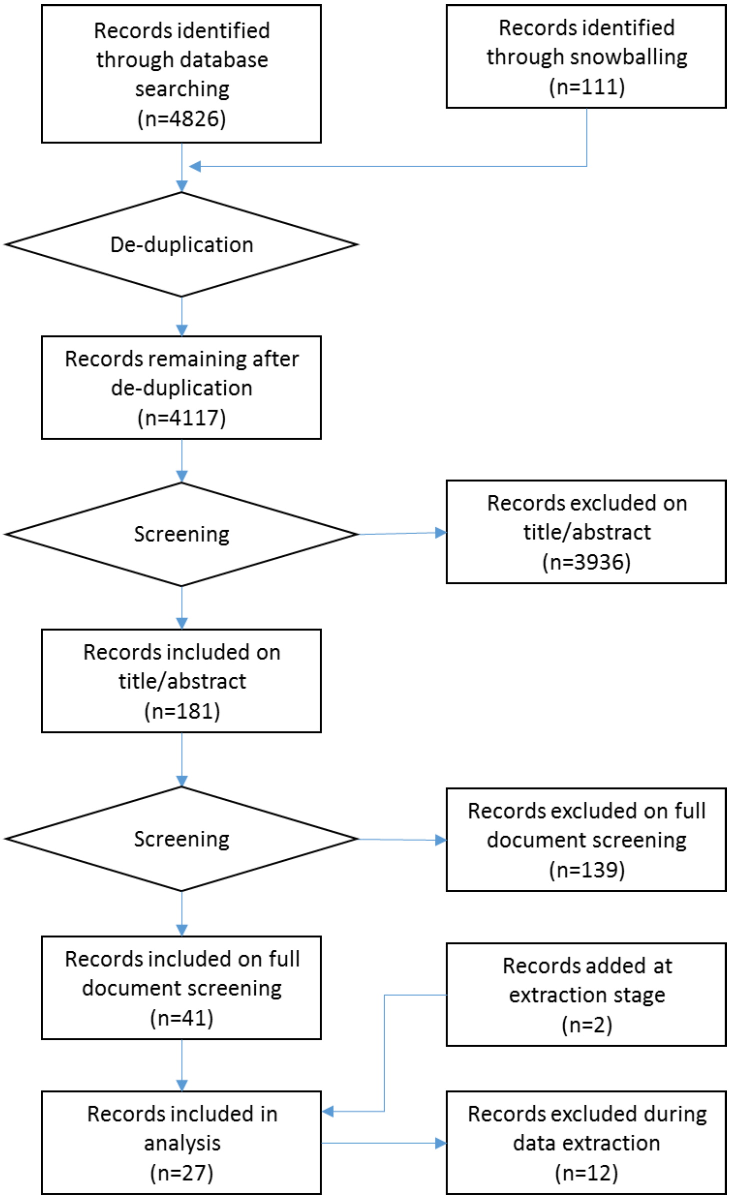
3.3.1 Results of the search

[19] Random effects models are the preferred method for meta-regressions using results from clinical trials which, unlike this study, intend to estimate a common effect size of a given intervention based on the results of multiple, independent randomised control trials (Kontapantelis and Reeves, 2010; Kelley and Kelley, 2012). This was rejected as a preferred specification in this context for reasons outlined in detail in Annex 5.

Figure 2 describes how the references identified through the searches were processed for this review. A total of 41 documents were marked for inclusion. During extraction, two subsequent studies (Schwartz et al., 2015; Verhagen et al., 2012) were added that were not already included because the authors recognized their absence and knew that they met the screening criteria, and 13 studies were excluded because they either did not report a measure of uptake or because insufficient information was provided to compute a measure of uptake. During synthesis, a further three studies (Dütschke and Paetz, 2013; Buryk et al., 2015; Schwartz et al., 2015) were excluded because the sources did not provide information on the distribution of responses across the Likert scale measure of uptake to compute the proportion of switchers. This left a total of 27 studies for analysis covering 66 individual measures of uptake to a TOU tariff[20].

[20] Some studies ran multiple trial arms so provide multiple methods of uptake.

Figure 2 Flow diagram of review process.



Notes: Diagram created by M.F.

3.3.2 Characteristics of included studies

Figure 3 presents a heat map of the key characteristics of the studies included in the review. The size of the square represents the number of measures corresponding to the level of each factor. As can be seen, the majority of the evidence on consumer demand for TOU tariffs is from the United States, with 15 measures of uptake from GB out of a total of 66 measures.

The majority of the evidence relates to uptake to static TOU tariffs and is based on stated willingness to switch to tariffs, as measured amongst participants in surveys, as opposed to uptake rates to commercially available tariffs or the proportion of participants who agreed to go onto a TOU tariff as part of their participation in an academic trial. Of the 12 measures that are based on the proportion of consumers signing up to a commercially available time-varying tariff, nine are from the United States, two are from France (EDF Tempo, EDF TOU) and one is from GB (Economy 7).

Most of the measures of uptake are based on opt-in rather than opt-out recruitment methods, very few used bill protection or an additional participant financial incentive to encourage uptake. The predominant way in which TOU tariffs in the sample were framed to consumers is to emphasise that TOU tariffs can save money, and just a small number of measures (n=2) are also drawn from studies which emphasised the environmental benefits. No other ways of framing the tariffs were used.

Figure 3 Characteristics of the studies included in the review.

Factor	Level	
Study type	Survey	34
	Trial recruitment	20
	Commercial uptake	12
Country	US	25
	UK	15
	Australia	15
	Netherlands	8
	France	2
	Norway	1
Tariff type	Static	19
	CPP	10
	RTP	10
	Static + CPP	5
	CPR	5
	DP	5
	CAP	3
	Static + CPP + CPR	2
	Static + RTP	1
	Static inverse	1
Automation	Yes	15
	No	37
	Unknown	7
Benefit frame	Money	48
	Money & environment	2
	Unknown	8
Default frame	Opt-in	62
	Opt-out	3
Bill protection	Yes	12
	No	49
	Unknown	5
Additional participant incentive	Yes	9
	No	19
	Unknown	4

3.3.3 Risk of bias in included studies

The Cochrane Collaboration's 'Risk of Bias' tool suggests that bias be considered along five domains – selection, performance, attrition, detection, reporting – and an 'other bias' category to capture threats to internal validity. Risk of bias was not assessed during the review but is being assessed here. Detection bias is a problem in this review insofar as that the review only included reports written in English, so figures may be more representative of English speaking OECD countries, which is a relative minority of the 35 OECD countries. This is not a problem for fulfilling the aims of this thesis which has a GB focus.

Reporting bias is highly likely to present an issue for generalising findings on the bill impacts of TOUs since very few studies reported bill impacts. When synthesising findings, the bill impacts are not interpreted as generalisable and these results are excluded from the summary statistic measures.

There is also a possibility of bias owing to the fact that most studies did not report the total sample size of participants solicited to adopt a TOU tariff or participate in a TOU tariff trial. It was therefore not possible to account for sample size when synthesising the evidence on uptake as is considered best practice in meta-analyses conducted in the medical domain. However, sample size is considered when interpreting the reliability of the results.

3.3.4 Consumer demand for TOU tariffs and factors correlated with demand

The variation in uptake is large, with enrolment ranging from a mean of 0%-96%. The mean enrolment rate is 29% with a standard deviation almost as large (sd=24%) and the median enrolment rate is 27%. The variation in uptake across studies may be explained by a number of factors, including study type, country and tariff design, as identified by the research questions. Table 5 presents a breakdown of the average uptake according to these factors, sorted in descending order of the mean (with the exception of the yes/no/unknown questions), with the lower and upper 95% confidence intervals also presented. For some measures, uptake is taken from studies in which participants were randomly assigned to one of two TOU tariffs (e.g. static TOU or static TOU combined with critical peak pricing) so uptake cannot be disaggregated by tariff type and is therefore presented as uptake for two or more tariff types.

Table 5 Average uptake to TOU tariffs by study design, country, tariff design, default frame, benefit frame, bill protection, additional financial incentive and automation.

Factor and level	Mean (%)	Median (%)	Lower 95% confidence interval (%)	Upper 95% confidence interval (%)	N
Study type:					
Survey	37	36	31	43	34
Trial recruitment	23	12	10	36	20
Commercial sign up	17	7	1	33	12
Country:					
Australia	51	54	46	56	15

UK	30	30	22	37	15
US	25	9	10	35	25
Norway	25	25	-	-	1
France	19	19	-	-	2
Netherlands	14	13	4	25	8
Tariff design:					
Static + (Static + CPP) + CPR	44	44	-	-	2
CPR	53	53	14	70	5
CAP	39	37	23	36	3
Static	35	35	24	46	22
CPP	28	21	12	43	10
DP	22	25	8	36	5
RTP	17	5	2	33	10
Static + RTP	12	12	-	-	1
Static + CPP	9	6	-	-	4
Static + (Static + CPP)	3	3	24	36	1
Static inverse	1	1	-	-	1

Default frame:					
Opt-out	83	87	57	108	3
Opt-in	26	25	21	32	62
Benefit frame:					
Money & Environment	36	36	36	36	2
Money	30	23	22	37	48
Unknown	26	26	14	38	16
Bill protection					
Yes	35	32	16	53	12
No	27	28	21	33	49
Unknown	35	25	-	-	5
Upfront cash payment:					
Yes	35	36	28	41	35
No	20	12	10	30	27

Unknown	37	26	-	-	4
Automation:					
Yes	31	28	16	46	15
No	32	33	25	39	33
Unknown	18	7	4	31	7

Note: Due to small sample sizes it was not possible to compute confidence intervals for all the variables recorded; these cells are marked with a dash to indicate that they are intentionally left blank.

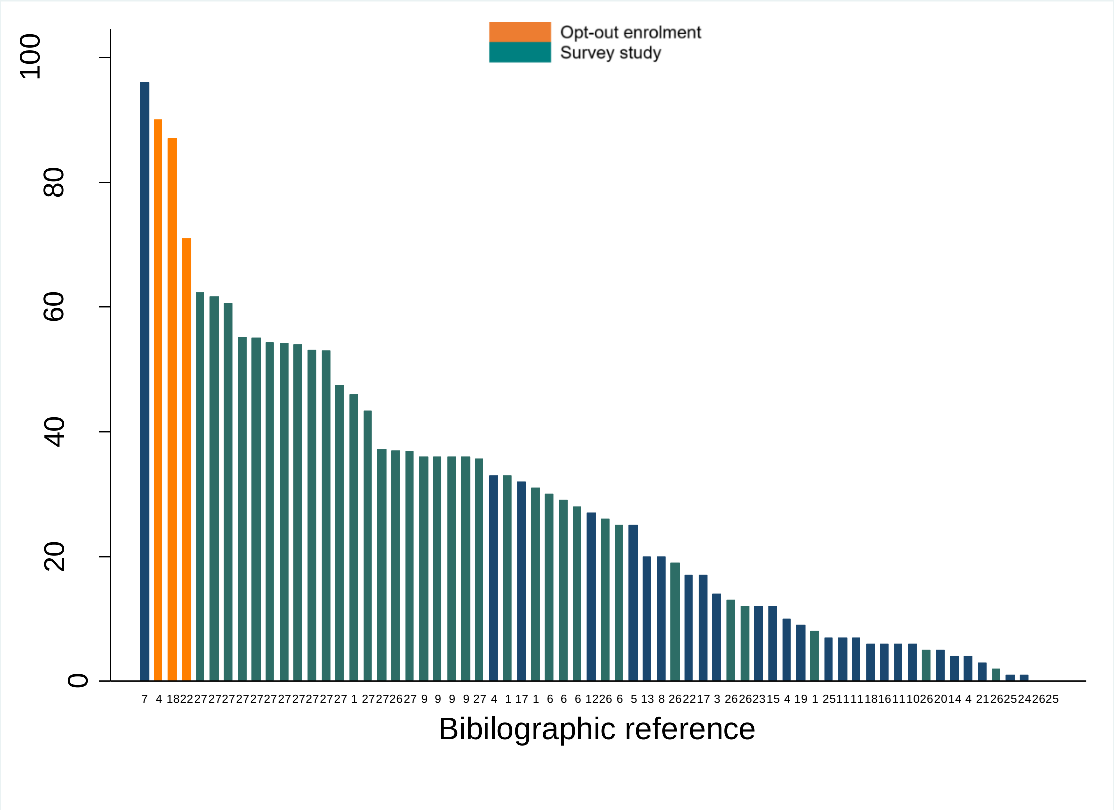
The most notable differences in uptake are those between study type and recruitment method, whether opt-in versus opt-out, a relationship which is made clearer in Figure 4, which is a bar chart of the mean uptake to any TOU tariff for each of the 66 measures of uptake obtained across the 27 studies. With just one exception (Hartway et al., 1999), the highest measures of uptake are recorded from studies using opt-out recruitment (Lutzenhiser et al., 2010; Lakeland Electric, 2015; Charles River Associates, 2005) and studies using willingness to switch as a proxy for potential uptake (BEIS, 2016a; Fell, 2016; M Nicolson et al., 2017; Verhagen et al., 2012; Stenner, 2015). Although the mean uptake for commercial tariffs is lower in magnitude than recruitment rates for trials the difference is not statistically significant (p=0.490) which is why these are grouped together with measures from commercial tariffs.

As a result, all analyses include controls for whether the study is a survey and whether enrolment is opt-out, with the results presented in Table 6. Since an analysis of variance test reveals that the intra-cluster correlation is 0.47 which is high and demonstrates that it is not appropriate to assume that the error term is independently distributed, fixed effects are used in nearly all analyses. Note that, study fixed effects will also penalise results that are strongly dependent on results from a single study or very few studies and which may therefore be less reliable than results from multiple studies. However, conversely, the fixed effects could also mask genuine effects that are constant across studies, which is why I use and interpret results which include these effects carefully.

Throughout columns (1) to (9) in which a range of control variables are added, uptake measures elicited from surveys are consistently estimated as being between 28 to 36 percentage points higher than uptake to commercially available TOU tariffs or tariffs people were able to sign up to in trials, after controlling for intra-cluster correlation between measures obtained from the same surveys using fixed effects. Opt-out enrolment is estimated as being consistently 70 percentage points higher, after controlling for intra-cluster correlation. When both measures are inputted into the regression analysis, the model estimates that they explain 85% of the variation in uptake to TOU tariffs (column 1, Table 6).

There are significant differences in uptake between countries, but when study type is controlled for the only significant remaining difference is between the UK and Australia ($p<0.05$). As the Australian evidence is drawn from a single study, this is most likely due to specific design considerations of this individual study.

Figure 4 Consumer measures of demand for TOU tariffs by study type and default frame.



Notes: Each bar represents a measure of uptake. Some studies obtained multiple measures so individual studies may appear multiple times. All studies used opt-in enrolment unless they are highlighted as having used opt-out. The horizontal axis provides the bibliographic reference for each study (see Appendix 0 for the references)

Table 6. Explaining variation in uptake of TOU tariffs.

	(1)	(2) Adding country controls	(3) Adding tariff type controls	(4) Tariff type controls only	(5) Money frame	(6) Environment frame	(7) Bill protection	(8) Participant incentive	(9) Automation
Survey study (1=yes; 0=trial/commercial)	0.340*** (0.000)	0.357** (0.002)	0.283*** (0.000)		0.340*** (0.000)	0.340*** (0.000)	0.360*** (0.000)		0.359** (0.005)
Opt-out enrolment (1=opt-out; 0=opt-in)	0.704*** (0.000)	0.717*** (0.000)	0.692*** (0.000)		0.704*** (0.000)	0.704*** (0.000)	0.704*** (0.000)	0.000 (.)	0.675*** (0.000)
Country:									
Australia		0.126 (0.309)							
France		0.043 (0.667)							
Netherlands		-0.241 (0.060)							
Norway		0.223* (0.044)							
UK		-0.017 (0.877)							
US (omitted reference)		Omitted							
Tariff type:									
Static TOU (omitted reference)			Omitted	Omitted					

Capacity pricing	-0.208*** (0.000)	0.019 (0.890)			
Critical peak pricing	-0.063 (0.141)	-0.089 (0.302)			
Critical peak rebate	-0.025 (0.602)	0.051 (0.651)			
Dynamic pricing	-0.086 (0.080)	-0.145 (0.199)			
Real time pricing	-0.129** (0.001)	-0.194* (0.027)			
Static & (static and critical peak pricing)	-0.104 (0.259)	-0.337 (0.151)			
Static & critical peak pricing	-0.084 (0.361)	-0.274* (0.029)			
Static and real time pricing	-0.014 (0.879)	-0.247 (0.290)			
Static inverse	-0.124 (0.180)	-0.357 (0.128)			
Static & (Static and critical peak pricing) & Critical peak rebate	-0.040 (0.618)	0.073 (0.661)			
Money frame			-0.000 (1.000)		
Environment frame				-0.000 (1.000)	
Bill protection					0.061

							(0.184)		
Participant incentive								0.224**	
								(0.001)	
Presence of automating technology									0.002
									(0.958)
Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	65	65	65	66	65	65	61	34	52
Adjusted R^2	0.851	0.848	0.906	0.077	0.847	0.847	0.840	0.723	0.830

Notes: Deviations in the sample size in each column from the total sample of 66 is due to missing data on some covariates i.e. studies for which there was insufficient information provided in the final report to enable extraction on that particularly covariate.

p-values in parentheses

* $p < 0.05$ (Benjamini and Hochberg [1995] adjusted p-value 0.0375), ** $p < 0.01$ (Benjamini and Hochberg [1995] adjusted p-value 0.0075), *** $p < 0.001$ (Benjamini and Hochberg [1995] adjusted p-value 0.0005)

The raw data also suggests there is substantial variation in uptake depending on tariff design. The regression model estimates that real time pricing tariffs are correlated with a 13 percentage point lower level of uptake when compared to a static TOU tariff ($p<0.01$), when controlling for recruitment method, whether uptake was measured in a survey and intra-cluster correlation in measures within surveys (column 3, Table 6). The model also estimates that static TOU tariffs are preferred to capacity pricing ($p<0.001$) and marginally statistically significantly more popular than dynamic pricing tariffs ($p<0.10$). No other differences approach statistical significance. This is possibly due to the low sample size for other tariff designs such as critical peak rebates and the inverse TOU tariff, which is only recorded once in the dataset. When regression analysis is run with only the different tariff designs as control variables (column 4, Table 6), the adjusted R-Squared value indicates that tariff design explains 8% of the variation in uptake, which is substantially lower than for the other factors considered so far.

There is no statistically significant difference in uptake across measures of uptake obtained from studies in which people were told about the potential financial savings from switching tariff ($p=1.000$) or the financial and environmental benefits ($p=1.000$), as reported in columns 5 and 6 of Table 6 respectively. This is not necessarily surprising; only one study (across 2 measures) tested the impact of environmental and financial messaging so it may be that the sample size is too small to measure any impact. Moreover, although a seemingly high number emphasised financial benefits, it was not possible to identify any particular framing from 20% of the studies and very few studies provided details of what messaging was used, making it difficult to understand how strong the messaging was e.g. emphasis, frequency etc.

Offering people bill protection (p=0.184) does not appear to have a statistically significant impact on uptake (column 7), however it does once removing the fixed effects which control for correlation in uptake across studies (p<0.05) which is likely to be reflective of the fact that only very few studies tested bill protection and all had relatively high levels of uptake (for brevity, results not reported in Table 6). Bill protection is measured in relatively few studies (7 studies), but in some studies multiple times, meaning that the fixed effects could also be masking the positive effect of bill protection. Unfortunately, with observational data, there is no way to disentangle the effect of measures being similar to each other by virtue of having been obtained from the same study (e.g. and therefore measured amongst the same participants, in the same country and for the same tariffs) from any potential causal effect of bill protection on uptake. It was not possible to control for differences in the sampling methods used across studies because many studies did not report the method used.

Providing people with upfront financial payments for signing up to a TOU tariff, either in trials or for commercial offerings (survey measures excluded), has a strong statistically significant positive effect on uptake (p<0.001) regardless of whether the specification controls for correlation in uptake within studies (p<0.01).

Some TOU tariffs are accompanied by automation devices (usually smart thermostats which customers can use to remotely control their space heating and cooling e.g. to avoid peak times) but the data suggests that uptake is not related to the presence of automation (p=0.958), even after removing controls for intra-cluster correlation (p=0.158).[21] In further exploratory analyses, not reported here, automation was also not found to have any effect on uptake to real time pricing

[21] For brevity, the result without fixed effects is not reported in Table 6.

tariffs or dynamic tariffs (p=0.502) or real-time pricing tariffs on their own (p=0.299), however this may be due to the low small sample size.

All results discussed above are robust to the adjustment of p-values to control for multiple hypothesis testing using the Benjamini and Hochberg (1995) method for controlling the false discovery rate. The adjusted p-values are reported in the notes to Table 6.

3.3.5 Variation in energy bill impacts amongst TOU tariff customers

Obtaining information on bill savings was difficult because it was rarely reported in final reports. Those that do report energy bill savings are outlined in Table 7 below which presents the proportion who saved money on a TOU tariff along with the average and maximum savings and losses, because it highlights the range of potential impacts on people's energy bills from switching to a TOU tariff.

Since many studies did not report the energy bill impacts, these results may not be representative of the savings or losses realised by all consumers enrolled on TOU tariffs. However, at least for GB, where there have only been three major TOU tariff trials[22], two of which reported the energy bill impacts (Carmichael et al., 2014; Sidebotham, 2014), the results provide a good indication of the likely impact on British consumers' energy bills. In these trials, the average impact is positive – a saving of between £21 and £31 per year – with some consumers saving nearly £400 a year. On the other hand, in both trials a sizeable proportion were made financially worse off – 40% in Sidebotham (2014) and 25% in Carmichael et al. (2014), with some financially worse off by up to £190.

[22] LCNF, CLNR and the EDRP trial.

Table 7. Bill savings from switching to a TOU tariff.

	Bill savings from switching to a TOU tariff				
	Proportion saving money	Average saving	Average loss	Maximum saving	Maximum loss
Hartway et al. (1999)	-	$57	-	-	-
Long Island Power Authority, (2015)	56%	$89	$80	$396	$274
Schare et al. (2015)	-	$60	-	-	-
Star et al. (2010)	-	$305	-	-	6.3% of total bill relative to flat rate
Carmichael et al. (2014)	75%	£21		£148	£40
Sidebotham, (2014)	60%	£31	£25	£376	£191

Notes: Column 1 presents the proportion of people who saved money on the tariffs and columns 2-5 the average saving, average loss, maximum saving and maximum loss respectively relative to the customers' previous tariff. The hyphens indicate missing data.

3.4 Discussion

3.4.1 Overall demand for TOU tariffs

Median uptake to a TOU tariff across 66 individual measures of uptake and 27 unique studies is 27%. However, the variation in uptake is huge with a range in uptake measures of 0%-96%. The results in Table 6 suggests this is most likely to be driven by variation in the way in which uptake is measured in studies as well as whether people were recruited to the tariff by default or via opt-in enrolment. Notably, the majority of the data in this review, particularly data from GB, represents stated willingness to switch to a TOU tariff obtained from participants in surveys and median uptake in surveys is five times higher than uptake to commercially available tariffs.

Therefore, demand for TOU tariffs is best expressed as a range, based on the minimum and maximum mean recorded uptake and expressed for opt-in and opt-out enrolment separately. Based on the evidence, if opt-out enrolment is used, uptake is most likely to exceed 57% but with an uncertain upper limit of enrolment approaching 100%. If consumers are left to opt-in, uptake to TOU tariffs is most likely to fall between 1% (the lower bound estimate for mean uptake to commercially available tariffs, most of which are offered in the US) and 43% (the upper bound estimate for mean willingness to switch obtained from surveys, most of which were run on nationally representative samples of British energy bill payers).

However, since the upper bound estimate of 43% comes from surveys measuring how willing people are to adopt a TOU tariff, it is best interpreted as capturing the maximum potential national uptake of TOU tariffs if every consumer who is willing to sign up to a TOU tariff at the time of the survey does indeed go on to sign up. Nevertheless, since it is well known that behavioural intentions are a relatively poor predictor of future behavioural action[23], it also follows that a 40% adoption rate is unlikely to be achieved in reality unless substantial efforts are expended on encouraging switching. Consumer inertia is a major problem around the world with the majority of consumers having never left their home supplier since privatisation of retail electricity markets began over two decades ago (Defeuilley, 2009).

At the same time, I also acknowledge that it is not possible to conclude with certainty whether observed differences in uptake between countries are due to genuine inter-country differences in consumer demand for TOUs (i.e. that consumers in GB and Australia are more in favour of TOU tariffs than consumers in the US) or due to differences in measurement method. Differences in uptake measurement method also overlap almost exactly with differences in the types of populations sampled. Survey recruitment has mostly been nationally representative (BEIS, 2016a; Fell, 2016; M Nicolson et al., 2017) whereas participants solicited to take part in TOU trials are, in many cases, very different to the average energy bill payer[24]. Also, unlike for country, the model does not include separate controls for differences in recruited populations because, in most cases, non-nationally representative participant solicitation overlaps exactly

[23] Unfortunately empirical studies testing the relationship between intentions and behavioural action do not provide a clear picture of the strength of the correlation between these two variables (Morwitz et al., 2007). One meta-analysis finds that intentions explain 28% of the variation in behavioural action (Sheeran, 2002) whereas another reports frequency weighted average correlation between these two variables as 0.53, with a lower 95% confidence limit of 0.15 and an upper limit of 0.92 (Sheppard et al., 1988).

[24] For example, in cases where the overwhelming majority of people solicited to participate have central air conditioning (Neenan and Patton, 2015; Hartway et al., 1999) or in cases where recruitment to a TOU tariff was undertaken amongst a pool of people who had already consented to have a smart meter installed as part of their participation in an earlier wave of the project (Carmichael et al., 2014).

with measurement method itself. However, on balance, my judgement is that it is highly unlikely that all of the variation in uptake across surveys and commercially available tariffs is attributable to cross-country variation in demand for TOU tariffs and is more likely to be attributable to the fact that, for a variety of reasons, people are more likely to express an intention to switch to a TOU tariff than they are to switch to one in reality.

In summary, the evidence suggests that there is therefore a strong risk that uptake to TOU tariffs in GB is more likely to fall closer to 1% than 43% unless effort is taken to encourage consumers to switch or enrolment is done on an opt-out basis.

3.4.2 Evidence on recruitment strategies to increase uptake to TOU tariffs

As predicted, these results suggest that uptake could fall substantially below the U.K. Government's 30% target (DECC, 2014; BEIS, 2016b). To get a sense for how tariff uptake might be increased I ran meta-regression analysis to help to obtain answers as to what methods could increase uptake.

The studies provide strong evidence that opt-out enrolment increases uptake because out of the three trials which tested this approach, two of them did so using a randomised control trial design with very large sample sizes and robust designs (Potter et al., 2014; Lakeland Electric, 2015). The outlying 96% uptake in an opt-in study (Hartway et al., 1999) is for a US programme in which most customers had central air conditioning that the programme allowed them to put on a timer to help avoid the peak prices. The paper reporting these findings states that “the high sign-up rate is directly attributed to an intense marketing effort consisting of phone calls, face-to-face meetings and workshops (Hartway et al., 1999, p.899). However, a number of other trials (Phillips et al., 2013; Bourne and

Watson, 2016; Carmichael et al., 2014) used similar recruitment methods and did not achieve these high enrolment rates so it is hard to explain why this programme was so successful and suggests it is best treated as an anomaly.

Providing small upfront financial rewards (e.g. shopping vouchers [Whitaker et al., 2013]) is estimated to increase uptake by 22 percentage points in the meta-regression. However I cannot confidently attribute the differences in uptake to this financial incentive rather than other differences between studies that do and do not use financial incentives. This is because none of the studies compare uptake to a tariff when a financial incentive is offered to the uptake in a control group that was not offered a financial incentive.

The meta-regression revealed no statistically significant difference in uptake across studies in which the tariff was offered with bill protection or automation. However, there is not enough data to be highly confident that this means that bill protection and automation have no effect on uptake or whether too few studies offered these features to provide sufficient power to detect an effect or because the impact is being masked by other confounding variables given that very few studies manipulated these factors experimentally. This is likely to be because, as mentioned above, the focus on the literature so far has been on whether tariffs change people's consumption patterns rather than whether or why people would sign up to such a tariff of their own accord in the first place. Only further experimental studies would be able to determine whether bill protection and automation will increase uptake to TOU tariffs in the population.

Determining the impact of the way tariffs are marketed and communicated to consumers is substantially harder to answer using existing data because nearly all studies, apart from one (M Nicolson et al., 2017), either tell people the tariff will save them money (a money frame) or do not specify what frame was used at all. Two studies excluded from this review because it was not possible to standardise their uptake measures (Buryk et al., 2015; Schwartz et al., 2015) – in addition to the study which was included (M Nicolson et al., 2017) – found mixed results as to the impact of telling consumers about the environmental benefits of TOU tariffs on uptake. Since nearly all energy tariff marketing already frames switching tariff as a way of saving money, there is no evidence as to whether changing this approach could increase uptake to TOU tariffs, which, are likely to provide much lower savings than just switching to the cheapest available flat-rate tariff.

3.4.3 The impact of tariff design

The model provides strong evidence that real-time pricing tariffs, in which the price of electricity can vary freely throughout the day according to real-time supply and demand of electricity, are less popular amongst consumers than static TOU tariffs, in which the price bands apply for fixed periods each day or season. Dynamic TOU tariffs, in which the price of electricity varies, usually within fixed parameters, freely throughout the day and capacity pricing tariffs are less popular than static TOU tariffs.

3.4.4 Energy bill impacts

Due to the high level of non-reporting of energy bill savings, the bill savings presented in Table 7 cannot be reliably used as a measure of average potential savings however they do illustrate that savings are likely to vary substantially.

The finding that the majority of domestic consumers save money (in this review between 56%-75%), with a sizeable remainder of consumers worse off on a TOU tariff than a flat-rate tariff, is discussed elsewhere (Citizens Advice Bureau, 2014) and is corroborated by another literature review on the impact of TOU tariffs on electricity consumption patterns (Frontier Economics and Sustainability First, 2012). It highlights that a key challenge faced by this area of research is how to devise recruitment strategies that increase uptake to TOU tariffs whilst respecting this very relevant heterogeneity in bill impacts.

4 Conclusions

This review outlined the vision the Government has for an increasingly flexible energy system in which domestic consumers have an important part to play. It contrasted this vision with the reality of domestic consumer engagement in the energy market. It then synthesised a range of evidence on domestic consumer demand for TOU tariffs from over 27 studies, incorporating 66 individual measures of uptake to various TOU tariffs in different countries, using different recruitment methods and measured in different ways.

The aim was to identify the likely uptake of TOU tariffs amongst domestic energy consumers and what factors might influence uptake, to inform the research questions and focus of this thesis. Four main conclusions are drawn from this literature review as a whole.

4.1 Evidence on domestic demand for TOU tariffs is imprecise and unreliable

The available evidence suggests that, if GB consumers are left to opt-in to TOU rates, uptake could be as low as 1% or could reach 43%. On the other hand, it is also possible that opt-in uptake could exceed 43% if new recruitment approaches are tested since, after all, the interval of 1%-43% is based on the existing literature which has only tested a limited number of ways of increasing opt-in uptake, namely small upfront cash payments and bill protection. Making enrolment opt-out rather than opt-in could generate uptake rates of almost 100%.

Although there are limitations to the estimate of uptake to TOU tariffs obtained through this review (it does not account for variations in uptake over time and it is based on evidence from multiple countries not just GB), given that the highest estimated enrolment rates were obtained from survey studies which may be vulnerable to hypothetical bias, the results suggest that there is a high risk that the proportion of consumers who choose to switch from a flat-rate tariff to a TOU tariff is likely to be lower than the 30% required by the UK Government to realise the business case for smart meters (BEIS, 2016b).

4.2 Lack of evidence on how to increase uptake to TOU tariffs, except for opt-out enrolment

There is very little evidence as to how uptake to TOU tariffs could be increased aside from using opt-out enrolment, which may or may not be appropriate in the case of TOU tariffs. Small upfront financial incentives, bill protection and automation all show promise but the relationship could be spurious.

There is even less evidence on how these tariffs should be framed to consumers. The majority of studies promote TOU tariffs as a way of consumers saving money, even though monetary savings from switching to a TOU tariff are modest and likely to be overshadowed by the savings from switching to the cheapest available flat-rate tariff. About 20% of studies do not indicate what messaging was given to consumers at all. The lack of evidence on how best to frame tariffs to increase uptake is therefore a particular oversight because, as the next chapter will demonstrate, unlike opt-out enrolment and potentially even bill protection, framing is likely to be more a more suitable method of attempting to increase enrolment to TOU tariffs.

4.3 A lack of real-world evidence on GB energy bill payers

In GB, the evidence on consumer demand for TOU tariffs comes from two industry field trials (Schofield et al., 2014; Sidebotham, 2014a), three survey experiments (Michael J. Fell et al., 2015; BEIS, 2016a; M Nicolson et al., 2017) and a measure of market uptake to the Economy 7 tariff (Consumer Focus, 2012). Just four studies experimentally manipulated the framing of the tariff and all were survey based (Verhagen et al., 2012; Schwartz et al., 2015; Buryk et al., 2015; M Nicolson et al., 2017). Purchase intentions are imperfect predictors of sales (Morwitz et al., 2007) and, with the exception of one (M Nicolson et al., 2017), the studies did not sample from populations of interest to distribution network operators, policymakers or DSR companies, being confined to Dutch university students (Verhagen et al., 2012), participants of online labour markets in the US (Schwartz et al., 2015) and a convenience sample recruited via social media and email (Buryk et al., 2015).

To enable robust causal inferences, any future research seeking to test the impact of framing on uptake must involve the random assignment of participants to variations of the same tariff to test which variation results in higher switching rates. More evidence is required which is GB specific and would measure uptake by offering GB consumers a tariff and seeing how many adopt it rather than measuring willingness to switch amongst market research participants presented in surveys, which may overstate demand because the scenarios are hypothetical. However, obtaining a measure of uptake based on actual sign up rates is likely to be challenging given that smart TOU tariffs are not yet commercially available anywhere in GB.

4.4 A lack of evidence beyond the average energy consumer

A final limitation of the evidence base is that it lacks nuance over the extent to which uptake may vary across consumer groups in the population. The academic and policy literature reviewed focuses predominantly on the so-called 'average' energy consumer who owns 'flexible' electrical loads such as dishwashers, tumble dryers and washing machines ('wet' goods), which, unlike cooking and lighting, are easier to defer to alternative times of the day but which presently have a much wider ownership than the much higher consuming flexible electrical loads such as EVs and heat pumps (when combined with automation and/or storage). The UK smart meter impact assessment, for example, is based on consumers with wet goods participating in DSR (DECC, 2014; BEIS, 2016b) on the assumption that heat pumps and EV loads will become important at a later date, once these appliances reach a higher market penetration.

However, focusing on the current 'average' energy consumer (as someone whose flexible appliances consist of 'wet' goods) is inadvisable for three reasons. First, whilst shifting individually small but collectively large loads from wet goods may have a large impact on the electricity network, the savings for each household from using their washing machine at 10pm, for example, rather than 8pm are relatively modest and, for a large proportion of consumers, are likely to be outweighed by the increase in electricity costs due to the other loads that the consumer cannot readily shift, such as those for cooking or television (this is discussed in more detail in the next section). Selling tariffs to these consumers may be less effective at reducing energy bills than targeting consumers with high flexible electrical loads.

Second, government subsidies for electric vehicles and low carbon heating technologies such as heat pumps have been associated with a recent and very rapid increase in ownership, meaning that the average energy consumer of today may be very different from the average consumer in the relatively near future. The uptake of electric vehicles, in particular, is growing almost exponentially (SMMT, 2017c) meaning that early planning will be required to help cope with this sudden increase in demand, particularly given that uptake is concentrated in particular regions and therefore on particular local electricity networks.[25]

Third, for reasons outlined in more detail in Chapter 3 and Chapter 7, early intervention to convert electric vehicle and heat pump owners onto time varying tariffs could be crucial for overall adoption rates if consumers are more susceptible to behaviour change campaigns at the point when they first adopt their new technology.

This marks the end of the second chapter. The next chapter provides an overview of the major theories of individual decision making that could be used to create testable hypotheses about how uptake to TOU tariffs could be increased without using mandates and which therefore respect consumer heterogeneity.

[25] This is based on the authors' own mapping of EV purchases in the UK obtained from the UK Office for Low Emission Vehicles, which administers the UK EV grant. It is not possible to reproduce this map in the thesis because it could risk identifying individual EV owners.

Chapter 3

Literature review, part (b):

Achieving the vision – economics, behavioural economics and "effective and selective" nudges

1 Introduction

The last chapter reviewed the empirical evidence on domestic consumer demand for TOU tariffs. It concluded that uptake to TOU tariffs could be far lower than required to realise the business case for smart meters (BEIS, 2016b) and the vision of a smarter energy system laid out in both government and industry strategy documents (BEIS, 2016b; Ofgem, 2017; Institute of Engineering and Technology, 2017; UKPN, 2017).

This chapter outlines two major theories of decision making that can explain the lack of consumer engagement in the retail energy market in GB, its likelihood of affecting uptake of TOU tariffs and what could be done to increase uptake to help realise the vision. One of these theories is classical economics, the leading theory used to explain consumer decision making under uncertainty (Barberis, 2013). Classical economics offers two explanations and solutions for low switching rates. The first is that the costs of switching are higher than the benefits, which can be solved by increasing the savings or lowering the costs of switching. The second is imperfect information about the benefits of switching, which can be solved by increasing access to information.

The other theory is behavioural economics, a sub-field of economics which fuses economics with psychology (Mullainathan and Thaler, 2000). Behavioural economics is one of the leading alternative theories used to explain sub-optimal decision making (Barberis, 2013). Behavioural economics implies that information and monetary savings on their own are unlikely to be sufficient to ensure optimal uptake of TOU tariffs but that another strategy, known as ‘nudging’, could be significantly more effective.

The rest of this chapter is structured as follows. Section 2 justifies the focus on classical and behavioural economics. Section 3 provides a brief summary of classical economics, concentrating on hassle costs as an explanation for low tariff switching rates. Section 4 outlines the major limitations of classical economics, namely that many of the model assumptions often fail to hold in reality. This section is sub-divided according to which assumptions are expected to be violated: the assumptions of the rules governing the market (the market failure explanation for low switching rates) and the assumption that humans are fully rational decision makers. This section lays out a range of evidence suggesting that consumer decision making often fails to meet the standards of a fully rational consumer and therefore that behaviour can be influenced by a much wider range of tools than incentives.

Section 5 outlines behavioural economics and nudge, theories which have shown how violations of the assumptions of rationality can be exploited to change behaviour. Section 6 outlines the limitations of anti-rationality arguments and the potential problems of generalising nudge to the energy domain and using opt-out enrolment to boost uptake to TOU tariffs. Section 7 proposes that many of these problems are caused by consumer and treatment effect heterogeneity. Section 8 suggests how this heterogeneity could be exploited to help increase uptake to TOU tariffs amongst EV and heat pump owners whilst reducing uptake amongst consumers groups who could be made financially worse off from switching to a TOU tariff, to answer research question 2; this section also draws on a number of findings from the nudge and behavioural science literature including message framing, prompts and habit discontinuity. Section 9 summarises the chapter and concludes by re-stating the research questions outlined in the introduction now that they can be linked to the two theoretical frameworks that informed them.

2 Why use economics and behavioural economics?

2.1 Accounting for price effects

Although any individual theory of consumer decision-making is likely to be wrong, some models will be more useful for explaining decision making over energy tariffs than others (Box, 1976). Economics is an obvious model to start with because models which can account for the actual or potential role that incentives play in consumer decision making over energy tariffs is likely to be more suitable than models which cannot. This is for two reasons.

First, although there is ample evidence from psychology, as well as other social science disciplines, to suggest that people are not as responsive to price as a classical economic model would suggest (Lambrecht and Skiera, 2006; Agarwal et al., 2015; Dupas and Robinson, 2015) there is no denying that people do respond to financial and non-financial incentives in predictable ways (Dellavigna et al., 2017); if a good is taxed, people consume less of it, if it is subsidised people consume more of it. People are also price sensitive to the cost of energy, as demonstrated in numerous TOU tariff trials (Frontier Economics and Sustainability First, 2012).

Second, whilst price may be only a minor and therefore expendable variable in some contexts, it is an important variable in the case of energy tariffs; if TOU tariffs are going to play a role in maintaining energy affordability in the transition away from fossil fuels, then price needs to play a role in consumer decision making over tariffs.

2.2 Accounting for psychological influences on behaviour

However, since incentives are not the only drivers of behaviour, including these additional psychological and contextual factors may provide a better, and potentially more useful, approximation of how consumers make decisions about energy tariffs than the classical economic lens alone. Behavioural economics integrates findings from psychology into a standard economic framework, thereby giving it explanatory power for the effect of price on behaviour as well as other contextual factors such as marketing, or what academics call 'message-framing' (Zhao and Pechmann, 2006; Chong, 2007; Spence and Pidgeon, 2010; Gallagher and Updegraff, 2012).

2.3 Distinguishing between behavioural economics and psychology

Psychology can also explain price effects. For instance, in the Means-Motive-Opportunity framework (Raw and Ross, 2011), money could be either a motive or an opportunity. The key difference between behavioural economics and psychology is not in the theory[26] or in its empirical predictions – which are often indistinguishable – but in the way behavioural economists and psychologists approach research. For the behavioural economist, the burden of proof is on behavioural economics to show that the classical economic model fails to provide a sufficiently good approximation of real-world behaviour so as not to be useful, and therefore tends to use the classical model as the benchmark against which its interventions are judged.

For instance, most behavioural economics studies will include a control group that receives a financial incentive (e.g. Halpern et al., 2012; Giné et al., 2010) or

[26] Although there are theoretical distinctions, they rarely have a major impact on the empirical predictions or the hypotheses formed by behavioural economists and psychologists.

will run additional robustness checks to demonstrate why the behaviour observed is inconsistent with the classical model, even after accounting for Friedman's (1953) "as if" defence of the rationality paradigm (e.g. Camerer et al., 1997; Della Vigna and Malmendier, 2006). Psychologists, on the other hand, are more likely to start from the assumption that behaviour is not approximately rational and proceed by applying different models such as the Theory of Planned Behaviour (Azjen, 1985) or the Means-Motive-Opportunity model.

This thesis follows the convention of behavioural economics by using classical economics as a benchmark against which the behavioural economic model is tested. This is for three reasons: (1) the UK Government, like many others, use classical economic models to conduct their cost-benefit analyses and to inform all their policy decisions, including over the roll out of smart meters and its wider benefits (BEIS, 2016b), of which DSR is one key secondary benefit; testing the validity of such a widely used model, and to what extent it applies to GB energy bill payers, is therefore important; (2) As will become clearer in Section 4.4, it is still not known whether classical economics could not be used to explain, and therefore solve, the lack of consumer engagement in the energy market (Deller et al., 2017); (3) Classical economics is a simple model – that is its main virtue – which makes clear predictions about what should be observed if the assumptions are true. It therefore lends itself well to being a benchmark.

Nevertheless, since the impact of marketing or message-framing is just as easily explained by psychology as behavioural economics, I will use the broader term 'behavioural science' interchangeably with behavioural economics as in the more recent literature on nudge (Cialdini et al., 2015; Benartzi et al., 2017).

2.4 Focusing on the individual

The review is confined to theories of individual decision making because the decision to switch tariff is undertaken by one or two household energy bill payers. In doing so, this thesis will not capture some of the potentially important wider cultural and social factors which may influence participation in DSR. These are discussed in the global discussion of this thesis.

3 A brief history of classical economics

Sometime after the 1600s, up until the Industrial Revolution, resources in most countries went from being distributed according to the whims of its kings or queens to a new system underpinned by a belief that the market would dispassionately, and therefore efficiently, allocate resources on the people's behalf.[27] This latter belief is the cornerstone of the classical theory of economics.

According to economic theory, under certain assumptions (

Table 8), individuals acting to fulfil their private interests will ensure an outcome that is not only best for themselves but also one which is best for society as a whole, as if by an "invisible hand" (Smith, 1776). An outcome which is 'best for society as a whole' is one in which "no one can be made better off without someone being made worse off" (Stiglitz, 2000, p.57). This is the definition of market efficiency.[28]

Market efficiency is achieved, according to the theory, by rational individuals each undertaking private cost-benefit analyses in which they weigh up the costs and benefits of a range of possible options to identify and select the one that will

[27] Of course, markets in the sense of people trading goods between one another began long before the creation of the market economy as we know it today. However it is the modern market economy that is relevant for understanding behaviour in the retail electricity market today.
[28] It is known as Pareto efficiency or the Pareto principle.

maximise their overall expected utility, which is the satisfaction they expect to gain from each good or service. This is called expected utility theory (EUT).

Table 8 Four key assumptions underpinning the classical economic model

#	Assumption	Brief description
1	Full rationality	Agents maximise their utility against a fixed budget constraint. Although there is disagreement about how rationality should be defined, most agree that it is composed of the following characteristics: (1) "people have well-defined preferences (or goals) and make decisions to maximise those preferences" (2) "those preferences accurately reflect (to the best of the person's knowledge) the true costs and benefits of available options" (3) "in situations involving uncertainty…people…update probabilistic assessments in light of new information" (Camerer et al., 2003, p.1215); (4) people make choices to maximise those preferences against a budget constraint (Stiglitz, 2000); (5) people have "unbounded computational capacity" to weigh up the costs and benefits of the available options to determine the optimal outcome (Allcott, 2011, p.98) and; (6) people only have preferences over certain types of attributes, for example, price and customer service but not attributes like the type of font or colour used in the marketing of the product.
2	Perfect information	All the information required to undertake the individual cost-benefit analysis required to maximise utility is available to consumers. For electricity tariffs this is electricity consumption and the prices charged by different suppliers on their respective tariffs.
3	Perfect competition	There are a sufficient number of buyers and sellers in the market that no individual seller or buyer has an influence on price. No monopolies.
4	No externalities	The true costs of consumption are reflected in the market price so that the private costs and benefits are equal to the social costs and benefits to avoid collective action problems. Ofgem is reforming electricity settlement rules so that suppliers are exposed to the true variation in the cost of supplying electricity to domestic consumers across the day.

Note: This list is not intended be exhaustive.

EUT is the dominant theory used to explain how people make decisions under uncertainty (Barberis, 2013) and it can be applied to explain how consumers make decisions about their energy tariff. When choosing between electricity tariffs, the outcomes of our decisions are uncertain because we have to predict our future electricity demand as well as the future price of electricity. Since we may not predict these values with full accuracy, the expected utility framework models each energy bill payer as an agent who will weigh up the *expected* benefits of switching (e.g. lower bills, a fixed rate tariff, or anything else they value) against the *expected* costs (e.g. the time taken to monitor prices, undertake the switch), based on the best available information about our future electricity demand and prices.

According to EUT, consumers will switch between flat-rate tariffs or switch from a flat-rate to a TOU tariff if and only if it will maximise their overall utility. By behaving in this way, each consumer plays their part in ensuring that retail energy prices will reflect wholesale energy costs. If this model is correct, consumers will ensure that uptake to TOU tariffs or other DSR services is optimal. Optimal uptake of TOU tariffs by domestic consumers can be defined as the level of uptake required to balance the supply and demand of electricity, after accounting for alternative and complementary methods such as energy storage, interconnectors and so on.

However, there are good reasons to believe that this model is incomplete. First, there is a substantial gap between the retail and wholesale price of electricity and gas (CMA, 2016b, 2016c), suggesting that the collective decisions of consumers are not leading to outcomes that are in the best interest of consumers as a whole. Based on their recent investigation of retail competition in the GB energy market, the Competitions and Markets Authority (CMA) concluded that suppliers have overcharged consumers to the value of over £2 billion a year (CMA, 2016c). Prices on the standard variable tariff (SVT) – the default tariff on which 70% of the customers of the Six Large Energy Firms are enrolled – are significantly higher than the wholesale cost of electricity and gas (CMA, 2016c).

What explains this disengagement in the energy market and what does it have to say for uptake to TOU tariffs? The next section considers two main explanations, market failures and violations of rationality.

4 Consumer disengagement: market failures vs violations of rationality

4.1 Market failures – imperfect information

Economists have long maintained that assumptions 2-4 outlined in Table 8 are ideals which never hold in reality (Friedman, 1953). Whenever any one or more of these conditions is not met, economists say there is a market failure (Stiglitz, 2000). According to the market failure argument, if people only knew how much they could save from switching tariff then they would switch. Consequently, the first-best solution – according to the theory – for ensuring the optimal number of consumers sign up to TOU tariffs is to make sure people know how much they could save from switching to one. This requires two main ingredients: smart meters for accurate billing and price comparison websites, which lower the costs of comparing tariffs to calculate savings.

Price comparison websites enable consumers to enter their postcode, provide details of their gas and electricity consumption (or, if unknown, an average value provided by the site) to obtain a list of energy tariffs sorted in descending order of the expected annual bill. Consumers can switch through the website so that they do not have to do any more than just wait for their direct debits to be switched over (and, without a smart meter, provide an initial meter reading). To work for TOU tariffs, price comparison websites would need access to energy bill payers' half-hourly electricity consumption data, or for real-time TOU tariffs sub half-hourly data, recorded by smart meters.

When market-based corrections fail, according to this model, more coercive Government interventions such as mandates, bans and subsidies *may* increase welfare (Allcott and Greenstone, 2012). However, in this case, forcing consumers to switch to TOU tariffs, as will occur in Ireland (Commission for Energy Regulation, 2014), is likely to be highly unpopular and could lead consumers to reject the installation of their smart meter to avoid being switched to a TOU tariff.[29]

However, there are at least two reasons to doubt whether smart meters and price comparisons will be sufficient to ensure optimal uptake to TOU tariffs. These are now outlined below.

4.2 Market failures – adverse selection

EUT predicts that price comparisons generated using accurate data on historical consumption patterns (in the absence of accurate projections of future patterns) would decrease switching rates to TOU tariffs, particularly amongst two of the most desirable candidates for TOU tariffs, namely EV and heat pump owners by exacerbating adverse selection, or the so-called ‘free-rider’ problem.

Some consumers will have consumption patterns that mean they would save money on a static TOU tariff without making any changes to the timing of their electricity use (Baladi et al., 1998; Herter, 2007; Train et al., 2016; Qiu et al., 2017). Others will face higher costs to switching to a TOU tariff. For example, most EV owners charge their vehicles when they get home from work, during the

[29] This is not farfetched when you consider that, in the Netherlands, a popular backlash against smart meters resulted in the Dutch Government reversing its decision to make smart meters mandatory (Metering.com, 2009).

existing evening peak (Zarnikau et al., 2015; My Electric Avenue, 2015; Capova et al., 2015), and households with heat pumps tend to run their heating systems all day and do not already own storage (Energy Saving Trust, 2013; Summerfield et al., 2016).

According to EUT, which predicts that decisions are made based on a rational evaluation of costs and benefits, TOU tariffs will attract a disproportionate number of those who already have low peak time electricity consumption, thus defeating the purpose of TOU tariffs which is to change peoples' consumption patterns (Baladi et al., 1998; Herter, 2007; Train et al., 2016; Qiu et al., 2017). This is called averse selection, and it was such a concern in the early days of TOU tariffs in the US, that nearly all US TOU tariffs were and still are deliberately designed to assess whether the consumption patterns of volunteers are different from those of non-volunteers by mandating TOUs for some and giving a choice to others (e.g. Baladi et al., 1998).

Providing consumers with a comparison of what they would pay on a TOU tariff compared to a flat-rate tariff based on their historical half-hourly consumption data would simply show consumers who have 'peaky' demand profiles that switching to a TOU tariff would increase their energy bill whilst making it clear to those with favourable consumption profiles that they could save money on a TOU tariff by default.

4.3 Violations of rationality – describing real-world consumer behaviour

> *Economics is a "dismal" science because it assumes man to be selfish and money-grubbing "a lighting calculator of pleasures and pains"…it rests on an outmoded psychology and must be reconstructed in line with each new development in psychology…(Friedman, 1953, pp.164–165).*

Market failures like adverse selection are one explanation for why information provision could fail to achieve the optimal level of uptake to TOU tariffs. Another is that, even when the market assumptions are met, outcomes will never be optimal if the people who participate in the market do not behave like the model predicts.

Empirical studies from cognitive and social psychology, sociology and neuroscience have, for over half a decade – as Milton Friedman's quote above attests – produced a range of evidence to suggest that real-world consumer decision making systematically violates many of the other assumptions implicit in the classical economic model's conception of how humans make decisions. These are summarised in Table 9. For instance, people are not just affected by the costs and benefits of different options, they are also affected by the way in which these costs and benefits are communicated to them (Tversky and Kahneman, 1981) and their ability to process information, or what Herbert Simon (1957) called bounded rationality.

Simon rejected the idea proposed by psychologists such as Freud who reduced all decision making to the product of a conflict between conscious and unconscious forces, but was also sceptical of the economist's model of a human as an omniscient information processing machine; instead, Simon proposed that the real-world behaviour of people lay somewhere in the middle (Parsons, 1995). According to Simon, people are "generally quite rational" in the sense that "they usually have reasons for what they do" (Simon, 1985, p.297). However, people are limited in their computational power and, the amount of information that any person must process and consider when deciding between alternative tariffs, pensions, health insurance plans and so on, is so great that "even an approximation" to full rationality "is hard to conceive" (Simon, 1957, p.79).

Another important determinant on behaviour is which option is the default, as shown by the differences in enrolment rates across opt-in and opt-out systems for organ donor registration (Johnson and Goldstein, 2003). The tendency people have to stick with the pre-selected option is called inertia or, more formally, status-quo bias (Samuelson and Zeckhauser, 1988; Kahneman et al., 1991).

Table 9 Some of the factors found to affect human decision making outside of the classical economics literature.

Factor	**Brief definition**
Affect	We are influenced by our emotional associations and feelings (Slovic, 2007).
Bounded rationality	Used to explain the limits on human information processing capacity (Simon, 1957).
Inattention/limited attention	People do not pay full attention to all information available or presented to them when making decisions (Loewenstein et al., 2013).
Framing effects	Used to explain the impact of marketing. People change their preferences depending on arbitrary features of the decision making environment or the way in which the choices are described, for example whether the outcomes of a choice are framed in terms of the losses or gains (Tversky and Kahneman, 1981), which choice is presented as the default option (Carroll et al., 2009) and the name or label given to a choice (Beatty et al., 2014).
Loss-aversion	People weight losses higher than equivalent gains (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991, 1992), which also has support at the neuroscientific level (Tom et al., 2007).
Other-regarding (pro-social) preferences	Refers to the finding that people cooperate rather than betray other players in economic games such as the Dictator Game (Andreoni, 1995), even though doing so results in lower earnings.

Priming	The finding that we are often influenced by subconscious cues (Bargh et al., 1996).
Status-quo bias	The preference for the current state of affairs (Samuelson and Zeckhauser, 1988; Kahneman et al., 1991), used to explain ‘stickiness’ in consumer markets such as mortgages, banks and energy tariffs.
Social norms	The way in which individual behaviour is influenced by other peoples’ behaviour, including how much energy we use (Slemrod and Allcott, 2011; Dolan and Metcalfe, 2013; Schultz et al., 2015).
Time inconsistent preferences	Refers to the finding that people will change their preference depending on whether the choice is present-framed or future-framed (Andreoni and Sprenger, 2012). Used to explain behaviours which require willpower such as personal savings, smoking cessation and weight loss (O’Donoghue and Rabin, 1999).

5 Behavioural economics, nudge and the environment – changing behaviour

A number of researchers, including environmental researchers, have drawn three key lessons from the difference in uptake across opt-in versus opt-out organ registration enrolment systems and the wider evidence from behavioural science.

5.1 Lesson #1 People are not rational

The first lesson that has been drawn is that decision making is not fully rational. If people made decisions purely based on the costs and benefits of alternative outcomes – a defining characteristic of a fully rational consumer – then contextual factors that have no effect on a decision makers’ incentives, such as the default option or the order in which choices are presented, would have no impact on their choice at all. The fact that consumers do respond to the way choices are framed means decision making cannot be fully rational.

A growing body of academics have argued that this means that classical economics should be reformed and its assumptions replaced by more ‘realistic’ ones based on empirical research from other social sciences, particularly psychology which has a large literature on framing effects. Inspired, in particular, by the early work of two psychologists (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991, 1992) and the political scientist Herbert Simon (1957), some economists have begun modifying economic theory based on the findings reported in Table 9. The output of this collective body of work is referred to as behavioural economics or, sometimes more broadly as behavioural science.[30] As noted at the beginning of this chapter, I use the two terms interchangeably.

Although there is no agreed-upon definition of behavioural economics, the various available descriptions of the field (Mullainathan and Thaler, 2000; Shiller, 2005; Shogren and Taylor, 2008; Lunn, 2013, 2015; Baddeley, 2017) can be combined to produce the following definition:

> *Behavioural economics integrates findings from social science disciplines, other than economics but particularly psychology, into a standard economic framework, whereby each modification is included depending on whether empirical tests demonstrate that it is relevant to the behaviour in question*.

In short, what this means is that behavioural economics adds variables from psychology and other social sciences to the standard cost-benefit analysis if empirical evidence suggests that these variables are relevant to the behaviour of interest.

5.2 Lesson #2 Out with the old and in with the 'nudge'

[30] Not all researchers in the field agree with the term 'behavioural economics'. For instance, the evolutionary economist Jason Collins (2015) said in a recent talk "I am going to refer to 'behavioural economics' today, even though what I am going to talk about is more rightfully called 'behavioural science'" because the latter term does a disservice to the field of psychology from which behavioural economics has drawn so much. Recent journal articles on nudge have also started referring to 'behavioural science' rather than 'behavioural economics' (e.g. Benartzi et al., 2017) and, in the United States, the team tasked with designing interventions informed by nudge is called the *Social and Behavioral Sciences Team*, whilst President Obama (2015) issued an Executive Order directing government agencies to use 'behavioural science' in the design of their programmes.

Further, these scholars argue that governments should use these findings to help promote policy outcomes, including those on the environment. For example, whilst a classical economic model would assume that smoking reflects an inherent privileging of short term pleasures over the long term health benefits of not smoking, a behavioural economic model could account for the possibility that smokers may indeed value their long term health over the immediate pleasures of smoking a cigarette but that they may lack the self-control required to abstain at the precise moment they experience a craving (Giné et al., 2010). Motivated by this potential alternative explanation for seemingly sub-optimal decision making, health and household finance researchers have run a range of studies demonstrating that the “same errors that trip people up can also be used to help them” (Loewenstein et al., 2012, p.1), for example:

> *…present bias can be used to advantage through programmes that offer small, frequent (and hence immediate) payments for beneficial behaviours. Such programmes targeted at smoking cessation, medication adherence, and weight loss have been shown to have major effects on behaviour. One recent study… incorporated a number of behaviourally informed features, most notably, frequent, mounting payments for documented [smoking] abstinence. The programme significantly increased smoking cessation rates at the end of pregnancy (41% v 10%) and the benefit was still evident 12 weeks postpartum (24% v 3%).*

Two seminal journal articles first promoting this idea were *Regulation for Conservatives* (Camerer et al., 2003) and *Libertarian Paternalism* (Thaler and Sunstein, 2003), however the concept of using behavioural economics to change behaviour did not gain substantial traction amongst policymakers until this approach to behaviour change was rebranded as ‘nudge’ by Thaler and Sunstein in 2008. In this book, Thaler and Sunstein defined a nudge as a strategy which changes:

> *…people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, [an] intervention must be easy and cheap to avoid (Thaler and Sunstein, 2008, p.6).*

Since the publication of *Nudge: improving decisions about health, wealth and happiness* (Thaler and Sunstein, 2008), governments are increasingly using 'insights' from behavioural science more broadly to supplement or replace traditional economic levers such as taxes and fines to influence citizens' behaviour to achieve public priorities (Benartzi et al., 2017). Whole units have been created within government dedicated to applying this research to policymaking, starting with the UK's *Behavioural Insights Team* in 2010 followed by similar teams in the Netherlands, Australia, Germany, Singapore and the *Social and Behavioral Sciences Team* in the United States, where President Obama (2015) issued an Executive Order directing government agencies to use behavioural science in the design of their programmes. Now almost every UK Government department has dedicated 'behavioural insights' functions that test ways in which behavioural science could be used to inform policies. This includes the Department for Health, Her Majesty's Revenue and Customers, Ofgem, the Foreign and Commonwealth Office, BEIS and many more.

There are two key virtues of nudge from a policymaker's perspective. The first is that they permit freedom of choice so can be easier to implement than taxes and mandates which may have limited public support. The second advantage is that nudges, when effective, achieve impact at very low cost. Nudges therefore provide a high 'bang for their buck' (Benartzi et al., 2017) relative to conventional policy tools such as financial incentives like the UK Government's Feed-in-Tariff or the Ultra-Low Emission Vehicle grant which deducts up to £5,000 from the value of eligible electric vehicles.

Unsurprisingly, support is therefore also growing behind the idea of using behaviourally informed interventions to help achieve environmental outcomes and low cost too. The European Commission published a set of guidelines for designing interventions to change energy behaviour (Dahlbom et al., 2009) all of which are non-coercive and do not rely on financial incentives, thereby fitting the definition of nudge (Thaler and Sunstein, 2008). The policy interest in nudge and behavioural interventions is also mirrored in the academic environmental literature with a range of review articles having discussed the potential application of behavioural economics to helping meet carbon emission targets (Shogren and Taylor, 2008; Hepburn et al., 2010; Pollitt and Shaorshadze, 2011; Sunstein, 2013a; Sunstein and Reisch, 2013; Gillingham and Palmer, 2014; Frederiks et al., 2015; Hobman et al., 2016; Lehner et al., 2016).

5.3 Lesson #3 Green by default

The last lesson is that opt-out enrolment results in extremely high participation whereas opt-in enrolment keeps participation very low. It has therefore been argued that the default option should be chosen to maximise the environmental benefits (Pichert and Katsikopoulos, 2008; Sunstein and Reisch, 2013; Faruqui et al., 2014; S. Fenrick et al., 2014; Broman Toft et al., 2014; Ebeling and Lotz, 2015; Egebark and Ekström, 2016).

A range of studies have shown that automatically enrolling people onto renewable energy tariffs, unless they opt-out, substantially increases uptake to renewable energy tariffs compared to when enrolment is opt-in (Pichert and Katsikopoulos, 2008; Hedlin and Sunstein, 2015; Ebeling and Lotz, 2015). The same finding has also been replicated in two US field experiments in which people were defaulted onto TOU tariffs (US Department of Energy, 2016), with industry papers arguing that people could also be 'smart by default' (Faruqui et al., 2014). Finally, a recent field experiment showed that, when printers are set to double-sided printing by default, paper usage is substantially lower than if people are expected to select double-sided printing each time they print a document (Egebark and Ekström, 2016).

5.4 Summarising the evidence on nudge

In summary, behavioural economics and nudge have developed a relatively large body of evidence to suggest that behaviour is much more complex than the classical economic model proposes. It also provides conclusive evidence that behaviour is significantly different under opt-in compared to opt-out enrolment systems (DellaVigna, 2009) and that behaviour can be influenced by a much wider range of factors than just financial incentives alone (Benartzi et al., 2017; Dellavigna et al., 2017).

However, as alluded to in the introduction and a House of Lords Select Committee Report (2011), we should be very cautious before assuming that all potentially undesirable behaviour – in this case low tariff switching rates – can be explained by behavioural biases or boundedly rational behaviour that nudges can solve. The problem with each of the lessons outlined above is that they are overly simplistic.

6 The limitations of anti-rationality arguments and the narrow evidence base of nudge

6.1 The exception does not break the rule: how do we know people are not approximately fully rational?

The literature from psychology and other social sciences suggests the importance of re-evaluating economic models that assume unbounded computational capacity, fixed preferences and choices made based on a desire to maximise expected utility (Allcott, 2011). However, it is difficult to prove using observational data alone that a particular choice does or does not deviate from rationality. Although research shows that consumers fail to exploit all the potential financial savings from switching tariff (CMA, 2016b), this does not necessarily imply energy bill payers are not making rational choices with respect to their energy tariff or supplier because the cheapest tariff is not necessarily the optimal tariff. Similarly, although it has been suggested that householders are ‘leaving money on the table’ when it comes to not investing in home improvements such as loft insulation, it has also been suggested that the energy efficiency gains from such improvements may be overestimated whilst the hassle costs of investment have been underestimated (Allcott and Greenstone, 2012; Gillingham and Palmer, 2014).

Low tariff switching rates and low investment in energy efficiency is perfectly consistent with a model of a fully rational consumer facing high information search costs (Wilson and Price, 2010). In the energy tariff market where people do not have access to accurate information about their energy consumption, a lack of information may be a key driver in explaining why consumers do not switch more often. Although switching rates have remained at a relatively steady 14% each year (Ofgem, 2008, 2011a, 2012, 2013b, 2014a, 2015), even after the advent of price comparison websites and a number of Government and media campaigns promoting the savings to be made from switching (), it is not known whether switching rates would have been worse in their absence. The impact of price comparisons and savings messages on switching has never been tested systematically.

Figure 5 Government tariff switching campaign from 2014 (the average annual savings have since increased to £300).

More importantly, the fact that individual choices do not always conform to the assumption of rational choice merely implies that classical economics is simplistic, not that the model is incorrect or not useful. Economists have long acknowledged that people often violate the assumptions of rational choice.[31]

[31] For example, Gary Becker, when accepting his Nobel prize in economics notes that "actions are constrained by income, time, imperfect memory, calculating capacities and other limited resources" (1992, p.1).

However, many economists have been reluctant to incorporate these findings into economic cost-benefit analyses for two reasons (Tyran, 1999). The first reason stems from the argument that the criteria for judging whether any model is a good model of decision making is not whether the model's assumptions apply to all of the people, all of the time but whether the assumptions are true for human decisions on average (Friedman, 1953; Box, 1976). As Friedman (1953) said, a perfectly realistic model of the wheat market would have to be so complex as to render the theory utterly useless for making clear and general predictions about the impact of different variables on the supply and demand for wheat. Second, the assumption is that, violations of the rationality assumption at the individual level will be so rare that it will not affect the predictive validity of the model to explain aggregate behaviour. This is known as the “as if” defence of the rationality paradigm because, as long as enough people behave in line with the assumptions of the model, then it will be true that people behave “as if” they were perfectly rational.

It has been shown that, in many cases, a large proportion of consumers do not conform to the model of the fully rational decision maker and therefore that, in these cases, the classical economic model fails to provide a good approximation of human decisions at the individual or aggregate level (Kahneman et al., 1991). However, just because many people struggle to make optimal choices in the context of household savings (Lusardi and Mitchell, 2006b, 2008; van Rooij et al., 2011; Klapper et al., 2013), does not mean that people will also struggle to choose the right energy tariff when equipped with all the information.

Choosing the optimal energy tariff is much simpler than planning for retirement which requires knowledge of much more complicated concepts than a kilowatt hour or a standing charge. Optimal retirement savings choices requires an understanding of "compound interest, inflation, financial markets, mortality tables, and more" (Lusardi and Mitchell, 2008, p.413). By comparison, according to the UK Department for Education's national curriculum (2013), the numeracy skills required to identify the optimal energy tariff are those expected of children leaving primary school in Britain. Moreover, one major lesson from behavioural economics is that, context has a major influence on decision making (Lunn, 2015). Therefore, just because people fail to make fully rational decisions regarding their household finances does not mean that it will also affect people's decisions over their energy tariff.

6.2 The challenge of generalising nudge to the energy and environment domain

The evidence behind the nudge toolkit is confined to a relatively narrow set of tools applied in a limited number of domains that are affected by particular biases or decision errors (House of Lords Science and Technology Select Committee, 2011). For instance, self-control is thought to explain why people struggle to stick to weight-loss plans, diets, exercise regimes and quit smoking (Mullainathan and Thaler, 2000). A number of studies have shown that commitment contracts, in which a person pledges money which they forfeit if they do not meal their goal, can be effective at helping people achieve all of these health related goals (Ashraf et al., 2006; Volpp et al., 2008; Giné et al., 2010; John et al., 2011; Milkman et al., 2014; Royer et al., 2015). However, compared to consuming chocolate or cigarettes, our overconsumption of energy is not primarily a failure of self-control. In particular, self-control is less likely to be relevant in the case of switching tariff since the gap in time between the costs and benefits is nowhere near as large as that in the health or climate change domain so a commitment device is unlikely to help increase uptake to TOU tariffs.

Research also shows that, in cases where there is a socially desirable behaviour in which a minority of people do not participate, publicising this can make the wayward minority behave more like the well-behaved majority (Schultz et al., 2007, 2008; Behavioural Insights Team, 2012), including to encourage high energy consumers to reduce their energy use in line with the average member of their neighbourhood (Slemrod and Allcott, 2011; Dolan and Metcalfe, 2013; Schultz et al., 2015). However, in the environmental sector, very few environmentally friendly behaviours are the social norm. In the UK, the overwhelming majority of consumers are on flat-rate tariffs. Therefore, social norms marketing and commitment devices will not necessarily contribute towards achieving all or even most of the behaviour changes that the UK Government is relying on in its 2050 Pathways (DECC, 2010), including increasing the proportion of people on TOU tariffs.

Inertia is thought to explain why so few people switch energy tariff and it has been shown that this tendency to stick with the status quo can be exploited to increase adoption of green energy tariffs (Pichert and Katsikopoulos, 2008; Ebeling and Lotz, 2015; US Department of Energy, 2016). However, opt-out nudges are not feasible in all cases. For example, whilst it may be easy to set a printer to double-sided printing by default as in Egebark and Ekstrrm (2013), a default rule cannot easily be created to guide consumers into taking public transport rather than a car or airplane when going on holiday (Sunstein and Reisch, 2013). Although it would be feasible to make TOU tariffs the default tariff type to which consumers are enrolled unless they ask to remain on a flat-rate tariff, there are other problems with green defaults which will be elaborated on below.

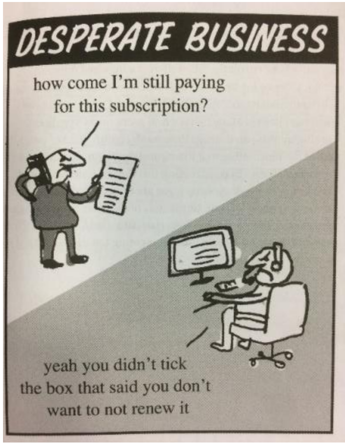
6.3 The limitations of ‘green by default’

Default, or opt-out, enrolment is one of the most successful nudges ever tested in terms of its impact on human behaviour (DellaVigna, 2009). It is curious, then, that so many years after the publication of a *Science* paper (Johnson and Goldstein, 2003) demonstrating that an opt-out policy for organ donation also substantially increases the number of organs donated and lives saved, there are relatively few examples of countries that have moved from an opt-in system to an opt-out. The main reason that countries do not adopt opt-out enrolment, even in cases where doing so can yield such large benefits, is that opt-out systems are not feasible or even appropriate in all cases.

Whilst opt-out enrolment is very appropriate in cases where there is a single optimal course of action that most people do not take but which can be favoured by making it the default, it is much less appropriate when the best course of action varies substantially across people because then an opt-out enrolment system risks enrolling many people onto services they do not want, or worse, which are not in their interest (Carroll et al., 2009; Keller et al., 2011). Not all consumers or even the average consumer will save money on a TOU tariff, with evidence suggesting that up to 40% of GB consumers could be made significantly financially worse off (Chapter 2).

The second disadvantage of opt-out enrolment is that it can violate a key principle of consent, which is that it should be given voluntarily by an individual with the capacity to make an informed choice. Opt-out enrolment can violate the standards of informed consent in one of two ways. One way is that people may be inattentive to the option that was pre-selected for them, resulting in ‘choice’ without awareness (Keller et al., 2011). Although opt-outs are commonly thought to work by exploiting people's tendency to stick with the status quo (Samuelson and Zeckhauser, 1988) a number of other overlapping mechanisms have also been cited including loss-aversion (Dinner et al., 2010), implied endorsement (Brown and Krishna, 2004), effort-minimisation (Samuelson and Zeckhauser, 1988; Thaler and Sunstein, 2003) and inattention to the default option (Smith et al., 2013a). It is well known that defaults can function through inattention from anecdotal evidence about the number of people who unknowingly consent to receiving unwanted marketing material or find themselves paying for subscriptions they did not actively renew (Figure 6).

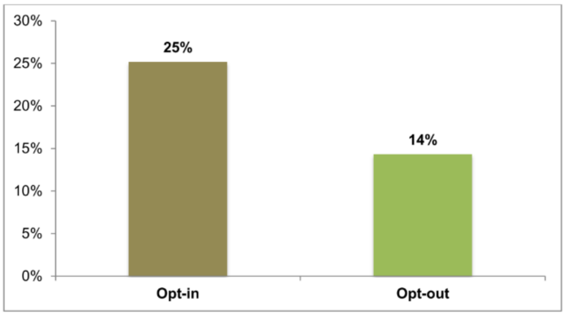
Figure 6 Inattention to default options.

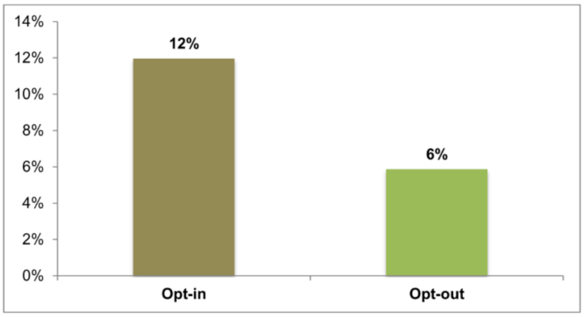


If consumers do not realise what option was pre-selected for them, this risks automatically enrolling consumers onto TOU tariffs without their knowledge, even if they are warned in advance. This is not unlikely given that many British consumers do not even read correspondence from their energy supplier and that, even those who do, most only read their bill to see what amount they owe (Consumer Focus, 2011). This risk is not just theoretical. Compared to those who were randomly assigned to an opt-in recruitment approach, Sacramento Municipal customers randomly assigned to be automatically enrolled onto TOU tariffs reduced their peak-time consumption by 50% less on the TOU tariff and

80% less on the critical peak pricing programme (US Department of Energy, 2015) as shown in Figure 7, indicating that they may have been unaware that they had been switched.[32] In one trial, not represented in Figure 7, participants who were automatically enrolled onto a TOU tariff did not reduce their peak consumption at all (US Department of Energy, 2013a), meaning that they would have certainly seen an increase in their electricity bill.

Figure 7 Peak load reductions across consumers enrolled onto TOU tariffs on an opt-in versus opt-out basis.





Notes: These diagrams are reproduced exactly from the US Department of Energy's report (US Department of Energy, 2015). The chart on the left refers to the peak load reductions seen in the SMUD trial of a TOU tariff and the chart on the right refers to reduction seen in the SMUD trial of a CPP tariff.

Another way is that, even if people notice the default option, they may not have the capacity to make a fully informed choice. The model of the fully rational decision maker from economics assumes that all agents have the capacity to make informed decisions, unless perhaps they have a medically diagnosed disability; however, if people are not fully rational, then this significantly widens the potential pool of people who may be disadvantaged by an opt-out policy. Bounded rationality has received much less attention as a potential disadvantage of opt-out enrolment but is particularly important in the area of TOU tariffs, where

[32] Another explanation, that is not mutually exclusive, is that those who opted-in to participate in the TOU tariff trial were just more enthusiastic about the programme and thus made more effort to undertake behaviours that would help them save money (Keller et al., 2011).

if people are unable to process all of the information required to identify whether such a tariff will increase or decrease their energy bill, they would not have the capacity to know whether to opt-out.

Although bounded rationality would affect people considering whether to opt-in too, opt-out enrolment combined with bounded rationality has larger negative welfare implications than bounded rationality combined with opt-in because opt-out enrolment is so effective and evidence suggests consumers will stay on a TOU tariff regardless of whether it is saving or costing them money, because “even bad defaults are sticky” (Carroll et al., 2009, p.1640). Indeed, retention rates in the US TOU tariff trials were the same across both opt-in and opt-out recruitment methods (US Department of Energy, 2015), suggesting that some people must have been losing out relative to a flat-rate tariff but yet did not disenroll.

Since opt-out enrolment is so effective, generating enrolment rates in excess of 57% and sometimes up to 100% (see Chapter 2), automatically enrolling consumers onto TOU tariffs or other automated DSR schemes could result in large numbers of people being switched onto unfamiliar tariffs that will increase their energy bills, particularly those with low-literacy.

Whilst the financial consequences of opt-out enrolment could be overcome through automated DSR, consumers and the regulator may consider it unethical for energy companies or other third parties to automatically enrol consumers onto TOU tariffs, DLC schemes or use their EV to discharge or charge without informed consent (vehicle-to-grid).

Some advocates of opt-out enrolment recognise the limited ability of opt-out enrolment to account for consumer heterogeneity but suggest that it can be overcome through modifications such as personalised default rules (Sunstein, 2013b) or that it is justified by the efficiency savings from enrolling many more people. I do not question that this is true in some contexts, however it is not the case here. Once smart meters are rolled out more widely, consumers and suppliers will have access to accurate information about past consumption; however, if only past consumption is used to inform whether a person would be suitable for a TOU tariff, this is likely to lead to the type of adverse selection feared by classical economists, whereby only those who already have favourable consumption profiles are defaulted onto TOU tariffs. A personalised default will therefore have to be based on a lot more than just electricity consumption alone and currently, as shown in Chapter 2, there is insufficient evidence for what information this would have to be, even if consumers would consent to providing it. Therefore, at least for the moment, personalised defaults are not a viable option for recruiting customers onto TOU tariffs. Even if they were, inattention to the default means they could be considered unethical.

Finally, although separate analyses suggest that opt-out enrolment will likely lead to higher demand reductions overall, given the relatively much higher enrolment rates (Cappers et al., 2016), policymakers are obliged to minimise the negative distributional impacts of TOU tariffs. Indeed, the distributional impacts of TOU tariffs are a major concern for Ofgem and BEIS. It is therefore desirable to determine whether it may be possible to increase active adoption of TOU tariffs, since this could help lower peak demand whilst protecting consumers.

6.4 Mixed results for ‘soft’ nudges

Aside from opt-out enrolment, the impact of ‘softer’ nudges, such as message-framing and commitment devices, is highly mixed. It is therefore not known whether nudge will always perform significantly better than would traditional tools such as information provision. Take, for example, framing effects. Consider an individual choosing between two products, *x* and *y*. According to EUT, the individual will make their choice based only on the attributes of each of the products *x* and *y,* an explanation that runs counter to the existence of an entire industry that enables companies to extract a higher purchase price for one product, than for another functionally identical product, based exclusively on how that good is communicated to people. Whilst most people call this marketing or advertising, in the academic literature, the observation that “seemingly arbitrary” (Goldin, 2015, p.238) contextual features of a decision such as the way a product is described (Tversky and Kahneman, 1981) also affect decisions is called ‘framing’.

One of the most well-known ‘framing’ effects is the finding that people are more willing to pursue risky rather than safe options when the risks are communicated to them in terms of the number of lives or money that could be lost (a loss-framed message) than when the risks are framed in terms of the number of lives or money that could be saved (gain-framed message) (Tversky and Kahneman, 1981, 1992; Druckman, 2001; Peer et al., 2015; Tom et al., 2007). That people seem to be more greatly motivated by messages that emphasise the disadvantages of not pursuing a course of action than the advantages of pursuing it, has also been replicated in studies in which there are no risks involved in the decision being made (Harper, 2012).

On the other hand, anecdotal evidence suggests that companies may be spending a lot of money advertising products that people would purchase anyway

(Blake et al., 2015).[33] The academic evidence on the effectiveness of message framing, based on studies in which the effect is tested systematically, finds that in some studies message-framing is effective, whereas in others it has no discernible effect and, in many cases, the effect will occur in opposite directions for the same message. For instance, out of the only two studies known to have tested the impact of loss-framing on TOU tariffs, one study found that loss-framed messages ("switch to a TOU tariff to avoid missing out on savings") had no impact on stated willingness to switch to a TOU tariff relative to a gain frame ("switch to save money") (M Nicolson et al., 2017) whereas another study found that a similar loss-framed message increase willingness to switch relative to the gain-framed message (Verhagen et al., 2012). In a study on attitudes towards climate change mitigation, gain framed messages were superior to loss-framed messages at increasing positive attitudes towards climate change reduction strategies (Spence and Pidgeon, 2010).

Moreover, it is not just loss and gain framing that garners inconsistent results. Two studies found that telling people about the environmental benefits of TOU tariffs increased willingness to switch to a dynamic TOU tariff (Buryk et al., 2015) and to a critical peak pricing tariff (Schwartz et al., 2015), but another study found that marketing a TOU tariff in terms of its ability to cut the cost of electricity and help the planet had no statistically significant impact on willingness to switch relative to just telling people that a TOU tariff could save them money (M Nicolson et al., 2017). A large study recently published in *Nature Climate Change* concluded that there is little evidence to support the assumption that "shifting the main justification for GHG [greenhouse gas] mitigation from benefits of reducing

[33] The nineteenth century retailer John Wanamaker famously said "Half the money I spend on advertising is wasted, the trouble is I don't know which half".

climate change risks” to other benefits such as green jobs or protection from health hazards would increase public support for climate change mitigation strategies (Bernauer and McGrath, 2016a).

7 Explaining heterogeneity

This does not mean that people are fully rational, that framing does not work and we should continue using EUT. EUT cannot, for example, easily explain why, in the CMA’s (2016b) survey of over 7,000 British energy bill payers, a total of 34% said they had never considered switching supplier. A rational consumer would always consider whether to switch tariff and then decide, based on full consideration of all the relevant costs and benefits, whether the switch will maximise their utility. There is therefore sufficient evidence to be strongly sceptical that the classical economic model is able to explain all of the behaviour in the energy market; it is just that it is more nuanced than both the classical economists and the behavioural economists suggest.

Given that message framing results are mixed even across framing studies with the same or very similar outcome variables and of varying sample sizes[34], one key possible reason for the inconsistency in these results is differences in participant samples. Verhagen et al. (2012) and Spence and Pidgeon (2010) performed their studies on Dutch and UK university students, Buryk et al. (2015) on a sample of participants recruited through the authors’ social media network, Nicolson et al. (2017) on members of a market research company’s online consumer panel whilst the other recruited US citizens through Amazon Mechanical Turk (Schwartz et al., 2015).

[34] Otherwise we might be concerned that a lack of statistical power could be driving results in studies which find no effect or that studies finding an effect are just false positives.

That studies with different participant samples generate different results is a finding to be explained, not an explanation in itself. What these differences point to is treatment effect heterogeneity (Athey and Imbens, 2016), some behaviours and people are more receptive to message framing than others and/or different behaviours and people respond to different types of messages. These are considered in turn.

7.1 Heterogeneity in rationality across behaviour and people – explaining null effects

Whilst some types of decisions, perhaps those that are complex and require lots of information processing, are particularly vulnerable to boundedly rational decision making, easier decisions are less likely to be affected. Meanwhile, some people may be more susceptible to making boundedly rational choices than others.

Studies in financial literacy do not find that all consumers are financially illiterate; rather, they find that financial literacy varies substantially across consumers (Lusardi and Mitchell, 2006a, 2008; Klapper et al., 2013). This cannot be accounted for using EUT – the “as if” argument – but it also means that some people do behave in line with the model. This could also be true of energy bill payers: some may be boundedly rational but others not. Given that not all people will save money from a TOU tariff, this creates four potential population sub-groups based on concrete factors such as whether they are able or willing to shift their electricity use away from peak times on a TOU tariff but also psychological factors such as whether they exhibit bounded rationality, as outlined in Table 10:

1. People who would save money on a TOU tariff and who do switch to one (optimal choice);

2. People who would save money on a TOU tariff but who do not switch (sub-optimal choice):
3. People who will not save money on a TOU tariff but who do switch to one (sub-optimal choice) and;
4. People who will not save money on a TOU tariff and do not switch (optimal choice)

Table 10 Heterogeneity in ability to save and bounded rationality.

	Tariff chosen	
Population sub-group	**Tariff A** **TOU tariff**	**Tariff B** **Flat-rate tariff**
Should choose TOU tariff (e.g. 0.60)	1	2
Should choose flat-rate tariff (e.g. 0.40)	3	4

Whilst a classical economic model focuses on whether the people in group (1) already have favourable consumption profiles (adverse selection) bounded rationality opens up the potential for a different type of 'behavioural' adverse selection, whereby people with unfavourable consumption profiles *do* switch to a TOU tariff, as represented by group (3). As argued above, the number of people in group 3 would be larger under an opt-out than opt-in system since opt-out enrolment results in much higher enrolment rates overall.

Nevertheless, another important question is what people are likely to be in each box even under an opt-in policy? Research from international development shows that people from rich countries have greater ‘mental bandwidth’ for processing information than people in rich countries (Mani et al., 2013). If this transfers to the rich and poor in developed countries, then it could be that early adopters of low carbon technologies – for example EVs and heat pumps who are key candidates for DSR – will be more rational than others. In which case, it may suggest that these consumers are likely to adopt TOU tariffs in higher numbers than others, in line with a classical economic approach and as assumed in the UK Government’s smart meter cost-benefit analysis (DECC, 2014, p.59). It could also make them much less susceptible to framing than other types of consumers. However, just because EV owners and heat pump owners say they are more likely to adopt a TOU tariff does not mean they will in reality – indeed, a major downside of opt-in enrolment is that enrolment rates are so low.

Further, it also does not mean that some consumers who will not save will not switch; a fairly sizeable minority of participants who signed up to take part in the TOU tariff trials reviewed in Chapter 2 were financially worse off compared to their original flat-rate tariff. Moreover, since EV and heat pump owners are unlikely to save money on a TOU tariff automatically, they would need to make inferences beyond their historical consumption patterns to a hypothetical scenario where they can alter the timing of their vehicle charging or heat pump operation to capitalise on the cheaper rates, a process requiring a great deal of effort and cognitive capacity in the absence of any tools to assist them.

7.2 Heterogeneity in message impacts – explaining multi-directional effects

Although variations in bounded rationality across people would explain why some studies find no impact from message framing, it does not explain why two studies find effects but just in the opposite direction. To explain effects of multiple directions, it must also be the case that the same messages have different impacts on different people, so-called treatment effect heterogeneity.

Consistent with this explanation, one study found that telling people about the environmental benefits of particular behaviours increased willingness to engage in those behaviours, but only amongst people who already had pro-environmental values (Haws et al., 2014). Indeed, one of the explanations for the failure of one-size fits all re-framing of climate change is the problem of confirmation bias (Klayman, 1995; Duarte et al., 2014), whereby messages which emphasise the environmental benefits of particular products or actions which are liable to be ignored by the very people whose actions are most likely to be un-environmental. This would suggest that the best approach is to tailor marketing messages towards particular groups but in ways that control for confirmation bias.

The fact that the same message will be effective on some people but not on others can be used to advantage in the context of TOU tariff recruitment since not everyone will be able to adjust their consumption patterns whereas others, such as EV and heat pump owners, have much greater potential to do so whilst also delivering much-needed relief to the electiricty grid. Instead of appealing to their potential environmental motivations, which may not be shared by all new EV and heat pump owners or future owners when they become more mass market (Haws et al., 2014), another approach is just to market TOU tariffs to EV owners and heat pump owners based on the fact they own an EV or heat pump, for instance, by calling it a ‘heat pump tariff’ or ‘EV’ tariff.

Since the name will make no difference to the design of the tariff itself, the classical economic model would imply that such names should make no difference to the tariff's appeal since someone who chooses a two-tiered TOU tariff called an EV tariff is no better or worse off than someone who chooses an two-tiered TOU tariff that is not called an EV tariff. However, the fact that many energy suppliers in the US and the UK are already offering or have offered 'EV' tariffs (see), many of which are available to all domestic customers and are no different to any other two-rate TOU tariff such as the UK's Economy 7 tariff in which electricity used overnight is charged at a lower rate than electricity consumed during the day, suggests that labelling may have an effect on enrolment.

Moreover, that people can be influenced by such labels has already been demonstrated in a study on the UK Government's cash-transfer called the 'Winter Fuel Payment'; Beatty et al. (2014) found that increasing the income of a pensioner by £100, without labelling it, increased their spending on energy by £3, while labelling the increase a 'Winter Fuel Payment' led to £41 of the £100 being spent on fuel. Like for the Winter Fuel Payment, these EV tariffs are EV specific in name only; the name is just a 'frame', which, if effective, could increase uptake to TOU tariffs amongst those who benefit.

Figure 8 EV tariffs

Notes: The top left panel demonstrates the existence of lump sum discounts offered to consumers who have EVs. The top right and bottom left panels demonstrate suppliers offering tariffs that are called 'EV tariffs' but which are available to any domestic electricity consumer and thus which are therefore EV tariffs in name only. The British Gas EV tariff in the top right is a TOU tariff although it is no longer available.

A complementary method of drawing heat pump and EV owners' attention to TOU tariffs is to tailor all the information provided by a supplier about their tariff to these two consumer groups. Tailoring "is a process of creating individualised communication" (Kreuter et al., 2002, p.272) on the basis that "greater perceived relevance and salience increases motivation to process information and enhance message receptivity, information processing and behaviour change" (Rimer and Kreuter, 2006, p.187).

Tailored communications have been most frequently used in the health education literature, where tailoring has been used primarily as a message strategy in which specific content is provided to individuals based on demographic variables (e.g. providing specific smoking cessation materials for blue-collar workers, older smokers and pregnant women), cultural variables (religion, collectivism, racial pride) and behavioural variables such as readiness to engage in behaviour change (Rimer and Kreuter, 2006). However, although studies have tested the impact of tailored energy feedback on household energy use (e.g. Abrahamse et al., 2007), tailoring has not been explicitly tested in the context of electricity tariffs.

8 A new approach to nudge: effective and selective

So far then, this chapter has shown that there are strong limitations to using opt-out enrolment to increase adoption of TOU tariffs. The alternative to opt-out enrolment when policymakers do not know or cannot determine what course of action is in a person's best interests is for decision makers to be left to make an active choice either way (Keller et al., 2011; Sunstein and Reisch, 2013). However, active choosing is costly (making difficult decisions when you are boundedly rational is hard) so could still result in very few people switching at all; indeed the systematised review in Chapter 2 suggested that opt-in uptake could be as low as 1%, which is substantially lower than the Government's target of 30% (BEIS, 2016b).

Moreover, allowing people to opt-in would not prevent people from switching who would not benefit from the tariff, as appears to have happened in a number of TOU tariff trials for whom a sizeable minority ended up worse off than if they had stayed on their flat rate tariff (Long Island Power Authority, 2015; Schare et al., 2015; Star et al., 2010; Schofield et al., 2014; Sidebotham, 2014b). It also would not guarantee that the tariffs would disproportionately attract consumers with high flexible electricity use such as EV and heat pump owners; plain active choice may mean some people enrol on a TOU tariff when it will not save them money whilst others might not enrol on a TOU tariff even though it would, as outlined in Table 10.

Johnson (2016), drawing on similar views expressed in Spital (1995, 1996) and Carroll et al. (2009), argues that in these cases a nudge is needed which is effective and selective: it ensures that that people who would benefit from an intervention receive it, whilst ensuring that those who would be worse off do not sign up. Although Johnson (2016) discusses this in the context of mortgage choices where the optimal mortgage will also vary from person to person, in this context, it would mean designing an intervention that increases uptake to TOU tariffs amongst those who can save money (maximising the number in box 1 of Table 10) that does not also attract those who cannot save (minimising the number in box 3), to increase the likelihood of 'getting people into the right box' (Johnson, 2016). The approach described above – tailored marketing – could be used to get people in the right box.

Nevertheless, there are alternatives that could be effective and selective which do not rely on nudge, which, as argued before, is only likely to be more effective if decision making is not approximately rational. Another solution to this problem, which may become available in the near future, is for services to be created which provide bill payers with a comparison of their energy bill under a range of TOU tariffs relative to the most competitive flat-rate tariffs that are based on realistic assumptions about how much the bill payer could adapt their consumption patterns.

These 'predictive' price comparisons could be created using algorithms trained on the electricity consumption data from similar consumers who switched to TOU tariffs. Such algorithms could assume that households with EV and/or heat pumps with storage would have a higher amount of electricity available for shifting into off-peak times than would consumers with just the standard 'flexible' appliances which the UK Governments lists as washing machines, dishwashers and tumble dryers (DECC, 2014; BEIS, 2016b). According to EUT, in the absence of any other market failures (violations of the assumptions in Table 8), such information would be sufficient to ensure enough people – and particularly those with EVs and heating – adopt a TOU tariff to realise the social benefits of DSR and prevent adverse selection. However, even if such services do become available, the same evidence from psychology discussed above suggests that this information will simply not be sufficient to motivate consumers to adopt a TOU tariff, regardless of what appliances they own.

Moreover, tailoring may not be sufficient. Another implication of behavioural economics is that people are not constantly updating their existing knowledge with new information (Camerer et al., 2003), meaning that, even if tailored information is available, it does not guarantee that energy consumers will pay any attention to it. This creates a role for prompts.

8.1 Prompts

Prompts have been effective in a range of contexts and through a variety of mediums as summarised in Table 11.

Table 11. Evidence on the effectiveness of prompts.

Sender	Type of prompt	Outcome
UK Government HM Courts and Tribunals Service	Text	145% increase in court fine payments (Haynes et al., 2013).
Will making service	Telephone	50% increase in the proportion of people who include a charitable bequest in their will during the will-making process (Sanders and Smith, 2016).

HM Revenue and Customs	Email	20% increase in the number of small business owners clicking through to find out about beneficial programmes e.g. Growth Vouchers (Behavioural Insights Team, 2015).
Department for Work and Pensions	Text	80% increase in the number of benefits claimants turning up for recruitment events (Behavioural Insights Team, 2015).
US Department of Defense	Email	40% increase in online enrolment in savings programmes (Social and Behavioral Sciences Team, 2015).
The UK Army Reserves	Email	80% increase in enrolment rates to army reserve (Social and Behavioral Sciences Team, 2015).

The research unequivocally demonstrates that sending some prompt is better than sending no prompt. However, consistent with the evidence on framing discussed above, there is also evidence to suggest that the framing and content of the prompt matters a great deal too. For example, although a text message prompt worked better than no prompt to increase payment of court fines, a second phase of the experiment found that personalising the text message to address the recipient by name increased the average amount paid by 41% from an average of £14.73 to an average of £20.87, which they estimated generated additional revenues of over £800,000 in the one week that the personalised text message was used in the trial (Haynes et al., 2013).

Using prompts to encourage consumers to switch tariff is one of the key recommendations made by the CMA (2016c) to help boost switching rates however it has never been robustly tested. To my knowledge, only one trial has tested prompts to encourage people to switch tariff but had difficulty in identifying the treatment effect because the prompt was delivered in a letter and the outcome was the number of visits to a price comparison website, resulting in a high rate of attrition and making it difficult to robustly identify the treatment to which website visitors had been assigned.[35]

8.2 Timing of information delivery and habit discontinuity

Evidence from the literature on habit formation suggests that the timing of prompt delivery can also be crucial. According to the habit discontinuity hypothesis (Verplanken and Wood, 2006; Verplanken et al., 2008) "behaviour change interventions are more effective when delivered in the context of life course changes…[because] when habits are (temporarily) disturbed, people are more sensitive to new information and adopt a mind-set that is conducive to behaviour change" (Verplanken and Roy, 2016, p.1). Although this evidence is mostly theoretical (Thompson et al., 2011), a small number of studies have tested it empirically amongst people who have recently moved home or otherwise relocated (Wood et al., 2005; Bamberg, 2006; Verplanken et al., 2008; Verplanken and Roy, 2016; Thomas et al., 2016).

In the context of vehicle users, it has been found that people with strong environmental attitudes have lower self-reported car use, but only after recently

[35] The two intervention letters were given unique URLs (e.g. goenergyshopping-test1.com and goenergyshopping-test2.com). However, because most internet providers have auto-complete address bars, it is likely that some proportion of people will have just visited the normal site goenergyshopping.com, and would therefore have been lost to analysis. This trial was run by the Behavioural Insights Team in June and September 2015 in partnership with the Department for Work and Pensions and had a sample size of 270,000 with five trial arms.

moving home (<12 months ago) (Verplanken et al., 2008; Verplanken and Roy, 2016; Thomas et al., 2016). Verplanken & Roy (2016) investigated the total length of this ‘window of opportunity’ for influencing behaviour after a life change and found that, although recent movers (moved under 6 months ago) were statistically significantly more likely to report having participated in new types of pro-environmental behaviours than those who had not recently relocated (moved >6 months ago), this effect disappeared after three months.

This raises the question as to whether, in the same way that moving into a new home is a potential ‘window of opportunity’ to influence people’s use of their vehicles, purchasing ones first EV or heat pump would be a good time to prompt EV owners or heat pump owners to switch to a TOU tariff. All of the Government’s existing tariff switching campaigns are targeted at the average energy bill payer () and timed to coincide with the start of the heating season, when energy bills are higher. However, the previous discussion suggests that such campaigns are unlikely to attract the attention of EV owners or heat pump owners and should instead be tailored to these groups specifically and sent as close to the time at which they purchase their vehicle or new electric heating system as possible.

9 Summary and remaining questions

According to classical economics, under perfect market conditions, the optimal uptake of TOU tariffs will automatically follow from the collectively rational decisions of all the energy bill payers in the market as they go about switching between tariffs to maximise their expected utility. However, since these perfect market conditions rarely materialise, the tariff that is best for the individual is unlikely to be the tariff that is best for society as a whole.

The aim of any TOU tariff recruitment policy should be to bring actual uptake in line with the socially optimal level of uptake. Governments have many tools at their disposal for achieving this, some of which are more politically acceptable than others (John et al., 2009). This includes regulation to mandate TOU tariffs or interventions to increase voluntary uptake such as information provision (to correct imperfect information) and, more recently, nudges, which aim to change “behaviour in a predictable way without forbidding any options or significantly changing their economic incentives” (Thaler and Sunstein, 2008, p.6).

However, there is still a lack of empirical evidence demonstrating the appropriateness or effectiveness of nudge in the energy and environmental domain. In particular, there is a risk that the effectiveness of opt-outs at boosting uptake to organ donor registers and renewable energy tariffs is used to justify an opt-out approach to recruiting domestic consumers onto TOU tariffs.

First, nudge will only be more effective than traditional market failure based interventions such as information provision if consumer behaviour over energy tariffs is not approximately fully rational. It is impossible to say whether energy bill payers are or are not making fully rational choices over their energy tariff solely based on the observation that they have not switched to the cheapest energy tariffs on the market since they may have rationally calculated that the costs of switching do not outweigh the benefits or that other non-price factors are more important (Wilson and Price, 2010). Whilst this explanation may seem unlikely in “a near-homogenous market like electricity”, it remains a possibility because “consumers may perceive that suppliers vary in attributes such as customer service or environmental awareness” or that there are practical non-price benefits of being with one supplier for both their gas and electricity (Wilson and Price, 2010, p.654).

Although it is well accepted by economists and non-economists alike that people will often make choices that do align with a model of perfect rationality (most people make mistakes sometimes, some people make mistakes a lot of the time), failures of rationality at the individual level do not necessarily imply that the classical economic *model* will be inaccurate on average (Friedman, 1953); it is only if a significant number of energy bill payers fail to make rational choices that the classical economic model will be inaccurate as opposed to just simplistic.

Second, even if consumers are boundedly rational, it is not clear that opt-out enrolment is the best nudge to increase uptake to TOU tariffs. The key advantage of opt-out enrolment is that it ostensibly respects freedom of choice and therefore respect for heterogeneity: “Suppose…people are facing serious economic difficulty… and if green energy is more expensive than the alternative, it may…be important to allow consumers to opt out” (Sunstein and Reisch, 2013, p.5). However, if consumers do not have the energy literacy skills required to identify whether a TOU tariff is optimal for them, then consumers may not opt-out of being enrolled regardless of whether a TOU tariff would decrease or increase their energy bill. On the other hand, if energy bill payers are able to rationally process the information required to identify whether a TOU tariff would be optimal for them, there may be no need to be concerned about the welfare of consumers under an opt-out policy. An alternative approach would be to design a nudge that selectively increases uptake amongst those who would benefit from being on a TOU tariff without also increasing uptake amongst those who would not. A promising approach suggested by the literature reviewed in this chapter but also in Chapter 2 would be to tailor the marketing of TOU tariffs towards consumer groups with higher than average flexible electricity use, and actively prompt them to switch at timely moments when theory suggests they will be more susceptible to behaviour change interventions.

EV and heat pump owners were both identified as key groups for participating in DSR in Chapter 2, since both the electrification of heat and transport are expected to place one of the greatest burdens on the future electricity network. Empirical evidence shows that EV owners substantially reduce their peak time and day-time charging when enrolled on TOU rates[36] (Zarnikau et al., 2015) and that the temperature set-point on heat pumps can be lowered at peak times for periods of up to one hour without consumer concern to deliver demand reductions of 3kWh[37] (Sidebotham, 2014a), a useful reduction given that estimates suggest that heat pumps could add 2.5kW each to peak load (Frontier Economics, 2012). Encouraging these consumers to adopt TOU tariffs could save them a significant amount of money, particularly heat pump owners given that electricity is substantially more expensive than gas (Palmer and Cooper, 2012), making affordability a key concern for the electrification of heat (DECC, 2012b).

This thesis therefore aims to answer two research questions, based on the theoretical frameworks discussed in this chapter:

1. Are perfectly informed consumers able to make optimal decisions over their energy tariff? This question can also be rephrased as, is consumer decision making over electricity tariffs affected by bounded rationality?
2. If bounded rationality does affect tariff decision making, could tailoring the marketing of TOU tariffs towards EV and heat pump owners be used to

[36] Peak time and day time charging reduced by 50% relative to a control group of EV owners that were not enrolled on a TOU tariff. The sample size consisted of 40 EV owners (36 on TOU and 6 in the control) which, to my knowledge, is the largest trial of TOU tariffs on EV owners.
[37] In this trial the heat pumps were accompanied with storage, however other trials in which the fabric of the building is used as storage do report overheating being a problem overnight (Fell, 2016).

increase uptake to TOU tariffs amongst EV and heat pump owners whilst reducing enrolment amongst other consumers for whom TOU tariffs could make them financially worse off?

The hypotheses belonging to each of these research questions are outlined in the results chapters because they are closely related to the design of the experiments.

This concludes Chapter 3. The next chapter outlines the broad methodological approach taken to answer the questions above.

Chapter 4

Methodology:

Field experiments combined with population-based surveys

1 Introduction

This thesis has two overarching aims: (1) synthesise the empirical evidence on consumer demand for TOU tariffs and; (2) provide evidence on how to increase British consumer demand without enrolling people onto TOU tariffs by mandate or by default. To fulfil the second aim this thesis intends to answer two research questions, namely: (1) What proportion of British energy bill payers can identify the cost-minimising tariff when given all the information required to choose between flat rate and TOU tariffs? and (2) Can tailored message framing be used to increase uptake to TOU tariffs amongst consumers who are more likely to save money from switching to one whilst reducing uptake amongst those less likely to save?

The design and results of the systematised review used to achieve the first aim was presented in Chapter 2. This chapter will justify the broad methodological choices made when designing the studies used to answer the two research questions relating to the second aim: online field experiments combined with online population-based surveys, with and without an experimental design.

The chapter will start, in Section 2, with an outline of why an online survey was used to answer research question 1. Section 3 will outline why online natural field experiments and an online survey experiment were used to answer research question 2, focusing on how the strengths of any one method will be used to help to overcome the limitations of another.

Section 4 concludes this chapter. The detailed description of the four individual studies (the methods) will be provided in the each of the study chapters themselves. The key threats to the internal validity of randomised control trials (RCTs) as well the ethical considerations of the approach used are in Annex 4.

2 Empirical strategy for research question 1

2.1 Online survey

The first research question asks whether energy bill payers' decision making over tariffs is, or could be, affected by bounded rationality. In line with work on financial literacy (Lusardi and Mitchell, 2006b, 2008; van Rooij et al., 2011), this will be tested using a survey in which energy bill payers are asked to identify the cost-minimising tariff in the presence and absence of TOU tariffs when given all the information required. In the similar way that financial literacy is measured by, for example, asking people to calculate savings from bank accounts with different interest rates (Lusardi and Mitchell, 2006b, 2008), participants will be presented with fictional individuals who are looking to switch tariff and asked to identify the cheapest of a set of three possible tariffs, given the individuals' electricity consumption in kWh and the price of electricity. In the first scenario, the set of tariffs will only include flat-rate tariffs but in the second scenario it will include a TOU tariff.

This exercise does not assume that the cheapest tariff is the optimal tariff; it merely tests people's abilities to undertake a costs-benefit analysis, or what economists sometimes call solving optimisation problems, in the specific context of an energy tariff choice. As discussed in Chapter 3, full rationality means having the unbounded computational capacity to undertake cost-benefit analyses whereas bounded rationality relaxes this assumption by implying there are inescapable cognitive limits on peoples' abilities to process the information required to make trade-off choices. If consumers cannot undertake a cost-benefit analysis based on one variable, in this case price, then it is unlikely that they will be able to undertake a cost-benefit analysis in which they also need to make trade-offs between multiple factors such as price, customer service, green energy, online account management and so on, particularly given that, according to the classical theory, people would have to assign a fictional financial value to these individual items to undertake the analysis.

The purpose of the Tariff Decision Making Experiment is not to mimic the decision-making process that British energy bill payers currently go through to choose a tariff since only a small sub-group of consumers switch tariff and it is likely that a large majority never consider the decision; in other words, the survey will not measure what proportion of consumers who switch tariff now are subject to bounded rationality. The question aims to understand what proportion would be able to make this decision optimally, in the sense defined by a classical economist, if everyone were put in a position where they had to decide which energy tariff to switch to (e.g. under an opt-out policy).

The survey will be administered online for two reasons. First, an online survey is a more suitable medium for administering the numeracy questions than a telephone or face-to-face survey. It is expected that people will need time to consider the numeracy problem presented. However, a telephone or face-to-face survey could make people feel pressurised to provide an answer quickly which could increase the likelihood of people guessing the answer, whereas people given the opportunity to solve the problem at home may have attempted the necessary calculation. Moreover, even if TOU tariffs were made the default tariff, consumers are unlikely to be required to decide whether or not to opt-out during the course of a single telephone or face-to-face conversation with their supplier.

Second, postal surveys are more expensive, without providing significant additional benefits over online surveys. Although both online and postal surveys could avoid 'interviewer' effects, the only major advantage of a postal survey over an online survey is that postal surveys can be administered to a random sample of the population of interest, whereas online surveys can only be administered to people with Internet access who have also agreed to participate in market research (Duffy et al., 2005). However, postal surveys still suffer from selection error due to participant non-response (Duffy et al., 2005).

A recent study which investigated people's attitudes towards TOU tariffs using postal surveys delivered to a randomly selected sample of addresses in Australia received a response rate of 5% (Stenner et al., 2015).[38] Moreover, coverage bias in online surveys is less of a problem now that 88% of British adults have Internet access (Office for National Statistics, 2016b) and, even so, the bias could be said to work in favour of the research. Internet access (Office for National Statistics, 2016b) and therefore participation in online surveys is higher amongst young people (Duffy et al., 2005) but numeracy skills decline with age (Department for Business Innovation & Skills, 2012). This would mean that a relatively young participant sample from an online survey is likely to provide a conservative estimate of peoples' numeracy skills compared to a similar postal survey, making it a more stringent test of the hypothesis that consumers are able to identify the cost minimising tariff when equipped with all the information.

Survey weights are sometimes used to try to correct for selection error. However, whilst this thesis will present both weighted and in-sample estimates of descriptive statistics, following the advice in (Solon et al., 2013), weights will not be used when estimating causal effects because there is no nationally

[38] Research shows that postal surveys tend to have relatively low response rates, as compared to face-to-face and telephone surveys (Duffy et al., 2005) and sometimes (Lonsdale et al., 2006), but not always (McDonald and Adam, 2003), online surveys.

representative dataset on British energy bill payers against which survey participants can be compared and from which reliable weights could be constructed. Instead, the thesis will present full descriptive statistics of the sample and interpret the results in light of the characteristics of the participants in the sample (see Annex 3 for a full justification of this choice).

Finally, although energy suppliers would likely write to their customers if they were defaulting them onto a TOU tariff – lending external validity to postal survey – an increasing number of bill payers manage their accounts online so would receive such a notification via email (Ofgem, 2015). Therefore, online surveys are more suitable than face-to-face or telephone surveys and, on balance, are likely to provide data of similar quality to a postal survey, much more quickly and at a substantially lower cost.

Although surveys are criticised as a research method for measuring future or past behaviour on the basis that people may intentionally or unintentionally misreport their behaviour (Whitehead and Blomquist, 2006; Morwitz et al., 2007; Kormos and Gifford, 2014), these criticisms do not apply here. This survey aims to measure whether people are able to correctly identify the cheapest tariff and the answer will be objectively right or wrong.

A survey is also the best available method to answer this question because it relies on being able to provide consumers with all the information required to compute the cheapest tariff, including their overall electricity consumption and their electricity consumption patterns across the day, as would be available to all smart meter customers in future. There is currently no way of directly observing the choice of tariff made by consumers in the real world which would also permit me to evaluate whether their choice was economically optimal given that smart meter data is not widely available; even if this choice was easily observable and verifiable, it would not provide the evidence required because, since only a small proportion of consumers switch tariff, the data would not provide any indication of the decision making abilities of the wider population of energy bill payers who do not switch tariff and it is this whole group, not the sub-group of switchers, who would be affected by a policy of opt-out enrolment for TOU tariffs.

Getting participants to solve the numeracy problem required to identify the cheapest tariff in a survey has two advantages over the only other known study (Wilson and Price, 2010) to have investigated whether consumers can select the cost-minimising tariff. The reasons for this are made clear below.

2.2 Strengths of the numeracy question approach

Unlike Wilson and Price (2010), the survey design described identifies whether consumers are able to recognise the cost-minimising tariff (i.e. regardless of whether in reality, they would also seek to maximise factors other than price) and whether bounded rationality, rather than imperfect information, could explain why consumers cannot identify the cheapest tariff, if any do not.

First, since participants in this survey are explicitly asked to identify the cheapest tariff, a failure to select the cheapest tariff cannot be interpreted as being due to the fact that people are trading off price against other non-price factors which they value; as discussed in Chapter 3 this possibility prevents researchers and the CMA from definitively inferring that unexploited savings from switching are evidence of sub-optimal decision making.

Second, since consumers have all the information they need to answer the question[39], information can no longer present a key barrier to getting the answer correct and therefore to optimal decision making; as discussed in Chapter 3, the finding that 80% of consumers appropriated between 30%-50% of the maximum gains available is “wholly consistent with that of rational consumers facing high search costs” (Wilson and Price, 2010, p.648). The time required to undertake the calculation should also be minimal if consumers have unbounded computational capacity.

Having eliminated energy information search costs, time costs and potential unobserved non-price factors – and based only on the theoretical models presented in Chapter 3 – only one other potential cost is not omitted from the two scenarios: this is ‘thinking costs’, the cognitive effort required to process the information. A classical economic model assumes that humans have unbounded computational capacity (see assumption 1 in Table 8 in Chapter 3) and therefore does not acknowledge the existence of ‘thinking costs’; the explicit purpose of this exercise is to test the validity of this assumption in the context of choosing between energy tariffs.

As outlined in Chapter 3, psychologists, and now behavioural economists, do assume that thinking costs play a role in decision making and it suggests two possible ways in which a participant might respond to a problem that imposes high cognitive costs. One approach is to avoid making a decision altogether, a tendency which is thought to account for inertia or so-called status-quo bias (Samuelson and Zeckhauser, 1988; Kahneman et al., 1991; Keller et al., 2011).

[39] The only type of information not provided is information on the method required to undertake the calculations. The implications of this will be reserved for discussion in Chapter 5, which presents the results of the study.

Another is that people may consciously or unconsciously process only some of the information, thereby lowering the cognitive costs; for instance, people may only process the unit rate of the tariff but forget to include the standing charge in their calculation. To distinguish between inertia and an inability to undertake the calculation, people will be given the option to say they do not know the answer (abbreviated to DK). According to behavioural economic theory, fully rational consumers will undertake the calculation correctly whereas boundedly rational consumers will either undertake the calculation incorrectly or not attempt the calculation at all and select DK. The null hypothesis implied by the classical economic model is that there is only one type of person: the fully rational consumer.

2.3 Addressing potential limitations of the approach using task simplification

The main limitation to the survey method employed is that it was not possible to financially reward participants for getting the question correct.[40] The concern may therefore be that people would select a 'don't know' response (abbreviated to DK) or even select a response at random, not because they are unable to do the maths, but because doing so would make no difference to what they are paid. However, this does not fundamentally undermine the ability of the study to achieve its aims, which are to: (1) test the validity of the assumption made by classical economics which is that consumers are fully rational, which is defined in part as having unbounded computational capacity (see assumption 1 in Table 8 of Chapter 3) and; (2) provide an indication of what proportion of consumers, if

[40] Participants were paid solely for completing the survey but the company running the consumer panel from which participants were recruited would not allow the participants to be paid extra for correctly identifying the cheapest tariff.

any, would fail to correctly identify whether a TOU tariff would increase or decrease their electricity bill if they were put in a position where they needed to make this choice e.g. under a policy of opt-out enrolment.

This is because the classical economic model presents a very high bar against which to judge human computational ability. Unboundedly rational consumers should require very little time to solve primary-school level numeracy problems, meaning that the proportion of people saying they DK or selecting a response at random should be negligible – at least according to classical economics. Therefore, both incorrect and DK responses are inconsistent with the assumption of full rationality. Given the simplicity of the task, if a large proportion of people get the answer wrong or say they don't know, this is much harder to explain using a model of a fully rational consumer than that of a boundedly rational consumer.

As regards the second aim of the study, the absence of an additional financial incentive means that survey participants have less of an incentive to identify the cheapest tariff than would people deciding whether to opt-out of being enrolled onto a TOU tariff or to sign up to a TOU tariff in real life. Although this does not mean that participants have no incentive to get the answer correct – people who participate in market research panels are under the expectation that they are being paid to answer questions correctly and to the best of their ability – the study is at risk of overestimating the proportion of people who would be unable to identify whether a TOU tariff would increase or decrease their energy bill relative to alternative tariffs under an opt-out or opt-in policy. To help counterbalance a possible overestimation bias, the vignette and problem will be designed so that it is substantially easier to identify the cheapest tariff in the vignette than in real life. Moreover, if a sufficient number of people get the question wrong, then the results will be meaningful regardless; for example, if 30% of people incorrectly identify the cheapest tariff, but this proportion is overestimated by 50% due to the imbalance in incentives, then depending on the representativeness of the sample, this may still imply that 15% of all energy bill payers (4.2 million people) cannot identify the cheapest tariff and could be adversely affected by an opt-out policy.

2.4 Summary

Asking consumers to identify the cheapest tariff in an online survey is a suitable approach for answering the question because it isolates energy bill payers' abilities to identify the cheapest tariff from other factors that might affect what tariff people choose. The possible influence of these other factors is what makes it unwise to draw the conclusion that people are boundedly rational from the observation that consumers are foregoing large savings by not switching tariff (CMA, 2016c).

Determining whether bounded rationality could be playing a role is important for verifying the underlying model that explains consumer decision making and therefore what types of interventions are likely to increase switching rates in general and to TOU tariffs in particular (research question 2). The second research question is a causal question and will be answered using RCTs, for reasons outlined in the next section.

3 Empirical strategy for research question 2

3.1 Advantages of field experiments: clean, generalisable causal analysis

The key virtue of RCTs is that they enable a clean estimation of causal effects (Rubin, 1974; Holland, 1986; Angrist and Pischke, 2008; Athey and Imbens, 2016). Consider research question two: can tailored message framing be used to increase uptake to TOU tariffs amongst consumers who are more likely to save money from switching to one? In a RCT, the treatment – whether or not a tariff is marketed as being suitable for EV and heat pump owners – is assigned to subjects at random. This means every heat pump or EV owner would have a known probability between 0 and 1 of being placed in the treatment group (the group in which the TOU tariff is marketed as being particularly suitable for EV and heat pump owners) or the control group (the group in which the tariff is marketed to the average energy bill payer).

Random assignment ensures that, on average, the units in the treatment group are the same as the units in the control group (Gerber and Green, 2012). Subject to two other identifying assumptions being met[41], the difference between average demand for the tariff in the tailored marketing group and average demand for the tariff in the generic marketing group is the *causal* effect (or treatment effect) of tailoring on demand for the TOU tariff, as laid out in the potential outcomes framework of causality (Fisher, 1925; Neyman and Pearson, 1928; Rubin, 1974; Holland, 1986).

Nevertheless, whilst RCTs permit the estimation of causal effects, there can be doubts over "the extent to which a causal relationship [uncovered in a RCT] holds over variation in persons, settings, treatments, and outcomes" (Shadish et al., 2002, p.83). For instance, RCTs run in laboratory settings are often run on student populations where the effect of the intervention is measured on proxies

[41] These assumptions are excludability and non-interference (Gerber and Green, 2012). The excludability assumption is that the outcomes are only affected by the treatment and not by any other factors such as "a variable that indicates which observations have been allocated to treatment or control" (Gerber and Green, 2012, p.39). The non-interference assumption is that the outcome for one unit is uncorrelated with the treatment assignment of other units. This assumption is also sometimes called the Stable Unit Treatment Value Assumption (SUTVA).

for the real outcome of interest, such as willingness to accept or adopt a TOU tariff, a measure commonly known as a ‘stated preference’. The experimental research on consumer uptake of TOU tariffs in GB is almost exclusively based on energy bill payers’ willingness to switch to a TOU tariff in stated preference surveys as shown in the review in Chapter 2.

However, the intention of Dutch university students to switch to a TOU tariff or how switching intention is influenced by how the tariff is described (Verhagen et al., 2012) may not be a very good predictor of what proportion of energy bill payers, or EV owners, will sign up to a TOU tariff regardless of how it is marketed. Whilst stated preference surveys can generate useful insights on how people feel about products or services (Johnston et al., 2017), there are many well-known problems associated with relying solely on measures of demand collected stated preference surveys (Arrow et al., 1993; Diamond and Hausman, 1994; Whitehead and Blomquist, 2006).

In the case of energy tariffs, people may pay less attention to the way a tariff is described in a hypothetical scenario than if the decision had real-world consequences or may even pay more attention because they are being explicitly paid to read and answer questions about one. Finally, there is no guarantee that the people who agree to participate in such trials are likely to have the same views or respond in the same way to treatments as the often much larger proportion of people who do not agree to take part (List, 2011).

To address such external validity concerns, researchers have started running RCTs in a natural setting amongst participants from the population of interest, which in this thesis is energy bill payers or EV and heat pump owners. RCTs run in natural settings are called field experiments (Gerber and Green, 2012). In addition to being run in a natural setting, field experiments will usually measure the impact of real-world interventions on behavioural outcome variables, such as switching to a tariff or signing up to receive email alerts about switching tariff. List (2011) distinguishes between two types of field experiments, namely "natural" field experiments and "framed" field experiments. Participants of the former are not informed that their behaviour is subject to scrutiny or that they are being randomised to treatments whereas the latter are informed. The treatment effect in a natural field experiment thus represents the average causal effect for the full population, "not for a non-random subset that chose to participate" (List, 2011, p.7) or an average effect that also captures the impact of being observed as being treated, known as evaluation driven effects such as the Hawthorne Effect (Glennerster and Takavarasha, 2013).

From the 1970s to 1990s, field experiments have been adopted as the key tool for policy evaluation in the US (Duflo, 2016) and, since the free text book trials and PROGRESA experiments in the 1990s, in development economics too (Cameron et al., 2016). In the UK, the Education Endowment Foundation (EEF), established with £125 million in funding from the Department for Education and the Sutton Trust, conducts field experiments in UK schools. Natural field experiments, in particular, are also becoming progressively more common. In 2010, the UK Government established the Behavioural Insights Team, a research team within the Cabinet Office that is now an independent social purpose organisation that has run hundreds of natural field experiments, mostly in the areas of education and health.

In contrast, RCTs and field experiments are rarely used in the energy domain (Allcott and Greenstone, 2012; Vine et al., 2014; Frederiks et al., 2016). For instance, the trials that were run to measure the impact of smart meters on household energy demand either had no control group or included groups that were called a ‘control’ group, even though participants were not randomly assigned (Raw and Ross, 2011). There has been significant criticism of the lack of use of RCTs in the evaluation of energy policies. According to Allcott and Greenstone (2012, p.5), the large literature assessing the impact of energy efficiency improvements on energy demand “frequently does not meet modern standards for credibility” (5) and that there is therefore:

> *…great potential for a new body of credible empirical work in this area [energy efficiency], both because the questions are so important and because there are significant unexploited opportunities for randomised control trials…that have advanced knowledge in other domains.*

A natural field experiment would therefore be an ideal method for answering research question 2, which aims to identify the causal impact of tailoring on demand for TOU tariffs but one which would generalise if the intervention was rolled out by suppliers or the energy regulator in real life. However, whilst field experiments are frequently hailed as the gold standard for impact evaluation and causal analysis (Gerber and Green, 2012; Glennerster and Takavarasha, 2013), they have limitations. The next section outlines these limitations as well as how this thesis aims to overcome them to answer research question 2.

3.2 Limitations of field experiments

There are three key limitations of field experiments that are relevant to the questions posed in this thesis. First, running experiments in the field provides substantially less experimental control. For instance, as noted above, to run a *natural* field experiment, participants cannot be made aware that they are participating in research. However, this makes it much harder to collect the baseline data required for measuring whether the treatment effect varies across different types of people, so-called treatment effect heterogeneity. Measuring treatment effect heterogeneity is crucial for answering research question two, because it involves determining whether tailoring the marketing of TOU tariffs not only increases uptake amongst EV and heat pump owners but also whether it decreases uptake amongst consumers who do not belong to these groups. Survey experiments make it much easier to collect baseline information on participants and to measure uptake to tariffs that do not yet exist.

However, relying on survey experiments alone is unwise because, as alluded to above, there is a well-known gap between behavioural intentions and action (Whitehead and Blomquist, 2006; Morwitz et al., 2007), a gap which may also explain why so many more people say they would switch to a TOU tariff in surveys than have signed up to commercially available TOU tariffs (Chapter 2). To obtain information on the people participating in the trial a number of field experimentalists administer baseline surveys to their participants (e.g. Giné et al., 2010; Fryer, Roland G et al., 2012; Milkman et al., 2014). However, randomising treatments to the sub-group of solicited people who completed the survey defeats one of the key potential advantages of running a field experiment (avoiding Hawthorne effects) and means that the results may only be generalised to the types of people who agree to participate in research (List, 2011).

Second, in a similar way that it would be hard, if not impossible, for an historian to use a field experiment to test the causes of wars that happened several hundred or thousands of years ago, it is also challenging for energy researchers to test the impact of interventions aimed at increasing the adoption of products and services that may not be widely commercially available for years and sometimes decades in the future. In particular, the technologies, products or services that we want to encourage consumers to adopt are either not widely commercially available due to their currently high price (e.g. electric vehicles, hydrogen vehicles, heat pumps, home batteries) or not commercially available at all (e.g. TOU tariffs, autonomous vehicles). The ideal field experiment would ostensibly involve partnering with an energy supplier that offers a TOU tariff to implement an intervention in collaboration with the supplier without alerting would-be customers that they are being randomly assigned to different conditions.

An alternative design that would also capture people who may not already be in the market for switching energy tariff is to implement an intervention independently of an energy supplier but that could be linked to data on switching rates by tariff type. However, as noted throughout this thesis, none of these types of tariffs or DSR programmes were commercially available anywhere in the UK (or indeed most of Europe) at the time of data collection. At the time of writing, there are now two smart meter enabled TOU tariffs in Britain, but arguably only one of these[42] is designed to address the challenges that will be faced by the future energy system.

Third, since the privatisation of the retail electricity markets, all data on customer switching is held by individual suppliers or price comparison websites. Even if Ofgem or another organisation implemented some intervention, it is not possible to measure its impact since the outcome data is not readily available. Although data availability is a challenge faced in many disciplines, I would argue that data availability is particularly problematic in the energy domain. For instance, the US

[42] This tariff is the TIDE tariff by Good Energy, which is a three rate TOU tariff of the type that features in this thesis. The other tariff, offered by one of the Big Six Energy Suppliers, arguably is not well suited to balancing renewable energy supplies with domestic demand or alleviating the evening peak in demand.

AID's Demographic and Health Surveys provide nationally representative individual level data on key health and employment variables across 90 countries around the world, available to researchers at the click of a button. In the UK, health researchers have access to longitudinal datasets such as the Whitehall II and Millennium Cohort Studies to study potential causal determinants of health outcomes. By comparison, up until very recently, energy researchers could not even access data on Energy Performance Certificates for homes, which contain modelled data on the household energy efficiency of properties and basic variables such as floor area and dwelling type that are crucial to understanding energy demand in the UK.

These challenges, as well as others, have led to some degree of scepticism in the energy area about the applicability of trials to energy research questions (Cooper, 2017), which has developed alternative methods of overcoming the challenges presented by undertaking research in a highly future-facing context including agent based modelling (e.g. Kowalska-pyzalska, 2015) and optimisation models such as MARKAL and UKTM-UCL (Usher and Strachan, 2010; Daly and Fais, 2014) which do not necessarily rely on collecting any empirical data. However, consumer preferences cannot be measured without empirical data. Causal inferences, at least in the social sciences, cannot be made without empirical data either.

It is therefore clear that a new approach is required to adequately answer research question two. Despite the challenges discussed above, lessons for how a natural field experiment, or series of field experiments, could be designed to answer research question 2 can be gleaned from areas outside of energy, namely, the literature on using Internet data for economics and psychology studies (Edelman, 2012; Wiedemann, 2013; Kosinski et al., 2015, 2016) and preference measurement and experimentation in the technology start-up industry (Ries, 2011).

3.3 Online experiments in academia and by tech-startups

Commercial organisations such as Facebook and Google have long recognised the benefits of frequent experimentation to improve the design of their websites (Varian, 2010). Academic researchers have also recently been exploiting the potential of the Internet to run a range of innovative field experiments (for a review of online economics experiments, see Edelman, 2012). In some cases, the experiments are run in partnership with existing websites, as in the study by Blake et al. (2017) on the effect of price salience on purchase choices of visitors to the ticket reselling website StubHub.com. In other cases, the experiment can be run by making use of an online retailers existing functionality; a case in point is the early eBay experiments, in which economists varied a range of features of eBay postings to monitor its effects on bidding behaviour (Katkar and Reiley, 2006; Paul et al., 2006; Hossain and Morgan, 2006; Einav et al., 2012).

More recently, increases in the technical expertise amongst commercial developers and academic researchers has made it possible to modify the design of entire websites without any involvement with outside commercial organisations at all (Schechter et al., 2007; Edelman and Duncan S Gilchrist, 2012). For instance, Edelman and Gilchrist (2012) investigate the impact of using clearer labels for paid advertisements that appear in Google search listings on peoples' propensity to click on the adverts. To do this, they built a proxy Google website that presents a random sub-set of participants with modified advert labels ("paid adverts" rather than the more euphemistic label, "sponsored adverts").

A limitation to the realism of the website proxy method is that it relies on giving the participants the proxy website address or configuring the Internet settings on the participants' device. Therefore, whilst the intervention is realistic, the context is not since it has to be run in a laboratory setting, thereby introducing the risk of Hawthorne Effects. A better option is to develop a website independently to which participants would be driven in the way recommended to would-be entrepreneurs (Ries, 2011).

In the influential book, *The Lean Startup*, Ries (2011) promotes the use of customer waiting lists whereby potential entrepreneurs create websites for their product or service as if it were commercially available today, to which potential customers are invited to express their interest by providing their personal details. In some cases, participants can pay for the product upfront as part of a crowdfunding campaign, as on Crowdcube.com and Kickstarter.com. Other companies have extended this idea into a model for their entire business; the website itself may be cryptic about whether the product or service has yet been developed and/or when it might be shipped to consumers, on the basis that if a sufficient number of potential customers express their interest, the product will become cost effective to create. This was the original business model of the online furniture retailer Made.com (Giudici, 2014).

The key advantage of the approach recommended in Ries (2011) is that the proportion of people who sign-up to such waiting lists or are willing to put their own money at stake in a crowdfunding campaign, are likely to provide would-be entrepreneurs with much better approximations of future sales of their product than would a market research survey that asks people to say how willing they would be to purchase the product if it came to market on a rating scale.

If the realism of the technology entrepreneurs approach was combined with the controlled experimentation used by the academic economists by creating a website that resembles an energy supplier's website (a fictional energy company) then the Internet could also be used to collect information on consumer demand for TOU tariffs depending on how the tariff is framed to consumers. This would enable data to be collected on switching as well as key causal antecedents[43] of switching such as obtaining a quote, page views and visiting the page of the website from which it is possible to switch. Similarly, an email experiment would generate data on the proportion of recipients who open the email and the proportion who click-through to visit information about switching to a TOU tariff.

These types of outcome measures – actions taken by people through digital products and services – are known as "digital footprints" (Kosinski et al., 2016, p.493) and they are much easier to measure than switching rates themselves. Digital footprints also generate a large amount of user data including "web browsing logs, records of transactions from online and offline marketplaces, photos and videos, global positions system location logs, media playlists, voice and video call logs, languages used in Tweets or e-mails, and much more" (Kosinski et al., 2016, p.493). This is also desirable because RCTs often require large sample sizes in order to detect small but substantively important treatment effects (Coe, 2002; Sanders and Chonaire, 2015).

Of course, there are still potential limitations to these approaches. First, there is still an element of self-selection of participants involved in the eBay experiments and there would also be self-selection involved in an experiment in which people

[43] A causal antecedent of switching is any behaviour which a consumer must or is likely to take prior to switching, such as visiting the website of a supplier to obtain a quote, given that suppliers will not allow consumers to switch without first obtaining a quote.

were visiting an energy supplier's website, whether that website was real or not. To avoid this, an intervention would also need to be tested in an online environment that is not already likely to be frequented by people who are more amenable to switching tariff. This would require using unsolicited marketing techniques.

Second, as outlined in Athey and Imbens (2016), results from a single field experiment will not necessarily generalise if and when any intervention tested is rolled out because an experiment will usually always be limited to a particular geographic location, time or subpopulation. According to Athey and Imbens (2016, p.6) "most concerns with external validity are related to treatment effect heterogeneity" with the solution being to run multiple RCTs in different contexts and comparing the results, as in Meager (2015), or to estimate treatment effects conditional on observed covariates.

This thesis will therefore answer the same research question using data generated from multiple RCTs run in the context of a natural online field experiment and a population-based survey experiment. A natural field experiment could be run on different sub-groups of the population of interest separately, for example, one trial run exclusively or predominantly on EV and heat pump owners to estimate the average treatment effect on that population sub-group. This effect could be compared with a heterogeneous treatment effect (treatment by covariate interaction) measured in a survey experiment involving all members of the population of interest because data can be collected to identify who is an EV or heat pump owner and who not. The advantage of using this combined approach is that the natural experiments enables the estimation of a treatment effect that is free of evaluation-driven effects on a behavioural outcome variable; the survey experiment enables the treatment effect to be estimated on multiple sub-groups in the same experiment.

Thus, field experiments combined with population-based survey experiments is a more suitable strategy for answering research question two than relying on field experiments alone; this combination can obtain an unbiased estimate of the causal effect of tailored message framing on demand for TOU tariffs amongst the average member of the population and sub-groups such as EV and heat pump owners that is also likely to generalise if the treatment was rolled out in real life.

3.4 Summary: online natural field experiments complemented by survey data

An empirical approach is required to answer both research questions in this thesis. The first research question – is consumer decision making over tariffs affected by bounded rationality? – is descriptive and requires the price of electricity and total amount of electricity consumed to be fixed so that there is an ex-ante optimal tariff. This question can therefore be most suitably answered using an online survey using narrative vignettes.

The second research question – can tailored message framing increase demand for TOU tariffs amongst EV and heat pump owners? – is a causal research question. Natural field experiments run on UK energy consumers are the most suitable empirical method to provide robust estimates of the treatment effect of tailored marketing on demand for TOU tariffs that is more likely to generalise if applied by energy suppliers in real life than if the experiment were conducted in a laboratory setting amongst a convenience sample of students.

Whilst the ideal field experiment would ostensibly involve partnering with an energy company that offers a TOU tariff, such a design is not an option because these tariffs were not commercially available to domestic consumers at the time of data collection. Even though one relevant TOU tariff is available at the time of writing, this would still severely limit the amount of experimentation that could be conducted since one supplier is unlikely to be able – or even willing – to host the number of experiments required to answer many of the unanswered questions about the likely consumer adoption of TOU tariffs and DSR services in general.

To overcome this challenge, whilst producing results which are likely to generalise to a real-world setting, two innovative field experiments will be used. Informed by the natural online field experiments conducted by economists, the first field experiment will involve creating a website for a fictional energy supplier which will promote a TOU tariff designed by a GB energy supplier to be commercially viable in GB in the near future. Informed by the research on digital footprints and the text message trial conducted by Haynes et al. (2013), the second will be an email experiment conducted in partnership with OLEV for which the outcomes will be click-through rates and open rates to tariff switching information, potential causal antecedents of switching tariff.

Running a natural field experiment, whether online or not, reduces the likelihood of obtaining baseline data on participants required for baseline randomisation checks and to test for treatment effect heterogeneity, the latter of which will be especially important if the treatment is only expected to work on consumers belonging to a certain group, as is the assumption here that tailoring information to EV owners will only be effective on EV owners. For example, in the eBay experiments (Katkar and Reiley, 2006; Paul et al., 2006; Hossain and Morgan, 2006; Einav et al., 2012), researchers were able to observe bidding behaviour in full but would not be able to identify any user characteristics. In Blake et al. (2017), data on participant characteristics was only available for the sub-group of participants who logged into their user profiles on StubHub.com.

This thesis aims to overcome this trade-off in four ways: (1) Targeted sampling for the field experiments to try to confine recruitment to participants of certain characteristics; (2) Embedding surveys within the context of the field experiment that appear to be part of the normal course of undertaking the behaviour in question to obtain descriptive statistics on the sample without alerting participants to the experiment; (3) Complementing the results of the natural field experiments with a population-based survey experiment (Mutz, 2011) amongst a nationally representative sample of British energy bill payers who are paid to complete baseline information prior to exposure to treatment; (4) Running a field experiment on a population that is already known to consist solely of EV owners. Population-based field experiments use "survey sampling methods to produce a collection of experimental subjects that is representative of the target population of interest [with] subjects…randomly assigned to experimental conditions by the researcher, and treatments administered as in any other experiment" (Mutz, 2011, p.2).

The field experiments provide authentic outcome measures, interventions, context and participants whilst the population-based field experiment provides authentic participants but greater experimental control to obtain a full range of baseline information on participants to make it easier to measure treatment effect heterogeneity. Measuring the impact of the same intervention in multiple settings and on different sample populations is recommended by Athey and Imbens (2016) to enhance the generalisability of results from field experiments.

The population-based survey experiment will, like the survey used to answer research question 1, be administered online. Online surveys provide a better medium by which to present people with tailored marketing of tariffs than a telephone survey and, since doorstop selling of energy tariffs is banned, a face-to-face survey would not provide results that are likely to generalise if such marketing was implemented in reality. As argued in Section 2 Empirical strategy for research question 1, online surveys provide a similar level of data quality as postal surveys at much lower cost.

Although it is becoming increasingly common to combine field experiments with surveys to collect baseline information on participants (Glennerster and Takavarasha, 2013), it is much less common to embed a survey within the context of a natural field experiment in a way that does not alert participants to the fact that an experiment is being conducted, to avoid compromising the generalisability of the results. Moreover, although there are a number of field experiments being run in a range of policy contexts such as education and health, it is rare for a researcher to answer the same research question using data generated from multiple RCTs.

Further, whilst field experiments have been adopted as the key tool for policy evaluation in the US since the 1970s (Duflo, 2016) and, more recently, for some policy areas in the UK and in the development economics literature too (Cameron et al., 2016), RCTs and field experiments have scarcely been applied to causal questions of interest in the energy domain (Allcott and Greenstone, 2012; Vine et al., 2014; Frederiks et al., 2016).

In the preceding section, I argued that this is likely to be due to the challenges involved in running field trials in highly future facing settings like energy where many of the low-carbon technologies of interest are not yet commercially available and policies have no international precedent. However, since consumer adoption is a key part of the success of these technologies or policies, it is not advisable to wait until the technologies function or the policies have been designed before conducting robust consumer adoption trials. One of the contributions of this thesis is to demonstrate ways in which field experiments could be used to answer causal questions of research in the energy domain despite the challenges.

4 Conclusion

The purpose of this section was to justify the research design in the context of the potential alternatives (the methodology). The detailed description of the four individual studies (the methods) will be provided in the each of the study chapters themselves. Chapter 5 will present the design and results of the Tariff Decision Making Study; Chapter 6 will present the design and results of both the Flex Trial and the Population-Based Survey Experiment and; Chapter 7 will present the design and results of the OLEV trial.

Chapter 5

Results (1):

The Tariff Decision Making Study – energy bill payers struggle to optimise

1 Introduction

This thesis has presented two research questions to address the gaps in the literature highlighted in Chapters 2-3 and an approach to answering these questions in Chapter 4. Chapter 3 proposed a theoretical model of consumer heterogeneity in which an energy bill payer's likelihood of adopting a TOU tariff is influenced both by whether they have the household appliances and consumption patterns required to save money on a TOU tariff, consistent with a classical economic model, as well as whether the consumer is fully or only partly (boundedly) able process the information required to identify whether a TOU tariff is the optimal tariff for them. This model motivated my argument that enrolment to TOU tariffs should be voluntary and that consumers could not be automatically enrolled onto a TOU tariff by default to boost enrolment rates because we could not expect boundedly rational consumers to be able to identify whether a TOU tariff was right for them and opt-out if it is not.

This chapter presents the results of the Tariff Decision Making Study, a population-based survey designed to test whether consumer decision making over electricity tariffs really is affected by bounded rationality (research question 1), as proposed in Wilson and Price (2010) and the theoretical model presented in Chapter 3. It also tests whether bounded rationality is more likely to affect TOU tariffs than flat-rate tariffs and whether it varies across consumers in low and high socio-economic grades.

Testing these hypotheses is not only important to identify whether there is empirical support for the hypothesis that motivates research question 2 (whether tailored marketing could work as an alternative to opt-out), but also whether ‘nudge’ in general is even an appropriate approach to increasing uptake to TOU tariffs.

As outlined in Chapter 3, the effectiveness of nudge is conditional on the idea that consumers are making sub-optimal decisions due to cognitive biases such as status-quo bias or limitations in their cognitive capacity to process the relevant information (bounded rationality) rather than just the usual market failures such as imperfect information or any other potential drivers of decision making (Benartzi et al., 2017). Nevertheless, the fact that many energy bill payers do not switch tariff despite the large savings on offer may or may not indicate that their decision making is sub-optimal. For instance, although we know that many consumers are not on the cheapest tariff (CMA, 2016b), it is hard to rule out the possibility that they are factoring other features into their decision other than price (Wilson and Price, 2010); if they are, then the fact that consumers are foregoing large savings is perfectly consistent with a model of a rational decision maker who is trading-off between price and non-price factors that they value.

Further, even if consumers are not making optimal choices, little research has asked whether this is due to a lack of access to the high quality information necessary to make the choice or whether it is because bill payers simply do not know how to undertake cost-benefit analyses very well (bounded rationality). In the absence of smart meters, it is highly likely that people do not have the information required to work out what tariff, of all the tariffs on the market, will maximise their utility and, as pointed out in Wilson and Price (2010), sub-optimal decisions in the context of high information search costs is perfectly consistent with a model of a fully rational consumer.

The Tariff Decision Making Study attempts to overcome these methodological challenges to identify whether consumer decision making is fully rational by testing whether participants can identify the cost-minimising tariff from a menu of three tariffs when given all the information required in the controlled environment of an online survey. This exercise does not assume that the cheapest tariff is the optimal tariff; it merely tests people's abilities to undertake costs-benefit analysis, or what economists sometimes call solving optimisation problems, in the specific context of an energy tariff choice.

As discussed in Chapter 3, full rationality means having the unbounded computational capacity to undertake cost-benefit analyses whereas bounded rationality relaxes this assumption by implying there are inescapable cognitive limits on peoples' abilities to process the information required to optimise (Simon, 1957). If consumers cannot undertake a cost-benefit analysis based on one variable, in this case price, then it is unlikely that they will be able to undertake a cost-benefit analysis in which they also need to make trade-offs between multiple factors such as price, customer service, green energy, electricity shifting potential, online account management and so on, particularly given that people would have to assign a fictional financial value to these individual items to undertake the analysis.

Although a growing literature has shown that people struggle to make optimal choices in the context of household savings (Lusardi and Mitchell, 2006b, 2008; van Rooij et al., 2011; Klapper et al., 2013), choosing the optimal energy tariff is much simpler than planning for retirement which requires knowledge of much more complicated concepts than a kilowatt hour or a standing charge. Therefore, just because bounded rationality affects decision making over pensions does not mean that it will also affect peoples' decisions over their energy tariff. Most importantly, it does not mean that the number of people it will affect will be so large as to make an opt-out policy undesirable or that models which assume fully rational decision making will yield poor predictions at the aggregate (macroeconomic) level (Friedman, 1953), the so-called “as if” defence of the rationality paradigm (Chapter 3). It is therefore crucial to identify what proportion of energy bill payers, if any, struggle to solve the type of optimisation problem involved in identifying the optimal energy tariff.

The rest of this chapter is structured as follows. Section 2 will outline the survey method. Section 3 will describe how the survey was implemented, including attrition rates and how screening was applied to obtain the final sample for analysis. Section 4 will present the descriptive statistics of the participants in my sample alongside the characteristics of a sample of participants from a different survey who were recruited to be nationally representative of the British population and who also identified as energy bill payers. Section 5 will present the results of the tariff decision making questions and Section 6 consists of a brief discussion about what these results mean in relation to the specific research question that the study was designed to answer (research question 1) and implications for the second research question. Section 7 will conclude with a summary of the key findings that provide empirical support for the theoretical motivation of research question 2 provided in Chapter 3.

This general structure will be employed for each of the results chapters, after which a global discussion section will interpret the results in light of the findings from each of the four studies undertaken for this thesis to answer the research questions.

2 Method

2.1 Population of interest

The population of interest for this survey is the average British energy bill payer. This population was chosen because the aim of this survey is to identify whether the average energy bill payer's decision making over energy tariffs could be affected by bounded rationality (research question 1).

Following the conventions in the literature, the population of interest is confined to domestic energy bill payers, rather than energy consumers more generally, because it is energy bill payers who will be responsible for making the decision over which tariff the household is on. An energy bill payer is defined as someone who is solely or jointly financially responsible for paying the energy bills in their home. It therefore excludes people who consume energy but are unlikely to be responsible for paying the bills such as children. Although it is possible to imagine situations in which someone may be responsible for paying an energy bill but not for choosing the energy tariff (e.g. if they live in shared accommodation and one adult chooses the tariff), a prior survey finds that there is an almost perfect overlap between being an energy bill payer and being responsible for selecting the household energy tariff in Britain; in excess of 97% of British energy bill payers also identified that they were solely or jointly responsible for choosing the household energy tariff (M Nicolson et al., 2017).

2.2 Recruiting amongst the population of interest

An online survey was administered in November 2016 by a UK advertising agency to its sample of online British market research panellists. Like other market research panels, these participants were recruited by the advertising agency to serve as members of their consumer panel in exchange for a small per-survey payment. The company aims to recruit people who live or work in urban locations, which they define as places with a population greater than 10,000 (England), 5,000 (Scotland) and 3,000 (Wales).

The advertising agency runs fortnightly topic-based surveys with its online market research panel. The company does not use quota sampling to attempt to ensure that a nationally representative sample of participants respond to the survey. The advertising company's clients are mostly based in London so when they survey its panellists they stratify based on region – inside London and outside London – and randomly select half of their London panellists and half of their non-London panellists to take part. However the company holds basic demographic data on its participants which will enable me to compare to the characteristics of the resulting sample to that of the general population using ONS statistics as well as to the characteristics of a nationally representative sample of British adults who also identified as energy bill payers in a similar survey conducted in 2015 (M Nicolson et al., 2017).

The questions used for this research were added to the agency's survey on household utilities, which includes questions on mortgages, internet packages, mobile phone and landline packages as well as the energy questions that I provided. The first question was used to identify whether the participant was an energy bill payer.

Although a nationally representative sample of British adults would be more closely aligned to the population of interest outlined above, this sample was used because it was made available at no cost to the researcher in return for permitting the company to use the results to inform its strategy in relation to its energy supplier clients.[44] As will be discussed in more detail later in the chapter, drawing from the urban population of GB does not fundamentally undermine the ability of the results to provide evidence as to whether consumer decision making over energy tariffs is currently or in the future likely to be affected by bounded rationality (research question 1). This is because numeracy skills do not vary geographically to a sufficient extent to be concerned that a slightly older and more rural sample would have been substantially better able to solve the problem presented (Department for Business Innovation & Skills, 2012).

2.3 Survey design

Participants were asked to respond to three energy related questions. The first question required participants to identify whether they are solely or jointly responsible for paying the household energy bills using the same question wording in Nicolson et al. (2017).

The second and third question presented participants with vignettes of two separate individuals whom they are told are looking to switch electricity tariff. In both cases, the participant is asked to select the cheapest of three possible tariffs given all the information required to compute the cost minimising tariff for the person concerned. Participants were not paid extra for getting the question correct but were paid a flat fee for completing the survey. Participants were advised to use a calculator to help them and were also able to respond with 'I don't know' (abbreviated to DK), to minimise people selecting a tariff at random and to help distinguish between participants who did not want to spend time

[44] The company was not involved in the design, analysis or interpretation of the results reported here.

working out the answer (inertia) and those who attempt the question but are unable to answer it correctly (bounded rationality), as explained in Chapter 4.

In the first vignette, the participant is provided with three flat-rate electricity tariffs from which the fictional individual is able to choose. The following information is therefore required to compute the cheapest tariff and is provided to the participant:

- The unit rate of electricity on each of the tariffs in pence per kilowatt hour
- The standing charge on each of the tariffs in pounds per year
- The individuals' yearly electricity demand in kilowatt hours
- Whether or not the tariff is accompanied by a paperless billing discount, a common type of discount used by suppliers

This is the same information that Ofgem (2013) mandates suppliers to provide to consumers on its websites as part of the 'Tariff Information Label'.

The first vignette was presented to participants as follows:

Selin lives with her partner. Their current tariff has come to an end and they're trying to choose a new one.

Take a look at the three tariffs they've got to choose from and then decide which tariff you think would be cheapest for them considering that they use **2,000 units** of electricity a year and they're happy to switch to paperless billing.

	(1) Flat-rate tariff 1	**(2) Flat-rate tariff 2**	**(3) Flat-rate tariff 3**
Unit rate	15p/unit	14p/unit	13p/unit
Standing charge	£68/year	£60/year	£95/year
Discount for switching to paperless billing	£30/year	None	None

Please select the tariff that you think would be <u>cheapest</u> for Selin and her partner. You may want to use a calculator to help you.

The second vignette is identical to the first except that, this time, one of the three tariffs includes a TOU tariff. Again, the same information is provided to the participant as was provided in the first scenario with the exception that, instead of providing information on paperless billing discounts, the participant is given information on the timing of the fictional individuals' energy consumption, as required to compute whether the TOU tariff might be the cheapest:

- The unit rate of electricity on each of the tariffs in pence per kilowatt hour
- The standing charge on each of the tariffs in pounds per year

- The individuals’ yearly electricity demand in kilowatt hours
- The proportion of electricity consumed at the different time periods in the day, corresponding to the times on the TOU tariff

The reason for including the information on paperless billing in the first scenario is to keep the total amount of information provided in both scenarios approximately equivalent.

The second vignette was presented to participants as follows:

Stephanie lives with her partner. Her current tariff has come to an end and she’s trying to choose a new one.

Take a look at the three tariffs she’s got to choose from and then decide which tariff you think would be cheapest for her considering that her family uses **3,100 units** of electricity a year at the following times of the day:

- 50% between 4pm-8pm
- 40% between 7am-4pm
- 10% overnight (between 8pm-7am)

	(1) Off-peak tariff 1	(2) Flat rate tariff 2	(3) Flat rate tariff 3
Super off-peak			
8pm – 7am	10p/unit	14p/unit	13p/unit
Off-peak			
7am – 4pm	14p/unit	14p/unit	13p/unit
Peak			
4pm – 8pm	30p/unit	14p/unit	13p/unit
Standing charge	£70	£60	£95

Please select the tariff that you think would be <u>cheapest</u> for Stephanie and her partner. Use a calculator to help you.

The level of mathematics required to answer the questions correctly – requiring the ability to undertake addition, multiplication and to compute fractions of whole numbers – is the level expected of children finishing primary school in England (Department for Education, 2013). This survey therefore presents a relatively low bar against which to test the classical economic assumption that consumers have unbounded computational capability.

Immediately prior to being presented with the vignettes, participants are given a brief description of what a TOU tariff is and how they compare to flat-rate tariffs as in Nicolson et al. (2017) so that knowledge of the key concepts is not a barrier to answering the question. This summary also introduces the idea of paying for electricity in pence per unit and defines the meaning of a standing charge ("a fee for having electricity delivered to your home”). Throughout the survey, I do not refer to “kilowatt hours” but instead “units” of electricity, for example, £0.14 per unit and 2,000 units of electricity used because this is the language used by most energy suppliers. Consistent with past research on financial literacy (Lusardi and Mitchell, 2008), the only information that participants were not given was training on the method required to solve the problem. The full questionnaire is provided in Appendix 1.

As stated in Chapter 4, the scenarios were intentionally designed to make it easier for consumers to identify the cost-minimal tariff in this survey context than if they were using the Tariff Information Labels for real-world tariffs. The motivation for this is to minimise participant fatigue and to account for the fact that, in real life, participants face a greater incentive to choose the optimal tariff since it has a consequence on their energy bill whereas in the survey it is hypothetical. First, the tariffs were designed so that there is one cheapest tariff (i.e. there is no tie). Second, the standing charge was given in pounds per year rather than in pence per day (as in the Tariff Information Label) so that participants would not have to perform the step of multiplying the daily standing charge by 365, the number of days in a year. Third, in reality, people would have hundreds of tariffs to choose from, not just three.

2.4 Outcomes

The outcome measure is the proportion of participants who correctly identify the cheapest tariff.

2.5 Additional data collection

Baseline data is available on the following participant characteristics which is collected when participants join the panel and which is also updated at periodic intervals: gender, age in five categories (16-24, 25-34, 35-44, 45-54 and 55+), region in 6 categories (London, South, Midlands or Wales, North, Scotland and Other) and socio-economic grade in three categories (A/B; C1; C2; D/E).

2.6 Sample size

The advertising agency's consumer panel consists of 6,240 participants, from which approximately 10-15% respond to any given survey. It was therefore estimated that approximately 600-900 participants would complete the survey which was estimated as being sufficient to obtain an estimate of the proportion of consumers who are able to identify the cheapest tariff with 95% confidence and a 5% margin of error using the formula outlined in Daniel (1999) and Naing et al. (2006), assuming that between 50% to 80% of people would correctly identify the cheapest tariff. The most conservative estimate – the one requiring the highest sample size – is 768 participants.

2.7 Randomisation and blinding

Although it would have been preferable to randomise the order of the scenarios, randomisation was not possible. There is therefore a small chance that people could be more fatigued in the second scenario and that this could affect their performance. On the other hand, given that the task is very short, and that people would not be told how they performed, it seems unlikely that fatigue would have a large impact. All participants were therefore presented with the flat-rate tariff scenario first, as it was felt this would be easier for people to answer and therefore reduce attrition.

Blinding was not necessary because the survey did not vary across participants.

2.8 Analysis plan

The pre-analysis plan for this study was registered prior to data collection on the Experiments in Governance and Politics (EGAP) online trial registry (20161110AC).

This study is associated with two hypotheses which the Pre-Analysis Plan states will be tested as follows:

Hypothesis 1: Some energy bill payers will fail to identify the cheapest tariff in both scenarios.[45]

> Test: to compute the proportion of participants who correctly identify the cheapest tariff in both scenarios (0=incorrect/DK; 1= identified cheapest tariff).

Hypothesis 2: A higher proportion of energy bill payers will fail to identify the cheapest tariff when a TOU tariff is included in the menu of tariff options than when a TOU tariff is not included.

> Test: a paired sample z test of the difference in two proportions will be used to find out whether any observed difference in the proportion of energy bill payers identifying the correct tariff in scenario 1 (all flat-rate tariffs) is statistically significantly different from the proportion who correctly identify the cheapest tariff in scenario 2 (includes a TOU tariff).

[45] It is acknowledged that this is a weak hypothesis because it does not propose how many consumers would be unable to select the cheapest tariff. However, there was insufficient evidence upon which to make a precise prediction of the number of customers who were likely to be unable to identify the lowest cost tariff. This hypothesis is exploratory.

Hypothesis 3: A higher proportion of energy bill payers in the bottom three socio-economic grades (C2, D, E) will fail to identify the cheapest tariff than energy bill payers in the top three socio-economic grades (A, B, C1) in both scenario 1 and scenario 2.

> Test: two paired z tests of the difference in two proportions will be used to find out whether any observed difference in the proportion of energy bill payers belonging to the bottom three socio-economic grades and who identify the correct tariff is statistically significantly different from the proportion who correctly identify the cheapest tariff and belong to the top three socio-economic grades in both scenario 1 and scenario 2.

3 Implementation of survey

The survey was sent to 6,239 members of the advertising agency's market research panel in November 2016, out of which 957 participants started the survey and a total of 932 completed it, which means the survey had a response rate of 15% and attrition rate of under 2%. Participants were paid in points which they can redeem for cash after completing a certain number of surveys.[46]

Prior to analysis, participants were screened for whether they were energy bill payers based on their response to a question in the survey which asked them whether they were solely or jointly financially responsible for paying their household electricity bills. Just under 13% of participants who started the survey indicated that they were not responsible for paying energy bills which is higher than the average for the adult population in GB of 5%-8%. These participants

[46] The value of the points approximately amounted to £3.

(121 participants in total) were excluded from all analyses, leaving a total of 811 valid responses for analysis.

4 Descriptive statistics of sample

Table 12 reports the characteristics of all participants with and without sampling weights to account for participant non-response and the oversampling of Londoners. The first column presents the characteristics of participants from a similar online survey performed on a nationally representative sample of British adults who identified as energy bill payers in 2015 (M Nicolson et al., 2017). The purpose of making this comparison is that, as noted above, a nationally representative sample of adults might be expected to be more similar to the average energy bill payer (the actual population of interest for the study) than participants in this survey who were recruited to be representative of the average member of the urban population of GB. Any differences in the characteristics of the two will be used to help interpret the generalisability of the results in this study to the average energy bill payer in the population.

The sample weights are inverse probability weights which account for differences in response rates across survey participants by age and socio-economic grade and increases the weight given to responses provided by individuals outside of London to help redress the fact that the sampling strategy led to a higher proportion of Londoners being recruited into the sample relative to their proportion in the general population.

Table 12 Characteristics of energy bill payers in the British population and in the survey sample with and without survey weights

	Population	**Sample**

	(%)	Unweighted (%)	Weighted (%)	N
Gender:				
Female dummy	51	50	50	811
Socio-economic grade:[47]				
A/B	22	35	36	811
C1	31	35	30	811
C2	21	9	11	811
D/E	26	21	23	811
Age in five year groups:				
16-24[48]	9	5	6	806
25-34	18	22	28	806
35-44	19	21	23	806
45-54	18	17	16	806
55+	37	35	26	806
Region:				
London	13	41	31	811
Outside London	86	59	69	811

The unweighted estimates more closely resemble the population statistics than the weighted estimates so participant characteristics are discussed in terms of the in-sample rather than weighted estimates. Whilst this might sound counterintuitive, research into weighting has shown that weights can often be counterproductive (Wooldridge, 2009; Solon et al., 2013) and, in this case, has a simple explanation; the response rates were lower amongst the younger

[47] The population values are for the average member of the British population from the Census 2011 because equivalent values were not available for the average energy bill payer.
[48] This is based on age groups 15-24 for the GB population because Census statistics are broken down into five year intervals in which 16-19 year olds are grouped with 15-16 year olds.

participants and participants belonging to the highest socio-economic grade, both of which are relatively overrepresented in the company's market research panel by comparison to the population proportions. Indeed, the unweighted characteristics of the sample are qualitatively very similar to that of the average energy bill payer in terms of gender and age and, in general, supports my decision not to use weighted estimates for statistical analysis (for more details see Annex 3). As noted in Annex 3, following Debell and Krosnick (2009), differences exceeding 5 percentage points are regarded as notable.

As evident in Table 12, although the sample has a relatively high proportion of participants belonging to the top two socio-economic grades (A/B) and a comparably low proportion of participants in socio-economic grade C2, the proportion of participants in the second socio-economic grade (C1) and lowest socio-economic grade (D/E) are very similar to the population proportions.

As expected, the sample substantially over-represents Londoners. However, there is no compelling reason to believe that the computational abilities and cognitive attention of market research panellists or Londoners would differ to people living elsewhere in Britain who do not participate in market research, at least not after controlling for social grade. The most recent research conducted in 2011 suggests that whilst numeracy skills are slightly lower in London than elsewhere the difference is small (Department for Business Innovation & Skills, 2012), whilst in the past (2003) Londoners were found to have slightly higher numeracy skills than average for Britain. I will conduct and report the results of a test of whether Londoners in my sample do outperform non Londoners to help in the interpretation of the results.

Socio-economic grade, on the other hand, is likely to be an important determinant so, as outlined in the methods section in Chapter 4, I will test for differences in decision making quality based on socio-economic grade.

5 Tariff decision making results

Bounded rationality implies that some British energy bill payers would be unable to identify the cheapest tariff from a menu of tariffs when given all the information necessary to calculate this (hypothesis 1). Since TOU tariffs are more complex than flat-rate tariffs, bounded rationality also implies that the ability to identify the cost-minimising tariff would be lower if the menu of tariffs included a TOU tariff (hypothesis 2). Recent research also suggests that bounded rationality may disproportionately affect those in lower socio-economic grades (Mani et al., 2013) and therefore that the ability to identify the cost minimising tariff would also be lower amongst those in the bottom three socio-economic grades relative to those in the top three socio-economic grades (hypothesis 3).

Before presenting these results it is first worth addressing the concern that, since participants were not paid an additional fee for getting the question correct, they may have selected response options at random to avoid expending the time (if they are fully rational) or mental effort (if boundedly rational) required to arrive at the correct answer. If all participants selected at random, the responses would be equally distributed across all three response options whereas Table 13 shows that this is not the case, with a one-way chi2 test indicating that the observed differences are statistically significantly different ($p<0.001$). Moreover, there is substantial variation in the number of people selecting each option, suggesting that, whilst I cannot eliminate the possibility that some people selected at random, the evidence suggests that the majority did not.

Table 13 Distribution of responses across response options.

Response option	Scenario 1 Flat-rate	Scenario 2 TOU
Tariff 1	**461**	104
Tariff 2	287	**402**
Tariff 3	88	223
DK	106	203

Notes: The number of people correctly identifying the cheapest tariff is highlighted in bold.

Moving on to the main results, Table 14 presents the responses to the energy tariff questions across the sample as a whole and for participants in the top three socio-economic grades and those in the bottom three socio-economic grades. The percentages in the table represent the proportion who correctly identified the cheapest tariff, those who either gave an incorrect response and those who said that they did not know the answer.

Table 14 Distribution of energy bill payers' responses by scenario and socio-economic grade

	All bill payers		High social grade (A, B, C1)		Low social grade (C2, D, E)	
	Scenario 1 Flat-rate	Scenario 2 TOU	Scenario 1 Flat-rate	Scenario 2 TOU	Scenario 1 Flat-rate	Scenario 2 TOU
Correct	49	44	51	47	44	39
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Incorrect	41	36	40	35	43	37
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
DK	10	20	9	18	13	25
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
N	811		563		243	

Notes: Values in cells represent mean proportion of participants who correctly identified the cheapest tariff or who got the answer wrong or said they did not know. In Scenario 1 the tariff menu only includes flat-rate tariffs. In Scenario 2 the tariff menu includes a TOU tariff. Standard errors reported in parentheses.

Consistent with hypothesis 1, the results show that 49% of British energy bill payers correctly identified the cheapest tariff from a menu of flat-rate tariffs.[49] Consistent with hypothesis 2, the proportion of energy bill payers who correctly identified the cost-minimising tariff is five percentage points lower when the tariff menu includes a TOU tariff (p=0.038).

Consistent with hypothesis 3, when the tariff menu included a TOU tariff, the proportion of bill payers belonging to the lowest socio-economic grades who correctly identified the cost minimising tariff was 8 percentage points lower than the proportion of bill payers belonging to the highest socio-economic grade. This difference is also statistically significant (p=0.035). Bill payers belonging to lower socio-economic grades were also less likely to identify the cheapest tariff compared to their higher grade counterparts when the menu only included flat-rate tariffs, although the 7 percentage point difference is only marginally statistically significant (p=0.068), suggesting that the biggest gap in decision making quality across socio-economic grades occurs when choosing between TOU tariffs and flat-rate tariffs as opposed to when choosing between just flat-rate tariffs.

The average difference in the proportion of respondents identifying the cheapest tariff is being driven by the bill payers who say that they do not know what tariff is cheapest, including also the differences across socio-economic grade. As is visible in Table 15, when excluding participants who gave a DK response, the

[49] See Payne et al. (1993) for a relevant discussion of multi-attribute decision making studies.

average number of correct responses is substantively identical across both the flat-rate and TOU rate tariff menus (54% vs 55%). Although there is still a relatively large gap in correct responses across those in the top and bottom socio-economic grades, regardless of whether the tariff menu only includes flat-rate tariffs (51% vs. 56%) or whether it also includes a TOU tariff (51% vs. 57%), exploratory analyses that were not pre-specified in advance find that these differences are not statistically significant.

Table 15 Proportion of energy bill payers correctly identifying the cost-minimising tariff by scenario and socio-economic grade excluding respondents who indicated they did not know

	Tariff menu scenario			
Sample group:	Flat rate only		Includes TOU tariff	
	Mean (%)	N	Mean (%)	N
All bill payers	54	811	55	811
	(0.02)		(0.02)	
Low social grade	51	243	51	243
(C2, D, E)	(0.03)		(0.04)	
High social grade	56	563	57	563
(A, B, C1)	(0.02)		(0.02)	

Note: Standard errors around the mean reported in parentheses.

Since the sample over represents Londoners, I tested whether there is any evidence that the Londoners in my sample have higher energy literacy than non-Londoners. An OLS and logit regression was run in which a dummy variable for being a Londoner was regressed against the dummy variable indicating whether the participant correctly identified the cheapest tariff in both scenarios. The results showed that Londoners statistically significantly outperformed non-Londoners by 13 percentage points ($p<0.01$) in scenario 1, without a TOU tariff, but that there was no statistically significant difference in their performance when the TOU tariff was included in scenario 2.

6 Discussion

This study shows that, when asked to identify the cheapest energy tariff in a survey, about half of British energy bill payers fail to do so even when given all the information required. As predicted, this study found that decision making quality declined when the menu included a TOU tariff, particularly for those in the lowest three socio-economic grades in British society (C2, D, E).

The next section will now discuss the implications this result has for the validity of the classical economic model as a framework for how consumers make decisions about energy tariffs, optimisation problems involving non-price factors and the way in which consumers are recruited onto TOU tariffs.

6.1 Fully rational or boundedly rational? Implications of the results for the classical economic model of decision making

According to the “as if” defence of the rationality paradigm, whilst the rationality assumption is sometimes false at the individual level (some people make mistakes all the time, most people make mistakes some of the time), the model is correct on average. In other words, bounded rationality either only affects very few consumers and/or the mistakes made by these consumers will not have any important impact on the market outcome, in this case, on how many consumers and what type adopt a TOU tariff. However, even in the simplest scenario involving only flat-rate tariffs, about 40% got the question incorrect and 10% said they did not know. This is entirely inconsistent with even a model which assumes consumers behave “as if” they are perfectly rational, even after considering that participants were not paid extra for getting the question correct. The numeracy skills required to correctly answer the questions presented to survey participants are those expected of children leaving primary school in Britain. Classical economic theory assumes that people have unbounded computational capacity to undertake calculations that are infinitely more complex than those presented to participants in this survey.

Given that nearly half of consumers got the question wrong, there are only two other possible explanations for the results. The first is that people did not know the method, since they were only given information on the attributes of the tariff required to identify the cheapest tariff. The second is that, despite knowing the method and having the information required to identify the cheapest tariff, there are limitations in peoples' abilities to process information (bounded rationality), or what could also be referred to as 'thinking costs'.

Although it is not possible to rule out that some people did not know the method, the results are still easier to explain using a model of boundedly rational decision making rather than a model that assumes consumers behave approximately in line with a model that assumes full rationality. All consumers would have been taught the numeracy skills required to undertake the task as school children; if they no longer recall these methods as adults, this would be easier to explain using a model of a boundedly rational consumer who may be inattentive at school or who may forget certain bits of information than it is by invoking the model of a fully rational consumer who, on average, is fully attentive and with perfect memory.

In contrast to the classical economic model, Simon's (1957) theory of bounded rationality assumes thinking costs are a key potential driver of the types of decisions people make. According to the literature reviewed in Chapter 3, boundedly rational consumers will attempt to limit the cognitive burden of solving problems in one of two ways, either by avoiding the decision altogether, leading to inertia or status-quo bias, or by undertaking the calculation by processing a sub-set of the information (e.g. ignoring the standing charge), which can lead to errors. Therefore, according to behavioural economic theory, fully rational consumers will undertake the calculation correctly whereas boundedly rational consumers will either undertake the calculation incorrectly or not attempt the calculation at all by selecting DK. Consistent with this model, the results show that many consumers got the question incorrect and a sizeable minority answered DK.

The results are therefore broadly supportive of the theoretical framework outlined in Chapter 3 which proposed that consumer decision making over energy tariffs could be affected by bounded rationality and not just household appliance characteristics that determine whether they can save money on a TOU tariff. Although the economics profession widely accepts that its rationality assumptions are “obviously…wrong” at the individual level (Tyran, 1999, p.159) – there are limits on human cognition, people make mistakes and so on – economists are reluctant to incorporate bounded rationality in economic analysis on the basis that the model is approximately correct at the aggregate level. Indeed, many policy decisions are still undertaken based on standard cost-benefit analyses using the expected utility framework, including the UK Government’s cost-benefit analysis for smart meters (DECC, 2014; BEIS, 2016b). Based on the results of this survey, bounded rationality would appear to be so pervasive amongst energy bill payers that it arguably could affect competition in the energy market, including explaining why retail prices are significantly higher than wholesale prices (CMA, 2016c). If consumers are unable to optimise over their energy tariff, then suppliers will be able to exploit this by increasing their prices.

6.2 Solving optimisation problems involving energy tariffs

Whilst the lack of a financial incentive is unlikely to fully explain the results, it is still possible that some participants would have performed better if they knew there was a financial reward for getting the question correct or if they were taught the method in advance. However, the explanation for the results does not change the seriousness of the real-world implications.

Given that the majority of energy bill payers were unable to identify the optimal tariff when the only factor they were asked to consider was price, energy bill payers are unlikely to perform substantially better in real life when they are likely to be trading off between multiple factors, such as customer service, green energy supply and whether the tariff comes with a free smart thermostat and so on. In addition, since Londoners outperformed non-Londoners in the first scenario, without a TOU tariff included, it is possible that the proportion of British bill payers who are able to identify the cheapest of an assortment of flat-rate tariffs would be lower than estimated in this study considering that the study overrepresented Londoners. A prior study suggested that consumers were failing to optimise when making decisions over their tariff because 80% of consumers appropriated between 30%-50% of the maximum financial gains available following the privatisation of the energy markets (Wilson and Price, 2010). However, it was unable to rule out the possibility that consumers were switching for reasons other than price or that information barriers were preventing rational consumers from exploiting the full potential gains from switching after the liberalisation of the energy markets. As they said, “Whilst non-price gains are likely to be small in a near-homogeneous market like electricity, consumers may believe they exist" (Wilson and Price, 2010, p.654). This study provides evidence that, even if such benefits do exist, that many bill payers may be unable to rationally weigh up the costs and benefits of alternative tariffs. That is why, a conclusion of this chapter is that consumers struggle to optimise over their energy tariff.

The results are also very similar to the performance of consumers in financial decision making studies, suggesting that, contrary to the discussion in the introduction and Chapter 3, consumers may well find choosing an energy tariff about as difficult as choosing a pension and even investing in the stock market. The proportion of consumers who correctly identified the cheapest tariff in this survey is slightly fewer than the proportion of US residents who were able to correctly answer a question aimed at assessing their understanding of interest rates – of which 60% correctly identified the correct answer – but about the same as the proportion who understood risk diversification when investing in the stock market (Lusardi and Mitchell, 2008).

The fact that consumers in the lower socio-economic grades perform worse at solving optimisation problems – whether because they are less likely to know the method or because lifestyle factors give them less mental bandwidth – is highly concerning considering that these groups may be expected to be at greater risk of fuel poverty. Fuel poverty is a function of the price paid for energy so these consumers are most in need of ensuring that, all other things being equal, they are not paying more for their energy than they need to.

Third, the results also have implications for recruitment onto TOU tariffs for either opt-in or opt-out. This is discussed in detail below.

6.3 Evaluating the implications of the results for TOU tariff recruitment

There are two main ways in which consumers could be recruited onto a TOU tariff. One option is for consumers to be left to decide whether or not to switch to a TOU tariff of their own accord (opt-in enrolment). Another option is for consumers to be automatically switched onto a TOU tariff unless they explicitly request to be kept on their flat-rate tariff (opt-out enrolment). There are two main factors that affect the extent to which the results of this study have any practical implications for the suitability of either of these two methods of recruitment. The first is the similarity between the participants of this survey and the average British energy bill payer. The second is the similarity between the task given to survey participants and the task that consumers would need to perform in the event of opt-in or opt-out enrolment.

To address the first point, the average survey participant was younger than the average member of the British population and was overrepresented by Londoners. However, given that numeracy skills decline slightly with age (Department for Business Innovation & Skills, 2012) and are relatively similar across regions in the GB, it is unlikely that the results would be substantially different amongst a nationally representative sample of energy bill payers; if anything, it might be expected that a nationally representative sample with a higher mean age would perform slightly worse.

To address the second point, the task presented to survey participants differs in three key potential ways to the task that would be faced by consumers contemplating whether to switch to, or opt out of being switched to, a TOU tariff: (1) the incentive to identify the cheapest tariff is higher when the stakes are real than in the hypothetical situation presented to survey participants; (2) in real life people can use price comparison websites so potentially do not need to be able to compute their estimated annual energy bill under any given tariff and; (3) in real life consumers have multiple opportunities to switch their tariff and would do so if and when they notice an increase in their energy bill having switched to a more expensive tariff regardless of whether recruitment is opt-in or opt-out.

I address each of these in turn but ultimately conclude that whilst the first point is a limitation in the ecological validity of the study, as noted above, the second and third are only apparent limitations to the ecological validity. Moreover, none provide sufficient reassurance that consumers will be substantially better able to ensure they switch to a TOU tariff only if it will save them money in either an opt-in or opt-out recruitment scenario.

6.3.1 Asymmetry in incentives

That the participants were being paid to complete a survey in which there are no financial consequences from choosing the wrong tariff has some bearing on the generalisability of the results to a real-world scenario in which consumers do face financial consequences if and when they switch tariff – however, less so than may appear at first glance.

First, given that there was no evidence that people were choosing between tariffs at random, participants who were unwilling to expend *any* effort to identify the correct response are likely to have selected a DK response; even when excluding those who selected DK, half of all remaining participants failed to identify the cheapest tariff.

Second, there are many reasons why survey participants would be more likely, not less likely, to identify the optimal tariff than consumers faced with the choice in real life. The task presented in this study is much simpler than the optimisation problem people actually have to solve when faced with switching tariff. If consumers cannot solve optimisation problems based only on price, then it is even less likely that they will be able to undertake a cost-benefit analysis in which they may also want to make trade-offs between multiple factors such as customer service, green energy, online account management and so on. Given that, in real life, consumers have to choose between multiple tariffs, not just the three tariffs as used in this survey, it is highly unlikely that consumer decision making would be substantially better just because there is are real financial consequences.

Third, in real life, people are not just faced with a choice over their energy tariff; rather, people are faced with a range of decisions, which according to the classical economic model, they are seeking to optimise, from choosing the best bank account to choosing the best hotel at which to spend their summer holidays, best school to send their children to, best job role from which to progress their career, best GP to visit when they are sick and so on. It is unlikely that, given the number and range of decisions people have to make every day, week and year that people would be more likely to identify the optimal energy tariff for their household in real life than they would in a survey where participants were being paid to exclusively focus on one choice.

Finally, even if the survey substantially overestimates the proportion of consumers who can identify the optimal energy tariff, the welfare implications are no less severe. Prior research suggests that about 16% of British adults have the numeracy skills of a child leaving primary school (Department for Business Innovation & Skills, 2012), which is about half as many as correctly identified the cheapest tariff in this survey, a problem that was also of primary school level. Therefore, even if people do make more effort in real life than the participants of my survey, the evidence suggests that this may only translate into improved choices for around half of the consumers. If the survey overestimates the proportion of energy bill payers who are unable to optimise by 50%, then given a domestic electricity customer base of 28 million customers (Ofgem, 2016d), this would still represent 6.7 million energy bill payers who are unable to identify the optimal tariff.

6.3.2 Price comparison websites forego the need for being able to undertake cost-benefit analyses

Price comparison websites could play an important role in helping people to make better decisions over their energy tariff because such websites will perform these calculations on behalf of consumers using data on average household electricity usage or estimated or actual meter readings. Indeed, it is highly unlikely that so few participants would have correctly identified the cost-minimising tariff if they were given three figures, each representing the estimated annual energy bill under each tariff, since this only requires an ability to identify the lowest number in a set of three.

The results of this study suggest that there would be substantial value in future research into how to identify which households may be able to shift demand out of peak hours, so that price comparisons for TOU tariffs can be based on potential but realistic changes to peoples' consumption patterns. This is because, quoting a consumer for TOU tariffs based on an accurate picture of their historical electricity consumption patterns would defeat the purpose of TOU tariffs which is to change the time of day that people use electricity. Empirical research would also be required to gauge the extent to which consumers understand that such estimates are predicated on them changing their behaviour, to avoid consumers experiencing large, unexpected increases in their energy bill.

On the other hand, given the level of inertia in the energy market, if consumers were defaulted onto TOU tariffs, many may not check a price comparison website to determine whether the tariff would increase or decrease their bill. Currently, of the 14% of engaged consumers who switch each year, just one third report having switched via a price comparison website (Ofgem, 2015). Moreover, half-hourly consumption data will only be available to suppliers if a consumer actively consents to this (Department of Energy & Climate Change, 2012) which, given customer inertia, may mean this data is unavailable for creating tariff projections for the majority of consumers.

6.3.3 The effects will be short-lived

It is arguable that, even if consumers were defaulted onto a TOU tariff inappropriately, they would soon opt-out once they saw the impact on their energy bill. However, wider evidence also suggests that poor decision making at the point of switching is unlikely to be corrected once people receive their energy bills; although consumers defaulted onto a TOU tariff in one US trial did not reduce their peak electricity use at all and would therefore have seen increases in their energy bill, retention rates were identical across both opt-in and opt-out groups (US Department of Energy, 2016). Therefore, we should not expect consumers who are inappropriately defaulted onto a TOU tariff to soon dis-enroll once they witness the impact on their energy bill.

That a bad default can be just as sticky as a good default is true in other domains too (Choi et al., 2004) and makes sense in this context given that there is “widespread consumer disengagement” (Consumer Focus, 2011, p.5) with energy bills. Around 20% of consumers in GB not read their bill at all, particularly those who pay by direct debit and therefore who do not need to find out how much they owe since the amount owed is debited automatically (Consumer Focus, 2011).

7 Conclusions

This chapter presented the results of a survey experiment aimed at answering the first research question: is consumer decision making over electricity tariffs affected by bounded rationality? What this study shows is that, even under ideal conditions in which energy bill payers are being paid to pay attention to energy tariff information and are only asked to maximise based on a single factor (price), nearly half of bill payers cannot identify the cheapest energy tariff. Moreover, the ability to identify the optimal tariff declined by five percentage points when the tariff menu includes a TOU tariff, particularly amongst consumers in the lowest socio-economic grades who may be more likely to be in fuel poverty, for whom the proportion of correct responses was 8 percentage points lower than those in the top socio-economic grades.

This study makes two contributions to this thesis and the wider literature. The first is that a key assumption behind nudging is that people's decisions are suboptimal. However, it is almost impossible to prove that consumers are making suboptimal decisions using observational data about consumer behaviour in the energy market alone. Just because there are unexploited gains from switching tariff does not mean that decision making is sub-optimal; people may be factoring other aspects into their decisions than just price, for example customer service or other actual or perceived benefits. Moreover, even if decision making is sub-optimal, it does not imply that peoples' decisions are not rational, since the failure to exploit all the possible financial gains from switching is perfectly consistent with a model of a fully rational consumer facing high information search costs.

This study ruled out information as a barrier to optimal decision making and showed that about half of all energy bill payers in the sample were still unable to identify the optimal tariff, even in the simple scenarios presented where they were only asked to optimise based on one variable, namely price. The results highly suggest that the model of the fully rational decision maker is not even approximately correct, and therefore that for tariff decisions, there is a strong justification for incorporating bounded rationality into economic cost-benefit analyses, such as the model used to evaluate the wider benefits of smart meters (BEIS, 2016b), of which TOU tariffs are one such wider benefit. In doing so the study provides support for the theoretical framework outlined in Chapter 3 which proposed that consumer decision making over energy tariffs is likely to be affected by bounded rationality and not just household appliance characteristics that determine whether they can save money on a TOU tariff.

This leads to the second contribution of this study which is that the consumer heterogeneity in both the ability to evaluate the costs and benefits of alternative tariffs and appliance ownership has implications for the effectiveness of both opt-out and opt-in enrolment for TOU tariffs. The results imply that, even under ideal market conditions in which consumers have perfect knowledge about how much electricity they use and at what time of the day (e.g. provided through their smart meter), TOU tariffs may not selectively attract the consumers who are most important candidates for DSR and who are most needed to go onto TOU tariffs or DSR programmes (e.g. those with high peak usage, EV owners, electric heating) who will switch whilst detracting those who are likely to be better off on a flat-rate tariff.

On the other hand, a policy of opt-out enrolment could be significantly more detrimental to consumer welfare. To avoid harming consumers, a policy of opt-out enrolment would need to result in consumers who would likely see an increase in their bills on a TOU tariff opting out whilst consumers who have a high electricity use at peak times with potential to reduce it sticking with the TOU default. However, the results of this study indicate that consumers do not have the energy literacy skills required to identify whether they should opt-out. Given that opt-out enrolment can result in recruitment rates to TOU tariffs approaching 100% (Chapter 2), a policy of opt-out enrolment therefore presents a real risk that millions of consumers could be signed up to tariffs that increase rather than decrease their energy bills, particularly consumers in the lowest socio-economic groups in Britain who performed substantially worse in the task.

Whilst the regulator is unlikely to be able to protect consumers from choosing to switch to a TOU tariff on the basis of a quote that may or may not accurately predict the change in their energy bill from switching away from a flat-rate tariff, automatically enrolling consumers onto a tariff on the basis of quotes that about half of all British consumers are unable to independently scrutinise is arguably much more problematic. This judgement is based on a distinction often made in philosophy, and for the most part upheld in modern legal systems, that it is morally worse to actively harm an individual than it is to allow an individual to be harmed (James, 1975; Kamm, 1996). Although this is not a settled debate in moral philosophy, it arises because of the average person's moral intuition that harming someone is worse than allowing them to be harmed, suggesting that if regulators made TOU tariffs opt-out and this increased some consumers' energy bills that this would be perceived much more harshly by the public than if the regulator failed to take action to prevent consumers from switching to inappropriate tariffs.

Nevertheless, taking action to help consumers make decisions which are better for them and for society as a whole, which in this is to increase domestic consumer participation in DSR, is exactly what Thaler and Sunstein (2008) proposes nudge can achieve.

The next chapter therefore presents the results of two studies – a field experiment and a population-based survey experiment – which test the effectiveness of designing a nudge that aims to increase uptake to TOU tariffs amongst consumers who are most likely to save money from switching to one whilst detracting consumers who are less likely to save (research question 2).

Chapter 6

Results (2):

The Flex Trial (2a) and Population-Based Survey Experiment (2b) – tailored tariff marketing is an effective and selective nudge

1 Introduction

The literature reviewed in Chapter 3 suggests that opt-out enrolment could potentially result in consumers being rolled onto tariffs which charge them a lot more for electricity at precisely the time of day they are most likely to use it, but without their knowledge. The results presented in Chapter 5 suggest that millions of British energy bill payers may be unable to work out whether a TOU tariff would increase or decrease their electricity bill, a pre-requisite for making an informed choice over whether to opt-out of being enrolled onto a TOU tariff or whether to actively switch onto one. This creates a challenge for creating an effective method of increasing uptake to TOU tariffs regardless of whether consumers are left to actively opt-in or whether they are enrolled onto a TOU tariff automatically unless they opt-out.

These findings therefore motivate the second research question which is to identify methods of increasing uptake to TOU tariffs without using mandates or default enrolment but rather using active choice strategies that are enhanced to increase the likelihood of enrolling consumers who are more likely to save money without enrolling those who could be made financially worse off. Following Johnson (2016), I call this a search for an 'effective and selective' nudge.

As argued in Chapter 2, consumers with EVs and households with heat pumps are two important candidates for participating in domestic DSR (DECC, 2010). Both these groups consume more electricity than the average domestic energy bill payer and are expected to place a much larger burden on the future electricity network (Frontier Economics, 2011). At the same time, since they use more electricity, they also stand to save more from adjusting their electricity consumption patterns; for EV owners this would involve using a timer on their charge point to charge their vehicle at a cheaper time of the day whilst heat pump owners could set their heating schedule according to the rates on the TOU tariff.

One plausible method of increasing the likelihood that heat pump and EV owners would actively choose to adopt a TOU tariff identified in Chapter 3 is for energy suppliers to tailor their marketing of TOU tariffs to these two consumer groups, for instance, by labelling their TOU tariffs “Heat Pump tariff” or “EV tariff”. This type of tailored marketing counts as a ‘nudge’ as defined in Thaler and Sunstein (2008) since it does not affect the underlying incentives of switching to the tariff, either by making information more readily accessible or the tariff rate or structure more favourable for heat pump and EV owners, for instance by offering a particularly cheap rate for EV owners or special ‘EV’ or ‘heat pump’ owner discounts which would increase the cost to suppliers of offering such tariffs and could be perceived as unfair considering these customers are already more likely to be wealthier than average.

According to classical economics, such marketing should have little to no effect on uptake because it makes no difference to the underlying incentive. If consumers do respond to such marketing, it would imply that a behavioural economic model rather than a classical economic model is a more appropriate framework for understanding how consumers will behave in response to TOU tariffs. However, it does not imply that traditional tools, such as information provision, would have no positive impact on uptake or even less of an impact than marketing. For instance, another plausible option mentioned in Chapter 3 is for energy suppliers to provide consumers with quotes tailored to them based on what household appliances they own that directly compare what the household would pay on a TOU tariff relative to a flat-rate tariff. To minimise the risk of only attracting consumers who already have favourable consumption patterns (adverse selection), these price comparisons could be made by building in assumptions about the proportion of a household's electricity use that is flexible, which would naturally lead to larger expected savings for consumers with higher flexible electricity use such as EV owners or households with heat pumps.

Although such a 'predictive' price comparison approach may be hard to implement in practice, it is possible to imagine a future in which machine learning techniques become sophisticated enough to provide reasonable approximations of the demand-flexibility potential of individual households. Moreover, this approach removes the need for consumers to be able to calculate the savings themselves (as the first study showed many struggled to do), so both a classical and behavioural economic model would predict it would have an impact on who signs up to a TOU tariff – although, according to behavioural economics the impact will be small because people are not motivated by reason and facts alone but by a range of factors such as who the message is communicated by, their emotional state, whether they know anyone else on a TOU tariff and so on (see Table 9 in Chapter 3). Nevertheless, although Ofgem surveys (2008, 2011, 2012, 2013, 2014, 2015) indicate that switching rates have not increased since they implemented a range of strategies to address imperfect information problems in the energy market, it is only by testing this systematically in a randomised control trial that the effectiveness of these strategies can be identified.

This second results chapter presents the method and results of the Flex Trial (study 2a), an online field experiment, and the Population-Based Survey Experiment (study 2b) which together test whether tailoring the marketing of a TOU tariffs towards heat pump and EV owners could increase uptake to TOU tariffs amongst those groups when they shop around for an electricity tariff online but without simultaneously attracting other consumers who are less likely to save.

The rest of this chapter is structured as follows. Section 2 will outline the research method of the Flex Trial (study 2a) according to the CONSORT statement's reporting checklist for randomised control trials (Schulz et al., 2010; Boutron et al., 2010) followed by details on the way the trial was implemented, descriptive statistics and the average treatment effect analysis. Section 3 will follow the same structure as the previous section but for study 2(b), the Population-Based Survey Experiment. Section 4 discusses the results of both experiments in relation to whether tailoring the marketing of TOU tariffs towards EV owners and heat pump owners is likely to be an effective and selective nudge (research question 2) compared to predictive price comparisons. Section 5 concludes with a summary of the key findings from both experiments and remaining questions for the third and final experiment of this thesis.

2 Study 2(a) "The Flex Trial"

2.1 Method

2.1.1 Population of interest

The population of interest for this trial is British energy bill payers, particularly the following two sub-groups who have higher than average potential flexible electricity consumption: (1) British consumers with plug-in EVs; (2) British consumers with heat pumps, the favoured substitute to gas boilers in individual buildings (DECC, 2010).

British energy bill payers who do not own heat pumps or EVs are part of the population of interest because these consumers could end up financially worse off if they switch to a TOU tariff so it is necessary to understand whether and to what extent these tariffs may attract such consumers and whether tailoring could deter them.

Energy bill payers rather than energy consumers as a whole are the target because it is assumed that only consumers who are solely or jointly financially responsible for electricity bills (the definition of an energy bill payer) and can be assumed to be responsible for making tariff switching decisions. British energy bill payers rather than UK bill payers are the target because the energy company that I worked with to design the tariff only had a licence to operate in GB.

2.1.2 Trial design

I designed a website for an energy supplier called “Flex” which promoted a three-tiered static TOU tariff[50] that was designed by a British energy supplier for this trial. The website was built by professional website and database developers. Participants were recruited to the website through online adverts placed on Google that were specifically targeted to recruit a high proportion of EV and heat pump owners and a smaller proportion of ‘average’ energy bill payers (more details on participation recruitment in section 2.1.3).

Upon clicking on an advert, participants would be randomly assigned to one of the following three versions of the website with a 0.33 probability:

1. Control website 1: a site which promotes the TOU tariff “Off-Peak Saver tariff” and invites people to get a quote for the tariff (“control”)

[50] The tariff is a three-rate static time of use tariff for which the price of electricity varies between three different rates at multiple but fixed times throughout all weekdays but at different times on the weekends.

2. Control website 2: a price comparison website, which promotes the TOU tariff “Off-Peak Saver tariff” and invites people to get a quote for the tariff, the results of which are compared to an average flat rate tariff (“predictive price comparison”)
3. The nudge: a tailored website, which promotes the TOU tariff as an “Electric Vehicle tariff” and “Heat Pump tariff” and invites to people to get a quote for these tariffs (“tailored marketing”)

The purpose of the second control website is to test whether information provision, the traditional method of correcting sub-optimal decision making, is more or less effective than a nudge intervention.

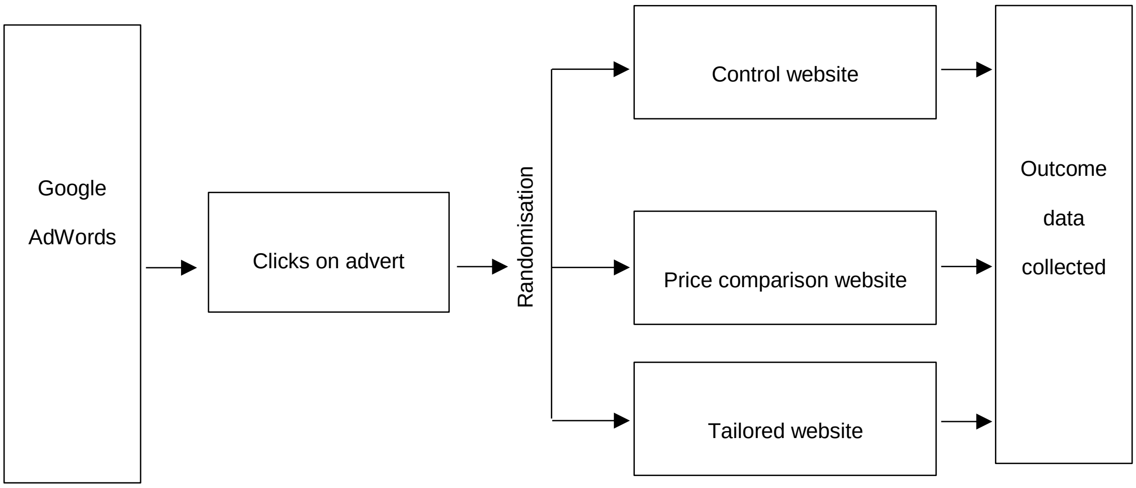
The design of the websites is described in more detail in Section 2.1.4 and the trial design is summarised in

Figure 9. Website visitors were not alerted to the fact that the website had been created for an academic research project upfront. Since the trial involved deception, no personal data was collected from participants and it was judged that, since fewer than 50 people[51] would switch to the tariff and the time taken to reach the end of the website was minimal (e.g. piloting suggested it takes <2 minutes), the risk of harm to participants was also minimal. The website stated clearly that any data provided would be used for research purposes[52] and, if any participants switched to the tariff, they were fully debriefed about the trial and given information on their likelihood of saving money on such a tariff, in attempt

[51] This was estimated based on Google analytic predictions of the number of website visitors, assuming a switching rate of 0.1%.
[52] This statement was written above the Switch to Us page of the website and did not specify what type of research the data would be used for, for instance, that it would be used as part of academic research.

to compensate them for their time. The trial was approved by the UCL ethics committee in June 2016 (project ID number 5701/002).

Figure 9 Overview of the Flex trial design



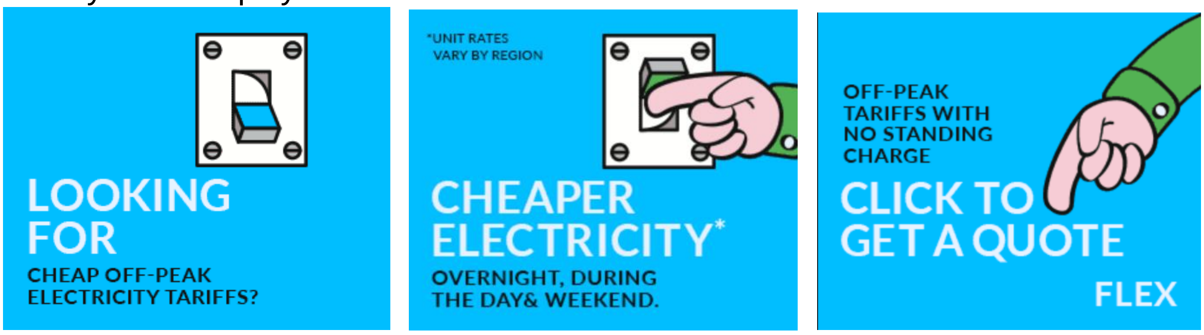
The three key strengths of this trial design are that: (1) it overcomes the problem of TOU tariffs not being commercially available by creating a tariff and presenting it to real consumers; (2) because participants are not explicitly told that they are participating in an experiment, it eliminates one potential concern around randomised control trials which is that people behave differently when they know they are being observed and; (3) since the website was built professionally and the visitors to the website are ordinary people who are looking for a new tariff to switch to, both the setting and participants are likely to be highly authentic (Gerber and Green, 2012).

2.1.3 Recruiting amongst the population of interest

Participants were recruited through targeted paid search and display adverts delivered through Google with a total budget of £2,270 from 24 November 2016 until 16 January 2017. The adverts do not refer to any of the treatment content on the website and only promote the fact that Flex offers a TOU tariff with cheaper rates during the day, overnight and at the weekend, something which is promoted across all three websites. Figure 10 below shows the text and the way the advert appears to potential participants through paid search advertising and Figure 11 shows the text that appears to potential participants through animated display advertising.

Figure 10 The advert shown to people who search for the keywords on Google.

Figure 11 The animated adverts which will be displayed on websites containing the keywords displayed in 2 .



The adverts were confined to GB, with further geographic targeting aimed at recruiting a much higher proportion of EV and heat pump owners relative to the average energy bill payer. First, all of the display advertising budget was allocated to targeting EV and heat pump owners by targeting special interest online magazines that were likely to be visited by heat pump or EV owners such as Next Green Car and Clean Technica.

Second, the paid search advertising (shown in *Figure 10*) was designed to recruit a higher proportion of EV and heat pump owners through a combination of keyword and geographic targeting. I bid for keywords that were *ex ante* judged by me to be correlated with heat pump or EV ownership such as “EV charging leads" and "heat pump controls" as well as keywords targeted at reaching the average energy bill payer such as "cheap energy tariffs"[1]; however, 80% of the budget was allocated towards EV specific and heat pump specific keywords.[53]

The geographic targeting worked as follows. Since the budget was limited, the adverts were confined to 150 postal districts in GB (the smallest geographic unit to which Google can target adverts), chosen from a total of 1,689 unique postal districts. The 150 postal districts were chosen by excluding areas of the City of London that were unlikely to be residential and excluding all districts that Google cannot locate[54] and then: (1) selecting the top 50 districts with the highest number[55] of heat pumps; (2) selecting the top 50 districts with the highest number of EVs; (3) randomly selecting 50 districts, that were not selected during stage (1) and (2) to target the 'average energy bill payer'. This allocation was performed in MS Excel. The purpose of reserving 2/3rds of the targeting for heat pump and EV owners rather than for the average energy bill payer was to help increase the likelihood that the majority of visitors to the website would own an EV and/or heat pump.

2.1.4 Intervention design

The blueprint for the design of each website was developed by me in MS PowerPoint. Every page on one website had an equivalent page on the other. The price bands and structure of the TOU tariff are identical across all

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[53] The full list of keywords are presented in Appendix 2. Note that, although the keywords include terms about price comparison, this would not bias the results since the keywords do not appear in the advert themselves.

[54] Google was unable to locate 24% of the postcode districts however very few of these districts were those with the highest number of heat pumps and EVs, meaning that this was unlikely to result in the study being unable to target locations with high numbers of EVs and heat pumps.

[55] The highest number of heat pumps and EVs was chosen instead of the highest density because postcode districts vary substantially in size meaning that very small districts with very few heat pumps could have a high density but very few people to target.

experimental conditions. The text varies across test websites, as required to manipulate the independent variables (summarised in Table 16), however the design (colour scheme, images, logo) remain constant, as shown in Figure 12.

Table 16 Summary of the intervention design across the three website versions in the Flex Trial.

	Control	Predictive price comparison	Tailored marketing
Homepage message	Off-peak electricity tariffs	Save up to £300 per year on our off-peak electricity tariff	Off-peak tariffs for electric vehicle and heat pump owners
Tariff name	Off-peak Saver tariff	Off-peak saver tariff	Electric vehicle tariff, Heat pump tariff
Homepage tariff information	Our off-peak rates: From 11.05p per unit, no standing charge	Our off-peak rates: From 11.05p per unit, no standing charge Average electricity rates: 14p per unit £69 standing charge	Our electric vehicle tariff: From 11.05p per unit, no standing charge Our heat pump tariff: From 11.05p per unit, no standing charge
Visitors are able to get a quote for what their electricity bill would be under the TOU tariff based on whether they own an electric vehicle, heat pump or neither of these	Yes	Yes	Yes
Visitors who obtain a quote for the TOU tariff also see an estimate of what they would pay on an average flat-rate tariff	No	Yes	No

Figure 12 The homepage for the control website (left), the price comparison website (center) and the tailored website (right).

When operationalising the concept of a price comparison, I followed the practices used by major price comparison websites and the academic marketing literature on comparison matrices (Häubl and Trifts, 2000; Lynch and Ariely, 2000). When operationalising the concept of providing tailored information I used two key sources identified during the literature review. The first was the literature on tailored communication in the health domain discussed in Chapter 3 where tailoring is defined as “a process of creating individualised communication” (Kreuter et al., 2002, p.272). A second literature is the literature on labelling effects. In the same way that the Government names the cash transfers it gives pensioners in Winter the ‘Winter Fuel Payment’ to encourage them to use it on heating (Beatty et al., 2014), the tariffs are labelled ‘Electric Vehicle Tariff’ and ‘Heat Pump tariff’ to indicate that the tariffs are ideal for EV and heat pump owners.

From each of the homepages, as well as at various other points throughout the website, visitors are encouraged to enter their postcode to get a quote for the tariff. When people enter their postcode they are asked three questions across all three experimental conditions:

1. How many bedrooms does your property have? The response options are: 1, 2, 3, 4+, in line with the categorisation used by the ONS to enable comparison with national statistics collected in the 2011 Census.
2. Do you own a heat pump or electric vehicle? The response options are: Heat Pump, Electric Vehicle, Both, Neither.

3. Do you have an Economy 7 meter? The response options are: Yes, No, Don't know.

The quote mechanism provides visitors with an estimate of their annual electricity bill under the TOU tariff based on whether they own a heat pump, EV or neither of these appliances, in other words, based on their response to question 2. These quotes were given to participants regardless of which of the group to which they were assigned.

The quotes provided to visitors are summarised in Table 17 and were based on the following realistic assumptions about total electricity use (since smart meters will permit actual usage to be used) but relatively idealistic assumptions about electricity consumption patterns to provide quotes that illustrate the best-case energy bill scenario for the average energy consumer (i.e. someone without an EV or heat pump) if they switched from the average flat-rate tariff on the market to the three-rate TOU tariff designed by the energy supplier to be commercial viable in the near future:

- Standard household electricity, excluding that used for an EV or heat pump, is 3,300kWh (UK median[56]) of which:
    - 10% is consumed at the peak time (4pm-7pm on weeknights)
    - 30% is consumed at the off-peak time (during the day)
    - 60% is consumed at the super off-peak time (overnight)
- Heat pump usage of 6,300kWh running all day except for during peak time[57]

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[56] Source is Ofgem (2011b).

[57] The two heat pump field trials in the UK show that heat pumps are run all day long (Energy Saving Trust, 2013).

- EV usage of 1,400kWh, consumed at super off-peak times

Table 17 Energy bill quotes provided to website visitors based on appliance ownership.

Appliance owned	Quote on TOU tariff (£/year)	Quote on average flat rate tariff (£/year)
	[visible in all conditions]	[only visible in price comparison condition]
No EV or heat pump	600	584
EV	630	730
Heat pump or heat pump & EV	1300	1480

Note: Respondents who indicated they had both an EV and heat pump were given the same quote as those who said they had just a heat pump to minimise the development work required to the website.

To my knowledge, there is no publicly available data on the electricity usage of EVs and heat pumps, so these were estimated based on published records of their technical efficiency and likely usage (see Appendix 3 for details). For consistency, all consumers were assumed to have the same level of flexibility over their 'standard electricity use'; these assumptions are idealistic in the sense that the DUKES data estimates that 'wet' goods (washing machine, dishwasher, tumble dryer) account for 17% of household electricity demand which BEIS assumes is available for demand-flexibility (DECC, 2014; BEIS, 2016b), compared to 60% super off-peak usage in this study. The same quote was given to customers who indicated that they had both an EV and heat pump as those who said they had just a heat pump to minimise the development work required to the website.

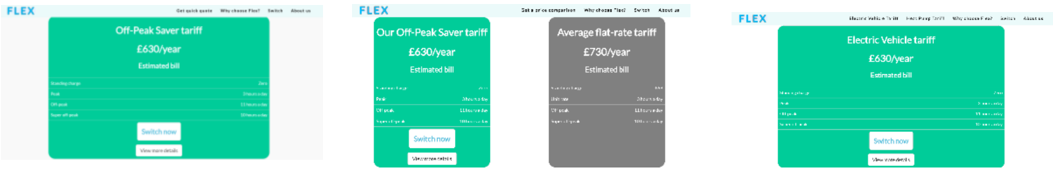
The key points to note are that: (1) although the monetary value of the quotes vary depending on what appliance people report to own, the values are identical across all three website conditions, with randomisation ensuring that, the proportion of EVs and heat pumps owned by participants across each group would be roughly the same; (2) in the price comparison condition, the estimate on the TOU tariff is compared to an estimate based on the average electricity rate for a flat-rate tariff in 2015 [58], which for electric vehicle and heat pump owners shows that they will £100 or £180 per year respectively relative to the average flat rate tariff but for the average consumer that they will lose £25 per year, despite the very idealistic off-peak usage assumptions (see Table 17); (3) in the tailored condition, there is no price comparison information but the tariff is labelled either an 'Electric Vehicle tariff', 'Heat Pump tariff' or 'Heat Pump and Electric Vehicle tariff' depending on their response to question 2.

Whilst it may seem surprising that non EV and heat pump owners would be financially worse off despite assuming that only 10% of electricity would be used at the peak time, it is not that counterintuitive considering that the peak rate is over 100% higher than the average flat-rate tariff rate whereas the off-peak rate is slightly more expensive and the super-off peak rate is only about 30% lower than the flat-rate (see Appendix 4 for prices). Moreover, whilst the magnitude in the savings or losses is likely to vary depending on the exact peak and off-peak rate differentials which could vary across tariffs, the overall result that the average consumer is worse off may not change much for two reasons. First, the price comparison here is made with reference to the average flat-rate tariff on the

[58] This is the average price across all regions and payment methods for standard rate tariffs in 2015 as reported in DECC's statistical tables "Table 2.24 "Average variable unit costs and fixed costs for electricity for selected towns and cities in the UK".

market so the savings or losses from sticking on a flat-rate tariff would be even larger if compared to the cheapest tariff on the market. Second, this magnitude of savings and losses is consistent with Ofgem's estimate of the total savings from having a smarter energy system and with the energy bill savings and losses observed in the trials reviewed in Chapter 2.

Figure 13 Quote results in the control group (left), price comparison group (middle) and tailored group (right) for visitors who reporting owning an EV



These savings or losses are made clear to visitors assigned to the price comparison group (see Figure 13) but underpin the labelling of the tariff as an 'electric vehicle' or 'heat pump' tariff in the tailored condition. Thus, whereas the price comparison condition uses reason and logic to help people work out whether the tariff will save them money, the tailored condition provides people with a signal as to whether the tariff may or may not be suitable for them without altering the underlying incentives of signing up to the tariff (the rates and overall estimated bill are the same as in the other conditions) or changing the costs associated with switching tariff (it does not lower search costs associated with finding the rates of other electricity tariffs). It therefore fits Thaler and Sunstein's (2008) definition of a "nudge".

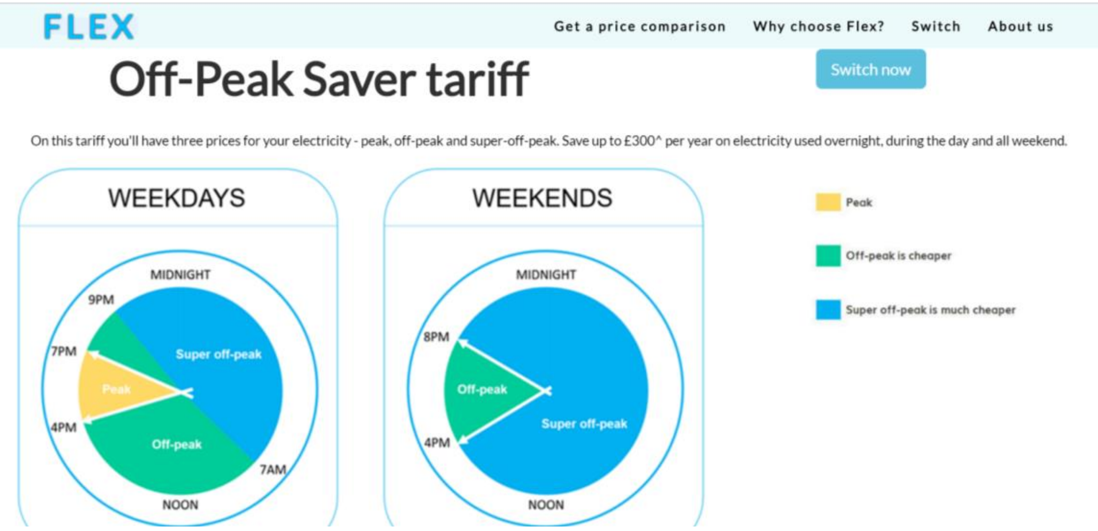
Participants were encouraged to 'Get a quote' at various other points on the website, not just the homepage, to increase the likelihood of exposure to the questions and the quote results, which offer an additional layer of treatment intensity above and beyond the homepage. To ensure that visitors to the homepage can get a quick understanding of what an off-peak tariff is, in the likely event that they have never encountered one before, a short scroll down the homepage reveals a basic description of the tariff and the idea of having peak and off-peak electricity rates, shown in Figure 14. It also prompts visitors to get a quote.

Figure 14 Basic description of how an off-peak tariff works on the homepage in all experimental conditions.

Participants who obtained a quote could also access a more detailed visual presentation of the tariff design, which was also framed differently depending on the intervention. In the control condition and price comparison conditions, the tariff is called an ‘Off-Peak Saver Tariff’. In the price comparison condition the tariff description includes the line “Save up to £300 per year on electricity used overnight, during the day and all weekend” (see

Figure *15*) and in the tailored condition the tariff is called either an ‘Electric Vehicle Tariff’, ‘Heat Pump Tariff’ or ‘Heat pump and Electric Vehicle tariff’ depending on the participants’ response to the questions and the description reads “[Charge your vehicle], [Run your heat pump], [Charge your vehicle and run your heat pump] for less overnight, during the day and all weekend”.

Figure 15 The Off-Peak tariff visualisation in the price comparison condition.



In summary then, the information given to participants is factually identical across all the website versions aside from the framing and the provision of price comparison information in the price comparison condition.

2.1.5 Outcomes

The main outcome measure is the proportion of people who enter their postcode to obtain a quote (binary 1=got a quote; 0=did not get a quote).

Secondary outcome measures include:

- Number of pages viewed (interval)
- Click through rate to the ‘switch to us’ page of the website (binary 1=clicked through; 0=did not click through)
- The proportion who switch to the tariff (binary 1=switched; 0=did not switch)

Obtaining a quote is being used as the main outcome measure rather than switching rates because, as switching rates are low in general, there is unlikely to be sufficient variation in switching rates to measure the impact of the manipulations. However, all the measures outlined above are arguably valid ways of operationalising demand for a TOU tariff.

2.1.6 Additional data collection

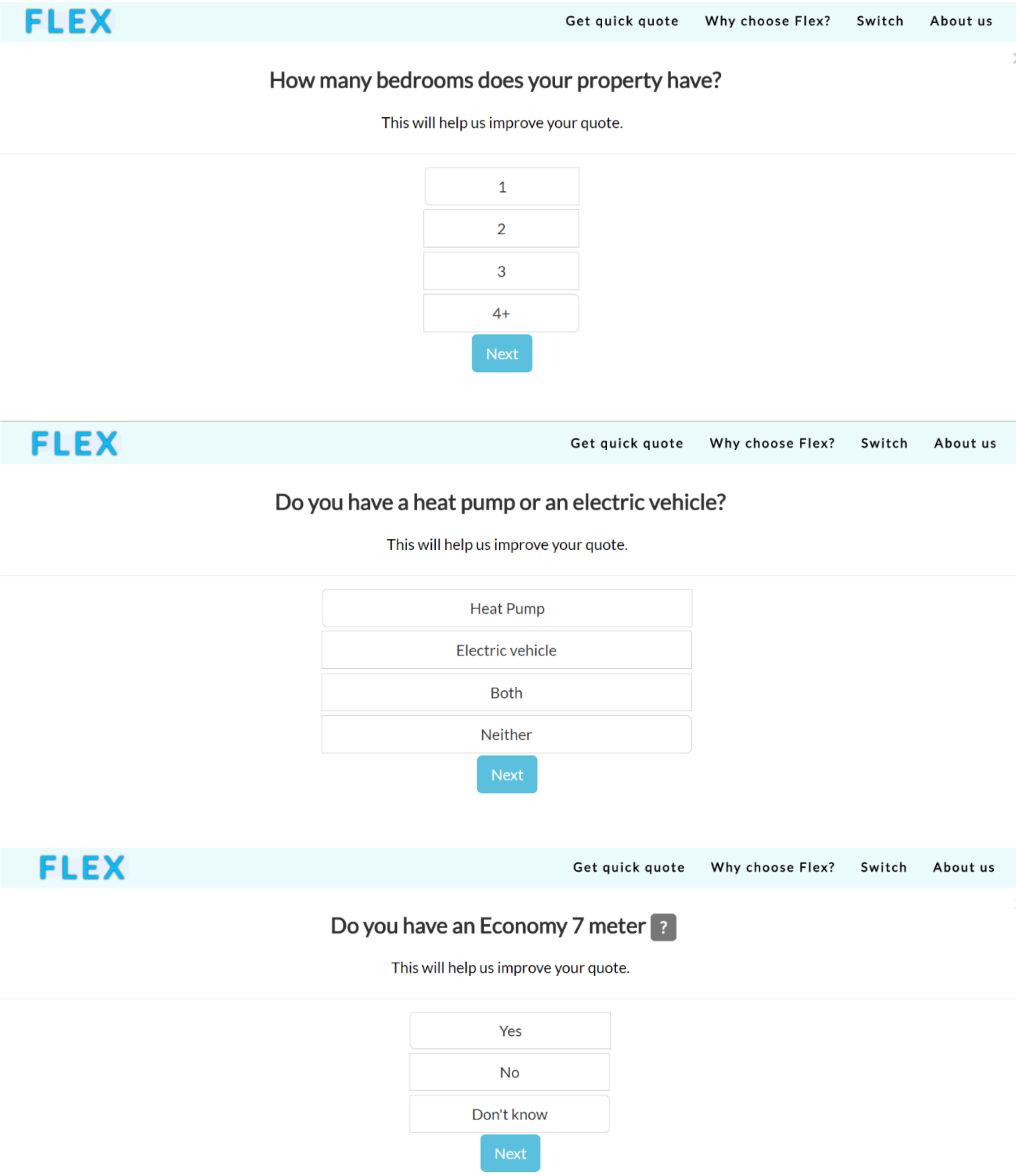
Gerber and Green (2012) encourage researchers to take advantage of opportunities to gather background data on participants that may be helpful in predicting the outcomes of interest and therefore for increasing the precision of treatment effect estimates. Instead of using a baseline survey administered to participants who are recruited in advance as in other field experiments, (e.g. Glewwe et al., 2009; Evans and Kremer, 2009; Hirshleifer et al., 2016), in this study surveys were embedded into the website at points at which it would be natural to collect data from visitors to an energy supplier's website: (1) when participants were getting a quote and; (2) when switching to the tariff.

As noted above, to maximise the likelihood of a visitor completing the surveys, the website was designed to prompt survey completion at various points throughout the website, as is common on most commercial websites. For example, if people scrolled down the homepage without inserting their postcode to get a quote, they would have another opportunity to get a quote because the next page would present the tariff and prompt them to get a quote.

This additional data collection was maintained to an extreme minimum to limit the amount of time that participants would spend on the website given that the tariff is not currently available to switch to and to minimise attrition. Data collection was generally reserved to obtaining data what appliances visitors owned in order to provide personalised quotes (as outlined in the Intervention section above), to get an insight into the effectiveness of the sampling strategy at driving a large proportion of EV and heat pump owners to the website and for including in treatment effect heterogeneity analyses. This data was not intended for use as covariates to estimate average treatment effects because the average treatment effect needs to be estimated based on the outcomes for the whole sample not just the sub-sample completing the surveys. The data collected at these two points is outlined below.

Data collected when getting a quote: The first point at which visitors were surveyed is when they entered their postcode to get a quote for the tariff. Only the first three characters of the postcode (the postal district) are stored in the database to minimise the likelihood of being able to identify individuals personally from the data provided. On entering their postcode, participants were asked three questions, namely the number of bedrooms they have in their home, whether they own a heat pump or EV and whether they have an Economy 7 meter, as described in section 2.1.4. This is approximately the same number of questions that suppliers normally ask of website visitors seeking a quote, and, as shown in Figure 16, these questions are presented like they would be presented on a supplier’s website not like a standard academic baseline survey.

Figure 16 Get a quote survey questions as presented to all website visitors in all



experimental conditions.

Information on number of bedrooms is collected because it provides a useful potential method for comparing the demographics of the website visitors to the average household in GB recorded in Census data.

Collecting information on EV and heat pump ownership is important for understanding any treatment effect observed on the tailored website relative to the control website, since the hypothesis that the tailored website will generate higher demand for the tariff relative to the control is premised upon the assumption that the majority of visitors will own these devices due to the targeted recruitment strategy. It is this variable that is used to customise the quote to participants.

Information on whether someone has an Economy 7 meter – the most common legacy TOU tariff in the UK – is collected for comparing the characteristics of the sample with those of energy bill payers from a nationally representative household survey (M Nicolson et al., 2017).

Since it was expected that the overwhelming majority of people would not switch to the tariff, and therefore reach the second survey, including this short survey which people would reach directly from the homepage was an important design strategy to help maximise the amount of total data collected on participants.

Data collected when switching to the tariff: The second point at which visitors to the website could be surveyed is when clicked on any button that said 'Switch to this tariff' or 'Switch'. A short form was presented with the following 5 questions:

1. How many bedrooms does your property have?[59]
2. Do you have any of the following on your house?[60]
    - Heat pump
    - Electric vehicle – leased
    - Electric vehicle – owned
    - Dishwasher

[59] This question was asked because it is commonly used by energy suppliers and price comparison websites to give quotes, so heightens the ecological validity of the website.
[60] Although ownership of these appliances would ordinarily be elicited across multiple questions in a survey, it was considered more time efficient in this context to elicit the responses in a single question.

- Tumble dryer
- Washing machine
- Washer dryer
- Electric shower
- Solar panels
- None of the above

3. What is your main method of heating your home?[61]
    - Gas central heating
    - Electric night storage
    - Heat pump
    - Underfloor heating
    - Other gas
    - Other electric
    - Other
    - Don't know
4. Do you have a smart meter? Yes, No, Don't know. Participants were able to click on a '?' icon to reveal a short description of what a smart meter is.
5. Do you have an Economy 7 meter? Yes, No, Don't know. Participants were able to click on a '?' icon to reveal a short description of what an Economy 7 meter is.

Heating is the principal source of demand in homes in the UK (Palmer and Cooper, 2012) and consumers without electric heating – or another high consuming appliance such as an EV – are less likely to save money from

[61] Question wording and response options adapted from the Energy Follow Up Survey (BRE, 2013) and as used in Nicolson et al. (2017). Adaptations were to make the response options shorter, by amalgamating less common heating types into an 'Other' category.

switching to a TOU tariff than consumers with high consuming electrical appliances. However, appliances like washing machines, dishwashers and tumble dryers are considered flexible electricity loads in the sense that they could be run at any point in the day (DECC, 2014; BEIS, 2016b), compared to cooking which is usually restricted to the morning and evening for the majority of working families. Collecting this data would also enable me to calculate what proportion of people who switch own these appliances so that, depending on how many people switch, it would provide insight into whether consumers are able to identify whether they are likely to save money on the tariff, as the results from the Tariff Decision Making Study suggest that many may not. The full survey with the response options is provided in Appendix 5.

Data collected from Google Analytics: Google Analytics was implemented on each of the websites using the Google Analytics snippet code.[62] This provides aggregate level data on website visitors including on their gender, age and region. Although it cannot be used in any of the analyses – since it is not individual-level data – it can be used to understand the characteristics of web visitors as compared to the average adult member of the population from Census data to help identify the population to whom the average treatment effect estimate applies.

2.1.7 Sample size

The minimum detectable effect size was ultimately[63] defined as the difference in the proportion of consumers obtaining a quote (the "conversion rate") required to

[62] Google Analytics is a free web analytics service offered by Google. It is the most widely used analytics service.
[63] Originally the minimum detectable effect size was defined as the difference between the two recruitment rates whereby the marginal cost of recruitment was higher than a pre-defined value of recruiting a flexible electricity customer onto a TOU tariff compared to when the marginal cost

reduce the marginal cost of converting a customer from the industry average of £50 to £10 which is what a small energy supply business is estimated to be able to afford (Littlechild, 2005). The actual minimum detectable effect size could therefore only be computed once recruitment had concluded, since the cost per conversion is a function of how many participants visited the website in total.

Although this is not the conventional way of running power calculations – ideally, sample size calculations are undertaken to guide researchers as to how large a trial should be conducted based on an expected baseline variation in the outcome variable – there was no reliable baseline data upon which to base sample size calculations. However, sample size calculations based on a range of measures of uptake based on the estimated sample size provided by Google given the budget (12,000 participants) suggested that the trial would be able to detect a treatment effect of 80%, which is in the region of some of the effect sizes observed from the framing reviewed in Chapter 3.

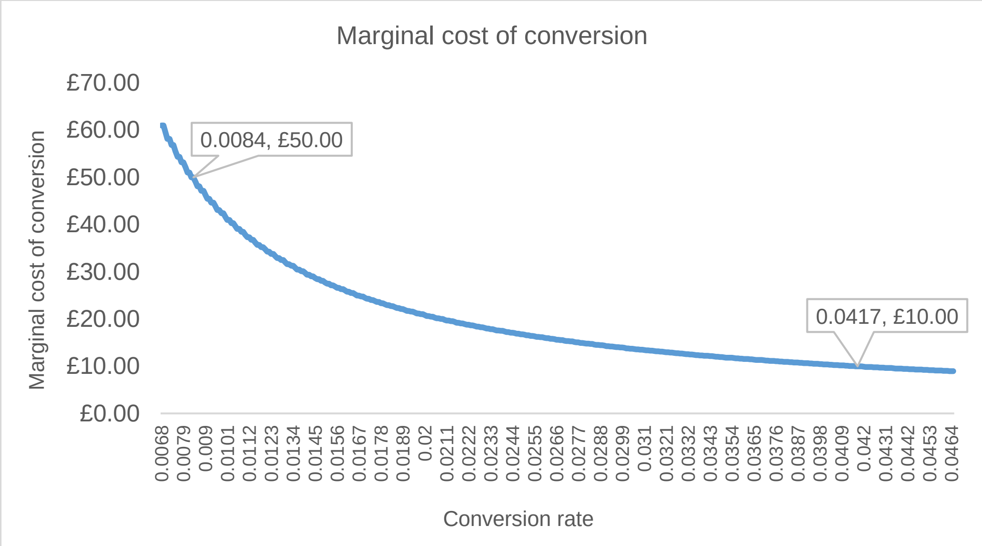
Recruitment concluded when the advertising budget was expended and the minimum detectable effect size was calculated as being 400%, as identified using

Figure 17, which is the percentage increase in conversions required to take the conversion rate from 0.0084 (with an associated marginal cost of conversion of £50) to a conversion rate of 0.0417 (with an associated marginal cost of conversion of £10). Whilst this may seem like a very large minimum effect, consider that the profit margins for energy suppliers are relatively low (just £47 in

of recruitment is the same as the pre-defined value. However, this method was later rejected and replaced with the one described above in an addendum to the original Pre-Analysis Plan prior to analysis of the outcome measures and also registered on the EGAP website alongside the original Pre-Analysis Plan.

the UK in 2015) and the former national supplier is estimated to have built up losses of £100 per customer to build the customer base (Littlechild, 2005).

Figure 17 Identifying the minimum detectable effect size based on the cost of participant recruitment.



I do not present the post hoc power calculations based on the realised sample size and variation in the outcome in the control group because, as noted in an update to the CONSORT reporting guidelines (Moher et al. 2010, p.8) “There is little merit in a post hoc calculation of statistical power using the results of a trial”.[64] Once an experiment has been run the power of the experiment is indicated by the confidence intervals around the point estimate of the treatment effect (Goodman and Berlin, 1994; Moher et al., 2010).

2.1.8 Randomisation and blinding

[64] As pointed out in Goodman and Berlin (1994): “there is not a unique power estimate to use; there is a different power for each underlying difference. Does one say that a nonsignificant result rules out a 25% difference with 90% confidence (because there was 90% power for a 25% difference); or that it rules out a 21% difference with 80% confidence; or that it rules out a 15% difference with 50% confidence?” (p. 202).

Randomisation mechanism: The treatment was randomly assigned at the cookie-level. Cookies identify a combination of a unique device (e.g. a persons' mobile phone, tablet or laptop) and an individuals' user profile on their chosen browser however for ease of understanding I refer to participants rather than browsers as is the convention established by other researchers for online studies.

When potential participants click on an advert, they are randomly redirected to one of the three different websites with a 1:1 allocation mechanism, using randomisation code implemented on the website. Although there is one website domain www.flexenergy.co which is inputted into the Google advert, there are three sub-domains www.flexenergy.co#1, www.flexenergy.co#2 and www.flexenergy.co#3, to which participants are randomly assigned. The website number is masked from participants to avoid alerting their attention to the existence of website variations.

Note that, this is different from implementing the three sub-domains into three independent Google adverts; this method was rejected because it would not necessarily give each participant an equal probability of being assigned to any of the three websites because Google will automatically increase the proportion of times that a particular advert is displayed if it detects that it has a higher conversion rate than other adverts in the group. Although there is no reason that think that identically worded adverts with slightly different URLs would perform differently, discussions with Google suggested that such a scenario was a possibility.

Blinding: Since the randomisation was performed by the algorithm on the website neither I nor the participants were aware of the treatment to which they were assigned; indeed, participants would not be aware that any randomisation was taking place.

2.1.9 Analysis plan

The pre-analysis plan for this study was registered with the Experiments in Governance and Politics (EGAP) trial registry (20161112AA) prior to participant recruitment.

Average treatment effect equation: The second research question asks whether tailored message framing information will increase uptake to TOU tariffs amongst consumers who are more likely to save money. The second research question is associated with three hypotheses about the average treatment effect of the interventions on demand for the tariff:

- **Hypothesis 1** 'Get a quote' rates will be higher in the price comparison group than the control group.
- **Hypothesis 2** 'Get a quote' rates will be higher in the tailored group than in the control group.
- **Hypothesis 3** 'Get a quote' rates will be higher in the tailored group than in the price comparison group.

Following Angrist and Pischke (2008) and the conventions in the most recent applied econometrics literature[65], the following statistical equations will be estimated using Ordinary Least Squares (OLS) regression to test hypotheses 1, 2 and 3 respectively[66]:

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[65] See, for example, publications in *American Economic Journal: Applied Economics*.

[66] The reason for running two separate regression equations rather than one equation with two treatment dummies as Glennerster and Takavarasha (2013) suggest for trials with more than one treatment arm is that controlling for the baseline value of the tailored arm could affect the coefficient obtained on the price comparison dummy (and vice versa). Running each equation

[1] $Y_i = \alpha + \beta_1 T2_i + \varepsilon_i$

[2] $Y_i = \alpha + \beta_2 T3_i + \varepsilon_i$

[3] $Y_i = \alpha + \beta_3 T3_i + \varepsilon_i$

Where in all equations:

- Y is a binary outcome measure (1=get a quote; 0=did not get a quote)
- α is a constant
- ε_i is the error term.

In equation [1]:

- $T2$ is the treatment dummy variable (1=price comparison condition; 0=control condition), thus excluding participants assigned to the tailored group
- β_1 is the coefficient on $T2$ which measures the effect of being in the price comparison group rather than the control group and is the coefficient of interest for testing hypothesis 2.1

In equation [2]:

- $T3$ is a treatment dummy variable (1=tailored condition; 0=control condition), thus excluding participants assigned to the price comparison group
- β_2 is the coefficient on $T3$ which measures the effect of being in the tailored group rather than the control group and is the coefficient of interest for testing hypothesis 2.2

separately should yield treatment effect estimates that are more similar to those obtained when computing the percentage difference in uptake across each treatment group using the raw data.

In equation [3]:

- $T3$ is a treatment dummy coded (1=tailored condition; 0=price comparison condition), thus excluding participants assigned to the control group
- β_3 is the coefficient on $T3$ which measures the effect of being in the tailored group rather than the price comparison group and is the coefficient of interest for testing hypothesis 2.3

Based on the review of the theory and literature outlined in Chapter 3, and the effectiveness of the targeting strategy to mainly drive participants with EVs and heat pumps to the website[67], I expect the coefficients β_1 , β_2 and β_3 to be statistically significant and positive.

The equations above were also run with the secondary outcome measures identified in Section 2.1.5 and the following pre-specified set of baseline covariates to increase the precision of treatment effect estimates by reducing unexplained variation in the outcomes (Gerber and Green, 2012):

- Whether they are a new or returning visitor (binary 1=yes; 0=no)
- The referring advert (fixed effects)
- The device the website was viewed on (binary 1=computer; 0=mobile/tablet) and;
- The time the website was visited, for instance 18:40 (fixed effects).

Note that none of these covariates are collected in the surveys but are collected from all consumers regardless of whether they complete the survey based on

[67] The Pre-Analysis Plan does not make this condition explicit although it was assumed when the plan was created.

cookies; this was so that average treatment effect analyses would be based on the average visitor not visitors who completed the surveys.

In some disciplines it is considered inappropriate to use OLS regression when analysing impacts on binary dependent variables. Following the conventions in the applied econometrics literature, robustness checks in which the equations are ran using logit with the associated marginal effects will also be run. If the results are substantively identical, then the OLS estimates will be interpreted because they offer an easier interpretation than marginal effects whilst generally providing substantively very similar results to limited dependent variable models such as logit and probit (Angrist and Pischke, 2008; Beck, 2011). If there are substantial differences between the OLS and logit estimates then this could indicate that the OLS model provides a poor fit for the data, in which case the logit specification reported with marginal effects will be used to interpret the results. See Section 2 of Annex 5 for a full account of why OLS was chosen as the preferred specification over logit.

Heterogeneous treatment effect equation: Although the recruitment strategy has been designed to drive a majority of EV and heat pump owners to the website, it is expected that a fraction of the participants will not own EVs and heat pumps since the strategy also targets some non EV and heat pump owners to the website. Depending on the ratio of heat pump and EV owners to non-heat pump and EV owners, the average treatment effect equation may not pick up the treatment effect of tailoring on its intended target audience. To get a more precise estimate of the impact of tailoring on EV and heat pump owners, an additional statistical model was designed to test for the presence of heterogeneous treatment effects to test the following hypothesis in answer to research question 2:

Hypothesis 4 'Get a quote' rates will be higher in the tailored condition than either the control or price comparison conditions amongst the population of interest (heat pump and EV owners).

The following statistical model was designed to test hypothesis 2.4 amongst the participants for whom there is data on whether or not they own an EV or heat pump:

$$[4] \qquad Y_i = \alpha + \beta_1 T3_i + \beta_2 \delta.index_i + \beta_3 T3_i * \delta.index_i + J_i + \chi_i + \mu_i$$

Where:

- Y is a binary outcome measure (1=get a quote; 0=did not get a quote)
- α is a constant
- $T3$ is the treatment dummy variable (1=tailored condition; 0=all others)
- $\delta.index_i$ is a 'diagnostic index' (Wydick, 2016), a dummy variable which indicates whether an individual has a high value on the diagnostic index (i.e. self-reported as having a heat pump or EV) compared to those who have a low value (i.e. self-reported as not owning a heat pump or an EV or did not report at all)
- β_1 is the coefficient on $T3$ which measures the effect of being in the tailored group rather than the price comparison group or control group for the average participant in the sample
- β_2 is the coefficient on $T3$ which measures the correlation between self-reporting to have an EV or heat pump compared to self-reporting not to have an EV or heat pump.

- β_3 is the coefficient on the interaction term $T3_i * \delta.index_i \mathrm{T3_i{*}\delta.ev\&hp_i}$, which measures the effect of being in the tailored group and having a high value on the diagnostic index (e.g. self-report as having either an EV or a heat pump) compared all other possible combinations and is therefore the coefficient of interest for testing hypothesis 2.4
- ε_i is the error term.

Based on the review of the theory and literature outlined in Chapter 3, I expect the coefficients β_1 , β_2 and β_3 to be statistically significant and positive.

2.2 Implementation of trial

Trial recruitment commenced in November 2016 and ended in January 2017 when the advertising budget had been fully expended.

Figure 18 summarises the flow of participants from initial recruitment through to randomisation and collection of the behavioural outcome measures. Approximately 3 million online users saw the adverts out of which 7,513 clicked on the advert and a total of 6,446 unique users landed on the website and were randomised to one of the three experimental versions of the site. Outcome data is available on 100% of users who were randomised and who are therefore participants in the field experiment.

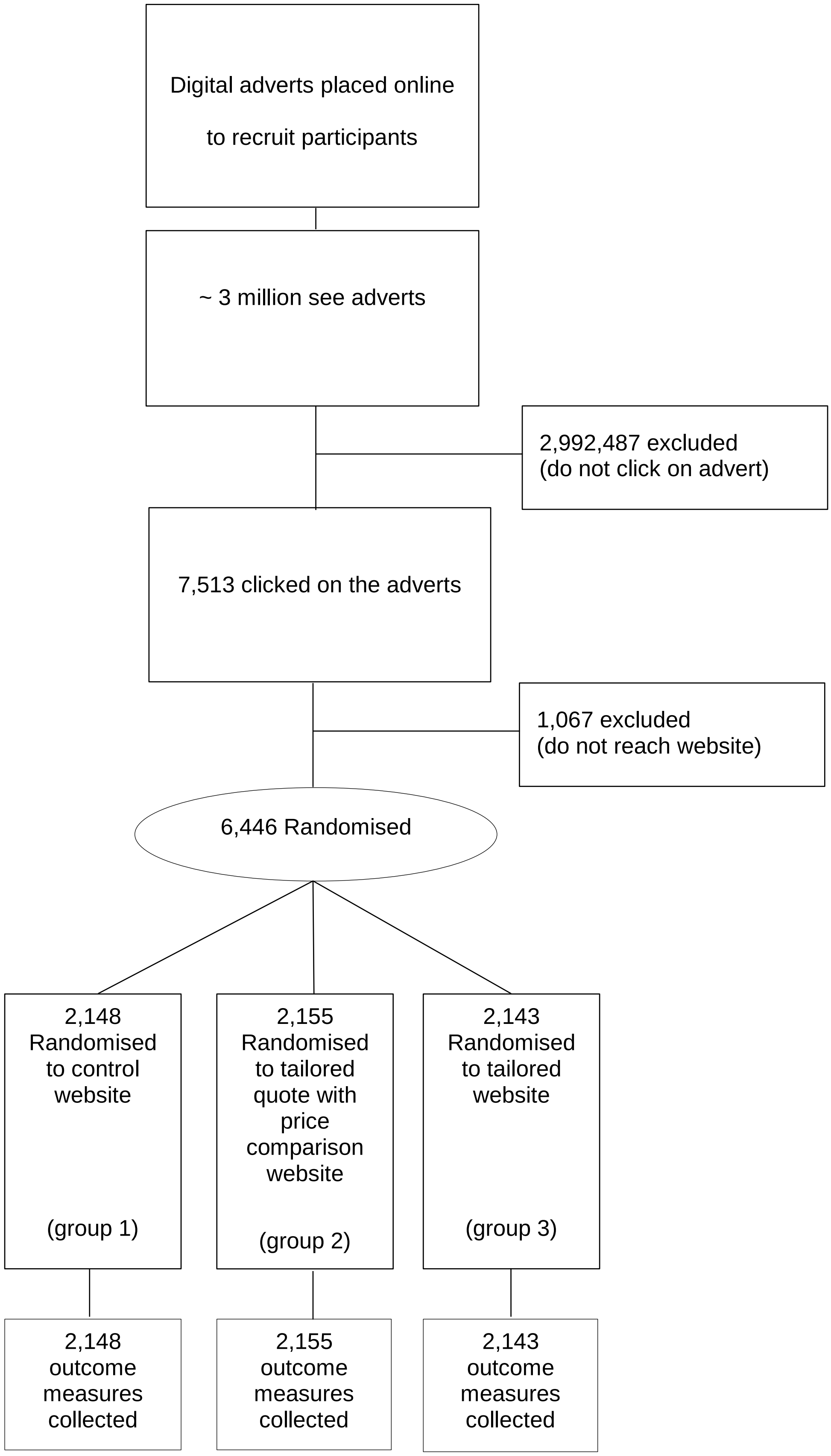
As shown in Table 18, the sample size is evenly distributed across the three groups in line with the randomisation mechanism which was programmed to provide each individual with a 1 in 3 probability of being assigned to any of the website versions. Given that the randomisation mechanism was effective, we can expect that the characteristics of participants in each group are the same, on average.

Table 18 Randomisation balance checks on sample size per experimental group

	Control (mean)	Price (mean)	Tailored (mean)	Control v. Price (p value)	Control v. Tailored (p value)	Price v. Tailored (p value)
Proportion	0.333	0.334	0.332	0.9150	0.9392	0.8548
N	2148	2155	2143	0.9263	0.9474	0.8740

Notes: The p-values were obtained by regressing the treatment dummy against the proportion of participants in each group using OLS linear regression.

Figure 18 Participant flow diagram for the Flex Trial (CONSORT)



2.3 Descriptive statistics of sample

2.3.1 Participant demographic profile

Table 19 presents the characteristics of British energy bill payers obtained from a nationally representative survey of British adults compared to the demographic characteristics of visitors to the website in the Flex Trial obtained from Google Analytics.

The average visitor is aged 25-35[68], living in England and is only slightly more likely to be male than female. This makes the sample population relatively representative of the wider adult population of GB in terms of gender and region but not in terms of age. The sample underrepresents people aged 55 and above and particularly over-represents 18-24 year olds who constitute 27% of my sample even though they make up only 9% of British energy bill payers in the general population.

Google also shows that 98% of the sample visited the website from within the United Kingdom, which means that the geographic targeting of the adverts was very effective.

[68] Age 25-34 is the modal age category.

Table 19 Characteristics of energy bill payers in the British population and in the sample from Google Analytics

	GB population	Sample population (Google Analytics)
	(%)	(%)
Gender:		
Female dummy	51	46
Age in six year groups:		
18-24[69]	9	27
25-34	18	34
35-44	18	16
45-54	18	13
55-64	15	6
65+	22	6
Region within the United Kingdom:		
England	84	94
Scotland	8	5
Wales	5	1
Northern Ireland	3	0.1
Unknown	-	0.04

2.3.2 Outcome variables

Descriptive statistics for the outcome variables in the Flex Trial are presented in Table 20. The proportion of people who get a quote for the tariff is the primary outcome measure and, as expected, it is the outcome with the greatest degree of variation. Approximately 2% of participants obtained a quote for the tariff. This means that the data is unlikely to be sufficiently robust to test for the presence of

[69] This is based on 20-24 for the GB population because Census statistics are broken down into five year intervals in which 18 and 19 year olds are grouped with 15-17 year olds.

heterogeneous treatment effects from tailoring on EV and heat pump owners to test hypothesis 4, since the sample size will be very small. The Population-Based Survey Experiment which collected appliance data on all survey participants will therefore be used to test hypothesis 4.

Variation in the secondary outcome measures is low; just 1% of participants clicked on the ‘Switch to Us’ icon on the webpage and just 0.3% of participants switched to the tariff. This low switching rate is in line with what I expected given that very few consumers do switch electricity tariff and it also suggests that the website was perceived as genuine. Approximately 98% of the sample only viewed one page, although approximately 1% viewed as many as 4 pages and a handful of participants viewed up to 9 pages.[70]

Table 20 Outcome variables in the Flex Trial.

	%	SE	Range	N
Got a quote (primary outcome)	2	0.02	0-1	6446
Clicked on ‘Switch to Us’ icon	1	0.01	0-1	6446
Switched	0.3	0.007	0-1	6446
	Mean	SD		N
Number of pages viewed	1	0.07	1-9	6446

[70] This variable does not represent unique pages viewed but is a measure of the number of pages loaded by the participant.

2.3.3 Web session characteristics

In the Flex Trial, data was collected through Google Analytics on what device the participant was accessing the website on as well as whether the visitor returned to the site more than once and how many times they did this. Since this data was collected on all participants and could be expected to explain variation in the outcome measures these variables, presented in Table 21, are used as covariates in the treatment effects equation.

As can be seen, the overwhelming majority of participants (93%) visited the website on a mobile phone, reflecting a growing trend for browsing the Internet on phones (Ofcom, 2015). The majority of visitors only visited the site on one occasion, with only 24 users (0.37% of the sample) having visited more than once.

Participants came to the website from 28 referred websites. Although I had planned to include this variable as a series of fixed effects in the covariate specification of the treatment effect equation, it is excluded from all analyses because it requires estimating more additional parameters than there is degrees of freedom to do so.

Table 21 Characteristics of web session in Flex Trial***.***

	%	SE	Range	N
Visited website on a mobile	93	0.03	0-1	6446
Returned to the website	0.37	0.07	0-1	6446

2.3.4 Appliance ownership and household data

Table 22 describes the self-reported appliance ownership and household characteristics of website visitors in the Flex Trial. Although the characteristics presented may not necessarily apply to website visitors as a whole, the data collected on the sub-sample of participants who completed the survey indicates that most participants did not own an EV or heat pump. Of those who completed either of the two surveys, approximately 30% reported owning or driving an EV and 8% reported living in households with heat pumps. Thus, whilst this data suggests that the advert targeting was relatively effective at driving a larger proportion of EV and heat pump owners to the website than their proportion in the population – the proportion of people reporting to own an EV is nearly 4 times higher than the proportion in the population and 20 times more people reported owning a heat pump than the proportion who own heat pumps in the population – it seems unlikely that it achieved its intended aim which was to ensure that EV owners and heat pump owners formed the vast majority of the sample.

This does not present a problem for estimating the impact of the interventions on the average energy bill payer since none of these variables are included or required for estimating the average effect. However, it does change the model's prediction about the direction of the effect of both the predictive price comparison and tailored marketing interventions on uptake to the TOU tariff from the hypotheses outlined in Section 2.1.9, as will be discussed in more detail in the discussion section of this chapter). ***This is because*** most participants in the price comparison condition would have been presented with a quote demonstrating that the TOU tariff would cost rather than save them money whilst most participants in the tailored condition would have been told the tariff was suitable for electric vehicle owners and heat pump owners and yet not have owned these appliances. A classical economic model would thus predict that the price comparison condition will reduce demand for the tariff relative to the control. The model outlined in Chapter 3 to explain the impact of tailoring, would also predict that the tailored condition would reduce demand for the tariff relative to the control.

Table 22 Self-reported appliance ownership and household characteristics in Flex Trial.

	Sample statistics			British population statistics
Appliance ownership:	%	SE	N	%
EV	31	4.2	124	8
Heat pump	8	2.5	124	0.3
EV & heat pump	5	1.9	124	0.03
Dishwasher	43	11	21	30
Tumble dryer	48	11	21	60
Washer dryer	14	7.8	21	23
Washing machine	71	10	21	90
Electric shower	47	11	21	-
Solar panels	14	7.8	21	0.7
Household characteristics:	%	SE	N	%
Electric heating	38	11	21	10
Gas central heating	62	11	21	77
Legacy Economy 7 tariff	36	4.4	121	21
Smart meter	33	11	21	10
	Mean	SE	N	Mean
Number of bedrooms	2.6	0.09	130	2.7

When looking at wet goods ownership, we can see that, of those who reported whether or not they owned a dishwasher, tumble dryer, washer dryer or washing machine, a higher proportion own a dishwasher in this sample than in the general population but a lower proportion report owning a tumble dryer and washing machine. The proportion reporting owning a washer-dryer is very similar in this sample to the general population. When looking at the household characteristics, we can see that the majority of participants (62%) have gas central heating, almost in the same proportion to those in the population (77%).

Although the running of wet goods can be relatively easily shifted into the off-peak hours on the TOU tariff (by comparison to cooking or lighting), because use of these appliances account for a much lower proportion of total household energy use than heating or than charging an EV (for households who have one), these participants would need to shift more than 60% of their electricity demand into the off-peak hours to save money on the tariff relative to the off-peak tariff – hence, why the price comparison shows that they would lose rather than save money, since it assumes a maximum of 60% super off-peak usage.

The average reported number of bedrooms is 2.6 which is very similar to the British average of 2.7. However, like the data collected on EV and heat pump ownership, the data collected on electric heating, presence of a smart meter and whether the household is on an Economy 7 tariff also points to the conclusion that the average participant in this study is different to the average British energy bill payer, as was intended.

2.4 Results – average treatment effects

2.4.1 Outcomes by experimental group visually

As is visible in Figure 19 and Figure 20, and contrary to the initial hypotheses laid out in Section 2.1.9, outcomes are consistently higher in the control condition relative to the price comparison condition and tailored condition for each of the three binary outcome measures (get a quote, clicks on the Switch to Us icon and switching) and the continuous outcome measure (page views). When looking just at the primary outcome measure – the proportion who got a quote for the tariff – 3% of those in the control condition obtained a quote by comparison to just 1.9% in the price comparison condition and 1.8% in the tailored condition, meaning that get a quote rates were 40% higher in the control condition relative to the price comparison condition and 42% higher in the control compared to the tailored condition.

Figure 19 Demand for the TOU tariff across experimental groups

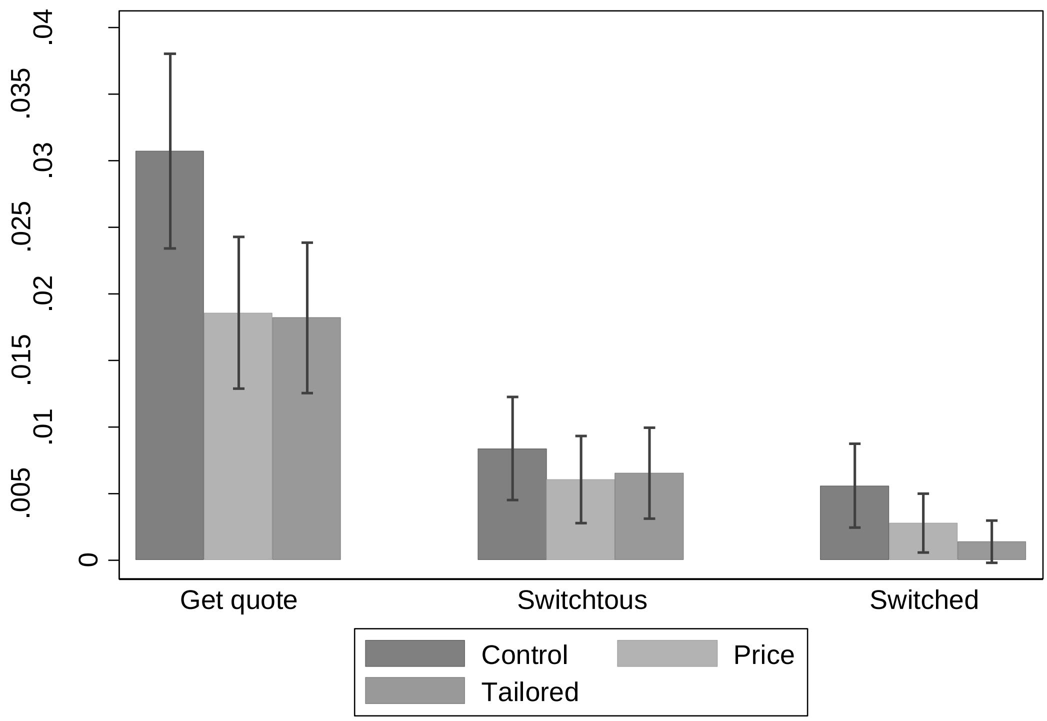
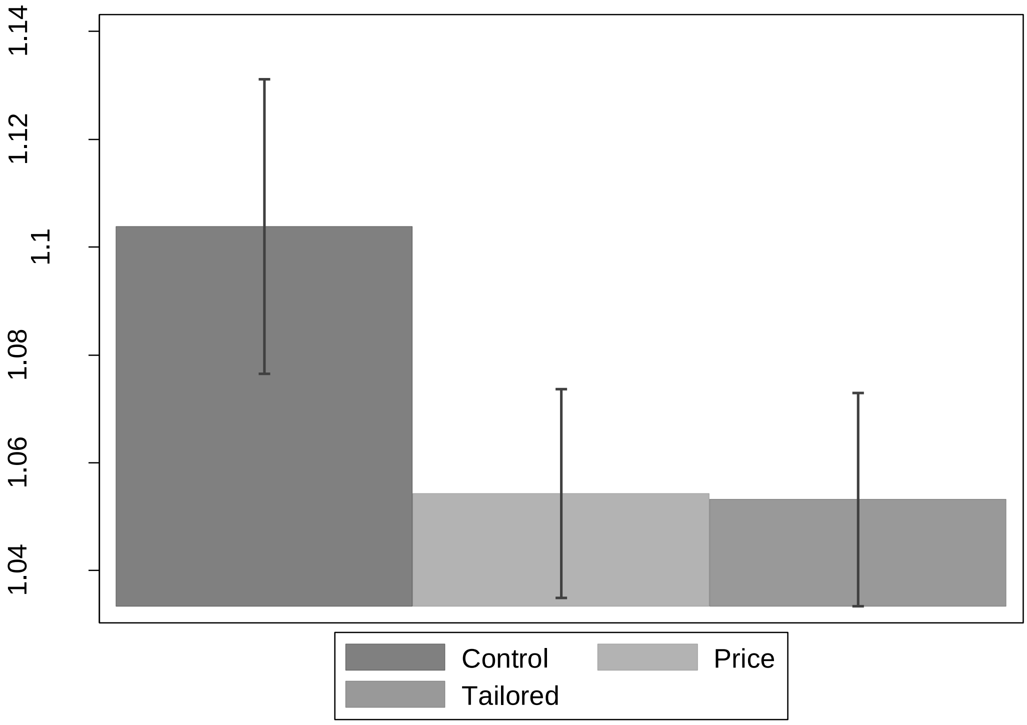


Figure 20 Page views by experimental group



The story is similar for the other outcome measures too: 0.8% clicked on the Switch to Us icon in the control group compared to 0.6% in the price comparison group and 0.7% in the tailored group; 0.5% switched in the control condition compared to 0.2% in the price comparison condition and 0.1% in the tailored condition and; the average number of page views was 1.1 in the control compared to 1.05 in the price comparison and the tailored groups.

The next section will present results of the regression model testing which of these differences are statistically significant.

2.4.2 Outcomes regression model and results

The results of estimating equations (1)-(3) set out in Section 2.1.9 are presented in columns (1), (3) and (5) of Table 23, with the intervening columns presenting the results of the same equations but with the pre-specified covariates.[71] The results tell the same story as the raw data presented in Figure 19 and Figure 20***.***

Looking now at column (1) of Table 23, we can see that the treatment coefficient is negative and statistically significant (p=0.010), indicating that the price comparison caused get a quote rates to decline by 1.2 percentage points relative to the control group in which participants received no information about what they would pay on the TOU tariff relative to the average flat rate tariff. Compared to the mean get a quote rate in the control group of 3%, this represents a 40% decrease in get a quote rates, which is what I had calculated from the raw data itself.

Table 23 Average treatment effect of price comparison and tailoring on get a quote rates to the tariff.

	Control vs. price		Control vs. tailored		Tailored vs. price	
Outcome = get a quote	(1)	(2)	(3)	(4)	(5)	(6)
Price comparison	-0.012*	-0.014**				
	(0.010)	(0.004)				
Tailored			-0.013**	-0.013**	-0.000	0.001
			(0.008)	(0.007)	(0.929)	(0.873)
Returning visitor		-0.019***		-0.019***		-0.016***
		(0.000)		(0.000)		(0.000)
Mobile visitor		-0.061***		-0.074***		-0.038**
		(0.000)		(0.000)		(0.003)
Observations	4303	4303	4291	4291	4298	4298
R^2	0.002	0.012	0.002	0.015	0.000	0.006

Notes: Traditional p-values reported in brackets. All regressions were estimated with robust standard errors.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[71] The equation with covariates presented in ***Section 2.1.9*** also included fixed effects for the date and time the website was visited and the referring website. However, this involved estimating too many additional parameters given the available degrees of freedom so these were dropped from all analyses.

Looking at column (3) of Table 23, the treatment coefficient is also negative and statistically significant, indicating that tailoring the marketing of the TOU tariff towards EV and heat pump owners caused a 1.3 percentage point reduction in get a quote rates compared to the control group who were not told the tariff was aimed at EV and heat pump owners, a 43% decrease in get a quote rates relative to the baseline get a quote rate in the control group.

When looking at column (5), the results are also consistent with what was shown in the raw data. The treatment coefficient is not statistically significant (p=0.929) and has no direction or magnitude of effect, indicating that there is no difference in get a quote rates across the price comparison and tailored conditions.

The results are robust to multiple comparison corrections using the Benjamini and Hochberg (1995) method of controlling the false discovery rate and the findings hold across all the outcome measures[72], regardless of whether the equations are estimated using OLS (Table 24) or using logit as a robustness check (see appendix 6)[73]. The impact of the price comparison on switching rates in Table 24 is of particular interest.

Recall that participants in the price comparison condition who, rather than just visiting the homepage and leaving the website actually went on to obtain a quote, were presented with their estimated annual energy bill under the TOU tariff (as in both the control and tailored conditions) but directly compared to what they would

[72] The adjusted p-values are computed based on all the significance tests used to produce Table 23 and Table 24. The modified p-value for the 5% confidence level is p<0.0125. See section 1.2.8 of Annex 4 for a discussion of why the Benjamini and Hochberg (2005) method was chosen over alternative methods of correcting for multiple comparisons.

[73] Although the coefficient on clicks on the Switch to Us icon are not statistically significant the coefficient is negative and the lack of statistical significance may be due to a lack of power because so few participants clicked on the Switch to Us icon. The coefficient on Switching in the price comparison is not statistically significant although the coefficient is negative, indicating the same direction of effect as seen in the other outcomes.

pay on the average flat-rate tariff based on what appliances they reported owning in the get a quote questions. Of course, since the majority of people who obtained a quote reported not owning these appliances, they would have seen that the TOU tariff would increase their energy bill relative to the flat rate tariff. Whilst the impact of price comparison information on switching rates is only marginally[74] statistically significant (p=0.080), the effect size is very large considering how few people switched in the control group; the model estimates that the price comparison reduced switching rates by 0.4 percentage points which represents a 133% reduction relative to the baseline switching rate of 0.3%.

The results are also much unchanged when including covariates, even though both covariates are statistically significantly correlated with each of the outcome measures. Being a returning visitor decreases the likelihood of obtaining a quote by 1.6 to 1.9 percentage points depending on the treatment group to which the participant was allocated, which may reflect the fact that returning visitors were exposed to the treatment more times thereby increasing the overall negative impact of the treatment. Participants who visited the website on their mobile phone were statistically significantly less likely to get a quote than participants who visited the website on a tablet or laptop or desktop computer. One explanation for this is that, although the website was designed to function across mobile and non mobile platforms, the aesthetic of the website was higher when viewed on a larger screen.

Overall then, the results tell us that providing website visitors with price comparison information and tailoring a TOU tariff towards EV and heat pump

[74] See Section 1.2.9 of Annex 4 for a discussion of the merits of interpreting statistical significance as a continuous measure rather than a binary measure in which p=0.049 is statistically significant and p=0.051 is not statistically significant.

owners reduced demand for the tariff, which leads me to reject both hypothesis 1 and hypothesis 2. The results also indicate that tailoring has no advantage or disadvantage over the predictive price comparison, leading me to reject hypothesis 3. However, I cannot yet reject the hypothesis that tailoring could increase uptake to TOU tariffs amongst EV and heat pump owners (hypothesis 4), because the data collected suggested that the average website visitor did not own an EV or heat pump and too few indicated whether or not they did own an EV or heat pump to test for treatment effect heterogeneity using the Flex Trial data.

Table 24 Average treatment effect of price comparison and tailoring on secondary outcomes.

	Control vs. Price			Control vs. Tailored			Tailored vs. Price		
	(1) Page count	(2) Switch to us icon	(3) Switched	(4) Page count	(5) Switch to us icon	(6) Switched	(7) Page count	(8) Switch to us icon	(9) Switched
Price comparison	-0.057** (0.001)	-0.003 (0.187)	-0.004+ (0.081)						
Tailored				-0.051** (0.003)	-0.002 (0.462)	-0.004*^ (0.018)	0.003 (0.809)	0.001 (0.611)	-0.001 (0.395)
Returning visitor	-0.054*** (0.000)	-0.004*** (0.001)	-0.002 (0.065)	-0.052*** (0.000)	-0.004*** (0.000)	-0.001 (0.186)	-0.041*** (0.000)	-0.004*** (0.000)	-0.002*^ (0.017)
Mobile visitor	-0.272*** (0.000)	-0.041*** (0.001)	-0.030** (0.003)	-0.363*** (0.000)	-0.050*** (0.000)	-0.034** (0.003)	-0.171** (0.003)	-0.027** (0.006)	-0.008 (0.152)
Observations	4303	4303	4303	4291	4291	4291	4298	4298	4298
R^2	0.018	0.016	0.015	0.025	0.019	0.020	0.009	0.008	0.002

Notes: P-values reported in parentheses. All regressions were estimated with robust standard errors.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
^ p-value is greater than the 5 percent significance threshold once correcting for multiple comparison testing using the Benjamini and Hochberg (1995) method.

2.5 Results – robustness check (not pre-specified)

Too few participants provided data on whether or not they owned an EV or heat pump to robustly perform treatment effect heterogeneity analysis along these variables. Instead, given that this hypothesis has been tested using the Population-Based Survey Experiment, this section focuses on presenting the results of a robustness check to test whether the price comparison condition may have been perceived as being less aesthetically pleasing to website visitors, which in turn may have reduced their propensity to get a quote or switch to the tariff. This concern is driven by the fact that the price comparison website naturally contained more information than the other two conditions, which may have made it less aesthetically appealing. If this is the case then the fact that fewer people got a quote for the tariff in the price comparison condition relative to the control condition may not be being driven by the price comparison information *per se* but may instead be a feature of the fact that providing price comparison information affects the aesthetic of the website.

To test whether this is likely to be the case, an exploratory analysis is run which compares outcomes amongst participants who were assigned to the price comparison website and who also visited the website on a mobile phone to all other participants, including participants who were also assigned to the price comparison condition but who visited the website from a tablet or desktop computer. To function on a mobile phone screen, the website had to automatically re-scale to fit the smaller size of the screen. The aesthetic of the website was therefore superior on a tablet or computer relative to on a mobile phone and this is particularly true for the price comparison website which naturally contained more text on it than the other two websites in order to provide the comparison information. Therefore, if the price comparison results are being driven by aesthetics, it should show up in a negative correlation between being assigned to the price comparison condition and visiting the website on a mobile phone, since this is likely to be the combination that provides the least aesthetically appealing browsing experience.

The regression equation used to estimate the impact of being in the price comparison condition on participants viewing the website on a mobile phone was not pre-specified so is presented below:

[7] $Y_i = \alpha + \beta_1 T1_i + \beta_2 mobile_i + \beta_3 T1_i * mobile_i + \varepsilon_i$

Where:

- Y is multiple outcome measures (Get a quote, clicks on Switch to Us icon, Switched, Page count)
- α is a constant
- $T1$ is the treatment dummy variable (1=price comparison condition; 0=in the control condition, excluding those in the tailored condition)
- $T1_i * mobile_i$ is the interaction term between being in the price comparison condition and visiting the website on a mobile
- β_4 is the coefficient on the interaction term and is the coefficient of interest for testing the hypothesis that demand for the tariff is lower amongst participants assigned to the price comparison condition and who visited the website on a mobile phone
- ε_i is the error term.

The results of this analysis are presented in Table 25***.*** The results show that there is a marginally statistically significantly positive, but not negative, relationship between being in the price comparison condition and visiting the site on a mobile (N=1,968) compared to being in the price comparison condition and visiting the site on a computer (N=187) or being in the control condition and visiting the site on a mobile (N=2,002) or computer (N=126). This is true for all the outcome variables and a robustness check using logit also finds a set of positive coefficients although they are not statistically significant (see appendix 7). Although it is possible that the sample size in per group for those visiting on a computer is too small to detect any negative impact of being in the price comparison condition and visiting the site on mobile, this cannot explain why the coefficient on the interaction term is positive rather than negative, particularly when the overall average treatment effect is a negative one. Arguably, there is therefore no compelling evidence that the price comparison condition reduced demand for the TOU tariff because this version of the website was less aesthetically appealing than the control group website.

Table 25 Treatment effect of price comparison on participants who visited the website on a mobile phone.

	(1) Get a quote	(2) Page count	(3) Switch to Us icon	(4) Switched
Price comparison	-0.079*	-0.398**	-0.045^{+}	-0.053*
	(0.019)	(0.009)	(0.083)	(0.022)
Mobile visitor	-0.102***	-0.488***	-0.067**	-0.062**
	(0.001)	(0.000)	(0.004)	(0.005)
Mobile visitor*Price comparison	0.070$^{*\wedge}$ (0.039)	0.366* (0.017)	0.044^{+} (0.087)	0.053* (0.022)
Observations	4303	4303	4303	4303
R^2	0.015	0.025	0.020	0.026

P-values in parentheses. All regression estimated using robust standard errors.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
^ p-value is greater than the 5 percent significance threshold once correcting for multiple comparison testing using the Benjamini and Hochberg (1995) method.

This marks the end of section 2. The next section presents the research design and results of study 2(b), the Population-Based Survey Experiment, following the same structure as used to present the Flex Trial, study 2(a).

3 Study 2(b) “the Population-Based Survey Experiment”

3.1 Method

3.1.1 Introduction to the study 2(b)

The driving factor behind testing the effect of tailoring on demand for a TOU tariff is that it is a potentially very promising way of increasing uptake to TOU tariffs amongst consumers who are more likely to save money on them whilst detracting consumers who are less likely to save. Although the Flex Trial provided a highly realistic environment in which to test this, the design presented some challenges. Testing the effectiveness of tailoring at recruiting EV and heat pump owners relied on the recruitment strategy driving a majority of EV and heat pump owners to the website which, based on the sample of data collected from participants, did not occur.

There are three ways of overcoming these potential problems. One method is to administer a baseline survey to all eligible participants and randomising those who complete the survey to experimental interventions in a field experiment such as the Flex Trial. I decided against administering a baseline survey to participants of the Flex Trial to avoid Hawthorne Effects.

A second method is to obtain a full set of baseline data on all participants and exposing participants to the interventions in the context of a population-based survey experiment (Mutz, 2011) rather than a field experiment. A third method which would avoid exposing participants to the fact a trial is taking place would be to sample from a population for whom baseline information already exists, for example, through the existence of administrative data; in this context, it would involve recruiting amongst people in GB known to have an EV or heat pump.

Although both these alternative methods are used in this thesis, the advantage of using a population-based survey experiment (the second method) over an administrative data on EV or heat pump owners (third method) is that it would enable me to test both whether tailoring attracts EVs owners, for example, whilst also detracting non EV owners, to answer research question 2 since surveys make it relatively easy to obtain a full set of baseline data on all participants.

This chapter therefore describes the design and results of the population-based survey experiment. The third method – in which tailoring is tested amongst a known population of EV owners – is reserved for the fourth and final study which is described in detail in chapter 7.

3.1.2 Trial design

This survey experiment was run as part of a larger programme of research on consumer demand for TOU tariffs commissioned by the consumer group Citizens Advice. The intervention tested in this trial was added to the same survey used for this larger research project, which means that interventions other than the ones of interest to this study were tested.

For the purposes of this study, participants were presented with the same three-tiered static TOU tariff but were randomly assigned to two experimental conditions:

1. Control – the tariff design was presented with no accompanying information about the types of consumers for whom it may be most suitable

2. Tailored – the tariff design was presented with accompanying information that said it was particularly well suited to EV owners

More details on the design of these interventions is provided in Section 3.5. Citizens Advice played no role in the design, analysis or interpretation of any of the results presented here. For brevity, the wider design of the survey is not presented here since it is not relevant to the specific research questions of this thesis, however the full questionnaire is presented in Appendix 8.

3.1.3 Population of interest

The population of interest is British EV owners and the average British energy bill payer who does not own an EV.

3.1.4 Recruiting amongst the population of interest

The participants are members of a professional market research companies' online market research panel who identified as living in Britain and being solely or jointly responsible for paying their household energy bills.

The first couple of questions in the survey screened out participants who resided outside of Britain and the UK and who were not energy bill payers.

The market research company recruited participants by sending a link to the survey in an email to its existing pool of online market research panellists. The research company uses quota sampling to obtain a nationally representative sample of the online population of Britain based on age, gender, region and social grade. Quota sampling involves over-recruiting amongst certain groups to account for differences in average response rates across the four demographic categories.

3.1.5 Intervention design

Participants in the control group were presented with the following description of the TOU tariff:

The SuperSaver tariff charges three different rates for electricity: super off-peak, off-peak and peak.

- *Super off-peak rate is 5p per unit, and applies 11 pm- 6 am on weekdays and all weekend.*
- *Off-peak rate is 10p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.*
- *Peak rate is 20p per unit, and applies 4-8pm on weekdays.*

There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.

By comparison, participants in the tailored group were presented with the following description of the TOU tariff:

The Electric Vehicle tariff charges three different rates for electricity: super off-peak, off-peak and peak.

- *Super off-peak rate is 5p per unit, and applies 11 pm- 6 am on weekdays and all weekend.*
- *Off-peak rate is 10p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.*
- *Peak rate is 20p per unit, and applies 4-8pm on weekdays.*

This tariff is particularly suited to people with electric vehicles, who use more electricity than the average household (that mostly just use electricity for lighting and kitchen appliances) and could therefore save more money by charging their vehicle during the cheap off-peak or super off-peak times.

There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.

Note that, the tariff has the same structure as the tariff presented to participants in the Flex Trial.

3.1.6 Outcomes

The outcome measure is a binary variable indicating whether or not the participant said they would be willing to switch to the tariff:

- Yes I would switch (1)
- Stick with the tariff I am currently on (0)

3.1.7 Additional data collection

Participants were asked to provide a wide range of background information on themselves, their household and what appliances they owned (see Appendix 8). For now, it is sufficient to say that all participants were asked to indicate whether or not they own or lease an EV.

The question used to identify this was adapted from Nicolson (2017) which also asked a nationally representative sample of British energy bill payers whether they owned an EV but did not ask participants to indicate whether they leased an EV. In this survey, I asked whether participants leased or owned an EV because, either way, evidence suggests that people will charge the vehicle from home (Knight et al., 2015).

Immediately after exposure to the tariff, a manipulation check consisting of a series of true or false questions about the tariff descriptions was performed to determine whether participants perceived the tailoring (see Appendix 9). One was used to check how much attention people were paying to the tariff structure by asking them to confirm whether the tariff charged the same rate for electricity regardless of the time of day. Another asked people to confirm whether the tariff was described as being particularly suitable for EV owners.

3.1.8 Sample size

A total sample size of 3,000 participants was chosen to fulfil multiple aims, including to test whether tailoring has different effects on EV owners to non-EV owners (the aim of this study). The survey was being run as part of a larger research project in which participants were being assigned to six experimental conditions (more details on this below), and power calculations indicated that a sample size of 3,000 (500 per group) would mean that the trial would be able to detect an 8 percentage point difference in the average intention to switch to the TOU tariff in each of the individual treatment groups from a baseline switching rate of 33% with 80 percent power and 95% statistical confidence in a two-tailed test. The baseline switching rate was based on the switching rate observed in two prior surveys of British energy bill payers (Michael J. Fell et al., 2015; M Nicolson et al., 2017). Since tailoring has not been tested on this population before it was not possible to predict in advance how large an effect it may have on uptake. However, an 8 percentage point difference from a baseline of 33% represents a standardised treatment effect of 24% which is in line with the treatment effects from message framing observed in the studies discussed in the literature review covered in Chapter 3.

With regards to the aim of this experiment which is to test whether the impact of tailoring varies across EV and non-EV owners, it was judged that 3,000 participants would result in the recruitment of a large enough sample of EV owners upon which to conduct the treatment effect heterogeneity analysis. A previous survey suggested that approximately 8 percent of British energy bill payers owns an EV (M Nicolson et al., 2017), meaning that a sample of 3,000 participants would deliver approximately 240 EV owners, with an average of 40 in the tailored intervention group and 200 split across each of the other five groups.

3.1.9 Randomisation and blinding

Randomisation was performed in the survey company's software which uses the same randomisation mechanism as MS Excel's random number generator. Participants were blinded to their treatment status since they were not made aware that there were any variations in the tariff presentation. Since the randomisation was carried out by the survey software, I was also blinded to the treatment assignment until the data was delivered.

The experiment was run as part of a longer survey designed to answer other research questions in which participants were randomly assigned to six experimental message-framing conditions with a 1:1:1:1:1:1 ratio as follows:

1. Flat rate tariff no message framing
2. TOU tariff no message framing
3. TOU tariff with 6 months' bill protection
4. TOU tariff is endorsed by the energy regulator
5. TOU tariff comes with appliance level consumption feedback
6. TOU tariff with EV tailoring (TREATMENT)

POOLED CONTROL GROUP

For this analysis, participants assigned to the flat rate tariff are excluded from all analyses and participants in groups 2-5 that were not given any tailored messaging are pooled together to create one large control group to increase statistical power by raising the number of EV owners in the sample for the treatment effect heterogeneity analysis. Participants in the experiment therefore had a 1 in 6 probability of being assigned to the tailored intervention and a 4 in 6 probability of being assigned to the control group.

Pooling intervention groups from multiple randomised control trials is commonly used as a method for undertaking meta-analyses in systematic reviews of clinical trials (e.g. see Rothwell et al., 2003) and for increasing statistical power in individual randomised control trials. One concern is that pooling participants who were exposed to different interventions could increase the variability in the control group, and thereby reduce statistical power. However, there is little risk of this because intention to switch did not vary significantly across the other treatments, aside from in one treatment where the difference was marginally statistically significant relative to the no intervention control (these results are presented in Appendix 9).

3.1.10 Analysis plan

The pre-analysis plan for this study was registered with the Experiments in Governance and Politics (EGAP) trial registry (20170403AA) prior to the researcher accessing the outcome data. Research question 2 asks whether tailoring could be used to increase uptake to TOU tariffs amongst consumers who are more likely to save money on them whilst also detracting customers without these appliances from signing up to a TOU tariff who may be less likely to save money. In the context of this study, these research questions are associated with two hypotheses about impact of tailoring on EV owners and its impact on non-EV owners:

- **Hypothesis 1** Willingness to switch will be higher in the tailored group than in the control group amongst EV owners.
- **Hypothesis 2** Willingness to switch will be lower in the tailored group than in the control group amongst non-EV owners.

There are no hypotheses related to the impact of tailoring on average willingness to switch so the equations used to test the hypotheses are both interacted models.

Heterogeneous treatment effect equation

The following statistical equations will be estimated using OLS regression to test hypotheses 1 and 2 respectively:

[5] $$Y_i = \alpha + \beta_1 T2_i + \beta_2 EV_i + \beta_3 T2_i * EV_i + \varepsilon_i$$

[6] $$Y_i = \alpha + \beta_1 T2_i + \beta_2 no.EV_i + \beta_3 T2_i * no.EV_i + \varepsilon_i$$

[7] $$Y_i = \alpha + \beta_1 T2_i + \beta_2 dk.EV_i + \beta_3 T2_i * dk.EV_i + \varepsilon_i$$

Where in all equations:

- Y is a binary outcome measure (1=intends to switch; 0=does not intend to switch)
- α is a constant
- $T2$ is the treatment dummy variable (1=tailored condition; 0=not tailored)
- ε_i is the error term.

In equation [5]:

- EV_i is a dummy variable indicating that the participant self-reported as owning an EV or not (1=yes; 0=no or don't know)
- $T2_i * EV$ is an interaction term between the treatment dummy and the EV dummy which indicates whether the participant has an EV and was assigned to the tailored condition (1=yes; 0=no)

- β_1 is the coefficient on $T2$ which measures the effect of being in the tailored group rather than the control group for the average participant in the sample
- β_2 is the coefficient on EV_i which measures the correlation between self-reporting to have an EV compared to self-reporting not to have an EV or self-reporting to not know and willingness to switch
- β_3 is the coefficient on the interaction term $T2_i * EV$ which measures the effect of being in the tailored group and self-reporting to own an EV rather than all other possible combinations and is therefore the coefficient of interest for testing hypothesis 1
- ε_i is the error term.

For equation [6], the variables have the same meaning as for those in equation [5] except that the included covariate captures people reporting that they do not own an EV (1) compared to those who say they do or that they do not know (0). The interaction term therefore interacts the tailored treatment dummy with not owning an EV to test hypothesis 2.

For equation [7], the variables also have the same meaning as for those in equations [5] and [6], except that the included covariate captures people who report that they do not know whether they own an EV (1) relative to those who report that they do or that they do not (0). The interaction term interacts the tailored treatment dummy with not knowing whether the person owns an EV. This equation is not associated with any hypothesis but is run for completeness to check that there is no statistically significant effect, as would be expected by the model.

Based on the review of the theory and literature outlined in Chapter 3, I expect the coefficient β_3 in equation [5] to be statistically significant and positive but the coefficient β_3 in equation [6] to be statistically significant and negative. I expect there to be no statistically significant coefficient on β_3 in equation [7].

A robustness check is run in which the equations above are estimated using logit with marginal effects estimates at the means of the covariates, with these results reported in an appendix.

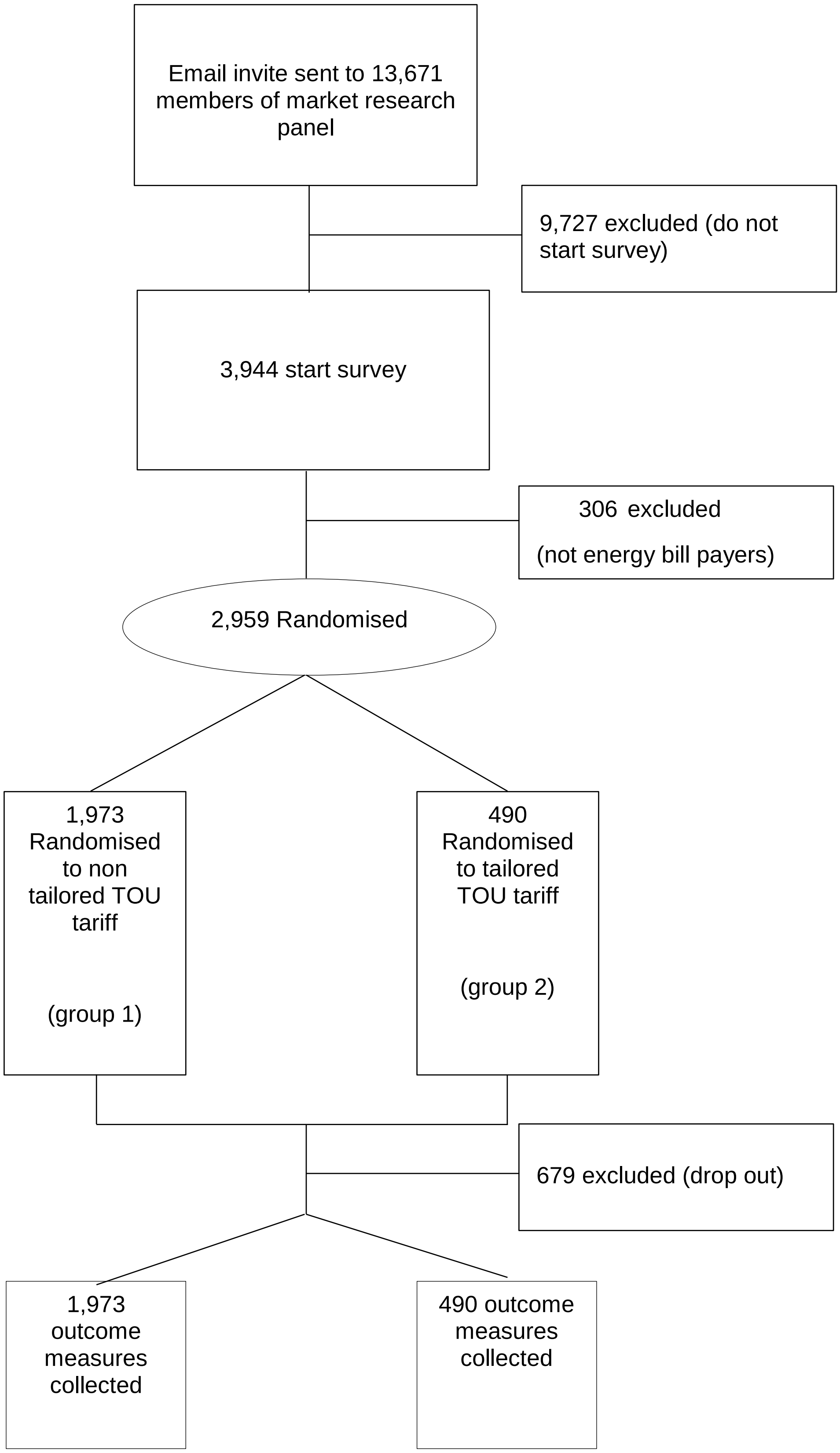
3.2 Implementation of trial

The survey was administered in March 2017 and Figure 21 charts the flow of participants from initial recruitment through to randomisation and collection of the outcome variables. The first question in the survey screened participants on whether they were energy bill payers beyond which non energy bill payers were excluded from the survey. The survey had a response rate of 28% and attrition rate of 19% amongst the population of interest (energy bill payers). This meant that the recruitment target of 3,000 was approximately met.

A randomisation balance check reported in Table 26 shows that the characteristics of the control group and intervention group are well balanced along all 11 baseline variables at the 95% significance level. The purpose of this exercise is to check whether randomisation has delivered groups of participants who are statistically indistinguishable from one another across control and treatment groups, such that the only difference between the treatment and control group is the website version to which they were exposed (the treatment). Although one p-value is slightly lower than the 10% confidence threshold indicating there are slightly more Welsh people in the control group compared to the tailored treatment group, this is no more than would be expected by chance alone[75] and there is no evidence to suggest that Welsh people have substantially different views on TOU tariffs to other British energy bill payers.

[75] When running 11 statistical significance tests it is expected that 1 p-value would be smaller than 0.10 (unbalanced at the 90% confidence level).

Figure 21 Participant flow diagram for the Population-Based Survey Experiment



(CONSORT)

Table 26 Randomisation balance checks on baseline characteristics in the Population-Based Survey Experiment.

Baseline characteristic (%)	TOU tariff (mean) (1)	Tailored TOU tariff (mean) (2)	P-value (1)=(2) (3)
Sole energy bill payer	57.1	59.6	0.316
Female	53.9	50.2	0.148
Age:			
18-24	17.5	15.9	0.398
25-34	18.4	19.2	0.686
35-44	22.1	23.5	0.511
45-54	19.0	17.1	0.333
55+	22.9	24.3	0.530
Region:			
England	86.5	88.4	0.267
Scotland	8.41	8.37	0.976
Wales	5.12	3.27	0.085
Supplied by British Gas	20.0	23.1	0.135

Notes: The p-values in column (3) were obtained from a linear OLS regression of each baseline characteristic against a treatment dummy in which the value 1 is assigned to those in the tailored TOU tariff group and a value of 0 to participants assigned to the non tailored TOU tariff group.

3.3 Descriptive statistics of sample

3.3.1 Participant demographic profile

The socio-demographic characteristics of survey participants in the Population-Based Survey Experiment are presented in Table 27. The unweighted and weighted estimates are very similar, although the unweighted estimates are slightly closer to the population estimates on age than the weighted estimates (particularly for the youngest age group) but slightly less similar to the population estimates for gender. Nevertheless, since the weighted estimates seem to over-weight young participants much more so than the unweighted estimates over-represent women, I discuss the characteristics of the sample in terms of the unweighted estimates throughout and do not apply sample weights to the analyses (for more details on this decision see Annex 3).

The average participant is aged 35-44[76], so about a decade older than the average participant in the Flex Trial who was aged 25-34, lives in England and, unlike in the Flex Trial, is slightly more likely to be female than male. The average participant belongs to social grades A or B[77] whereas the average member of the adult population belongs to grade C1. However, although the sample underrepresents people in social grade C2 and over-represents those in grades A and B, it does a good job of representing those in the lowest social grades (D and E); 21% of participants in the sample belong to grade D or E compared to 26% in the general population. This is very similar to the distribution for social grade observed in the Tariff Decision Making Study, which also overrepresented

[76] Age group 35-44 is the modal age category.
[77] Social grades A-B is the modal category.

grades A to B, and underrepresented grade C2 whilst covering grades D to E well.

Table 27. Characteristics of energy bill payers in the British population and in the survey sample with and without survey weights.

	Population	Sample		
	(%)	Unweighted (%)	Weighted (%)	N
Gender:				
Female dummy	51	54	50	2959
Social grade:[78]				
A/B	22	37	37	2959
C1	31	28	29	2959
C2	21	14	14	2959
D/E	26	21	21	2959
Age in five year groups:				
18-24[79]	9	17	25	2959
25-34	18	19	16	2959
35-44	19	23	19	2959
45-54	18	18	18	2959
55+	37	23	23	2959
Region:				
England	86	87	86	2959
Scotland	9	8	9	2959
Wales	5	5	5	2959

[78] The population values are for the average member of the British population from the Census 2011 because equivalent values were not available for the average energy bill payer.
[79] This is based on 20-24 for the GB population because Census statistics are broken down into five year intervals in which 18 and 19 year olds are grouped with 15-17 year olds.

In summary, the participant sample in the Population-Based Survey Experiment is roughly nationally representative of the British adult population, despite the fact that it slightly over-represents people in the highest social grades relative to those in the middle social grades and over-represents people aged 18-24 relative to those aged 55 and above. The sampling strategy has been effective at capturing people in the lowest social grades and those aged 25-54 as well as evenly representing people by region and gender.

3.3.2 Outcome variables

Table 28 presents overall intention to switch to the TOU tariff across both the treatment and control groups with weighted and unweighted estimates reported. Consistent with what we know about inertia in the energy market, most people were not willing to switch. Approximately 30% of participants said they were willing to switch to the tariff presented to them. The weighted estimates are substantively identical to the unweighted estimates, although as expected, the unweighted estimates have a smaller standard error. The unweighted in-sample estimates will be discussed here since they are substantively identical to the weighted estimates.

Table 28 Outcome variables in the Population-Based Survey Experiment.

	%	SE	Range	N
Intention to switch (unweighted)	30	0.92	0-1	2960
Intention to switch (weighted)	31	0.97	0-1	2960

3.3.3 Appliance ownership and household data

Table 29 describes the participants in the Population-Based Survey Experiment in terms of the electrical appliances they own at home as well as well as some characteristics of their household such as their main method of heating their home and whether they are on an Economy 7 tariff. For the most part, the data collected in this survey is identical to that collected in the Flex Trial with the exception that no data was collected on whether participants have solar panels or a smart meter. Instead of collecting data on the number of bedrooms, data was collected on the number of household occupants (both serve as a proxy for household size and therefore total energy demand).[80]

There is a complete set of observations for the EV variable. The survey therefore fulfils its main purpose which is to provide an experimental dataset testing the impact of tailoring TOU tariffs to EV owners in which it is known which participants do and do not own an EV. Although only 5% of the sample in this study owns or leases an EV (N = 155) – a much lower proportion than in the Flex Trial – because the data indicates who does and does not fit this criteria, the equation presented in Section 3.9 can be used to test for the presence of a treatment effect heterogeneity, thereby testing hypothesis 4.

The proportion of participants who own a heat pump is also much lower than in the Flex Trial, which was specifically targeting heat pump owners, and is very similar to the proportion obtained in another similar nationally representative survey (M Nicolson et al., 2017). The proportion who own a tumble dryer and dishwasher is remarkably similar to the proportion in the Flex Trial, although

[80] As mentioned in Chapter 4, the survey was run to answer a large number of research questions of which one was the research question posed in this thesis. This explains some of the small differences in the type of data collected.

different from the estimates obtained from the other nationally representative survey.

As expected for a nationally representative survey, the majority of participants have gas central heating (89%) and only a small portion have electric heating (10%), much smaller than the proportion who reported having electric heating in the Flex Trial (38%) which targeted electric heating users.

The final column of Table 29 includes the descriptive statistics from another nationally representative survey of British energy bill payers run in 2014 (M Nicolson et al., 2017). A total of 18% of participants reported being on an Economy 7 tariff which is also in line with the estimates from other recent nationally representative survey of British energy bill payers (Michael J. Fell et al., 2015; M Nicolson et al., 2017). The average number of household occupants is 2.6 which is slightly higher than the 2.3 obtained in another nationally representative survey but the difference is not so large as to be a cause for concern, especially given that household occupancy is not a variable of interest in this thesis.

Table 29 Self-reported appliance ownership and household characteristics in Flex Trial.

	Sample					Population
	Unweighted		Weighted		N	
Appliance ownership:	%	SE	%	SE		%
EV	5	0.4	6	0.5	2959	8
Heat pump	0.3	0.12	0.3	0.12	2959	0.4
EV & heat pump	0.03	0.003	0.05	0.005	2959	-
Dishwasher	46	1	47	0.9	2959	30
Tumble dryer	49	1	49	1	2959	60
Washer dryer	23	1	25	1	2959	
Washing machine	86	1	85	1	2959	90
Electric shower	-	-	-	-	-	
Solar panels	-	-	-	-	-	0.7
Household characteristics:	%	SE	%	SE	N	%

Electric heating	10	0.54	10	1	2959	10
Gas central heating	89	1	79	1	2959	77
Legacy Economy 7 tariff	18	1	20	1	2959	13-21
Smart meter	-	-	-	-		10
	Mean	SE	%	SE	N	%
Number of bedrooms	-	-	-	-	-	2.7
Occupants	2.6	2.4	2.5	2.5	2959	2.3

Notes: the population estimates are from a nationally representative survey of British adults who identified as energy bill payers run in 2015 (M Nicolson et al., 2017).

3.4 Results – manipulation checks

Manipulation checks show that participants generally perceived the manipulation as intended; whereas 35%[81] of participants in the control group agreed with the statement that the tariff was described as being particularly suitable for EV owners, 80% of participants allocated to the tailored treatment group agreed, a difference which is statistically significant at the 99% statistical confidence level.

There was no statistically significant difference in the proportion of participants who correctly answered the knowledge test question on the tariff structure across those in the control and tailored group, indicating that the tailored marketing does not detract from the attention people were paying to the tariff structure itself. For brevity the results of these checks are presented in Appendix 10.

3.5 Results – heterogeneous treatment effect

The results of the analysis used to test hypothesis 4 are presented in Table 30, with column (1) presenting the results for EV owners and column (2) the results for non EV owners. Consistent with prior research (M Nicolson et al., 2017), the results also show that being an EV owner is already associated with a much higher baseline willingness to switch to the TOU tariff; the raw data shows that baseline willingness to switch amongst EV owners is 75%. The p-value associated with the coefficient on the interaction term between being an EV owner and being in the tailored group is positive but falls just short of being

[81] I acknowledge that this is a relatively high proportion. One possible explanation is that these participants in the control group thought the tariff structure would be suited to someone with an EV and that they were thinking of this when answering the question (even though the control group was not told the tariff was suited to EV owners through the tailored marketing).

significant at the 10% level (p=0.108). This may reflect the relatively small number of EV owners assigned to the tailored group (N=31) however further testing amongst a larger sample of EV owners would be required to establish more robustly whether, consistent with hypothesis 4, tailored marketing could be used to increase uptake to TOU tariffs amongst high-consuming electricity users such as EV owners.

Just as importantly, and consistent with hypothesis 4, the tailored marketing is selectively effective; the results indicate that tailoring substantially reduces average intention to switch to the tariff as observed consistently across the outcomes in the Flex Trial. The coefficient on the interaction term between not owning an EV and being in the tailored group (N=459) indicates that willingness to switch decreases by 19 percentage points, representing a 60% decrease in willingness to switch relative to the baseline amongst non EV owners of 33%, a result which is significant at the 5% confidence level. Once controlling for this interaction effect between tailoring and not owning an EV, the coefficient on the tailored dummy representing the average effect of tailoring on intention to switch drops from significance (p=0.676), illustrating that the negative average impact of tailoring on intention to switch is being driven by the large group of non EV owners in the sample.

Table 30 Does tailored TOU tariffs towards EV owners increase demand amongst EV owners whilst suppressing demand amongst non EV owners?

	(1) Has EV	(2) No EV	(3) Don't know EV
Tailored dummy	-0.154^{***}	0.037	-0.140^{***}
	(0.000)	(0.676)	(0.000)
Has EV (1=yes; 0 no/dk)	0.443^{***}		
	(0.000)		
No EV (1=no EV; 0=has EV, dk)		-0.335^{***}	
		(0.000)	

Don't know EV (1=dk, 0=has EV, no EV)			-0.003 (0.973)
Tailored*Has EV	0.148 (0.108)		
Tailored*No EV		-0.192* (0.032)	
Tailored*Don't know EV			0.150 (0.474)
Observations (total)	2464	2464	2464
R^2	0.070	0.060	0.015

Notes: *p*-values in parentheses. All regressions estimated using robust standard errors.
$^{+}$ p < 0.10, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
^ p-value is greater than the 5 percent significance threshold once correcting for multiple comparison testing using the Benjamini and Hochberg (1995) method.

This latter result is robust to corrections for multiple comparison testing[82] and all OLS coefficients are substantively identical to the marginal effects estimated following a logit analysis. The only key difference is that the coefficient on the interaction term between having an EV and being in the tailored group is statistically significant at the 10% level, providing some additional reassurance that there is a genuine relationship between these two variables which may be stronger in a larger sample of EV owners. The logit results are presented in Appendix 11.

4 Discussion

4.1 Why did the predictive price comparison reduce average demand for the TOU tariff in the Flex Trial?

The price comparison condition substantially reduced demand for the TOU tariff relative to the control group. This result is visible in the raw data and is robust to

[82] The adjusted p-values are computed based on all the analyses run to test for heterogeneous treatment effects, namely the results in Table 25 using the Benjamini and Hochberg (1995) method. The modified p-value for the 5 percent significance threshold is p<0.0375.

a range of model specifications including the addition of covariates and estimation using logit rather than OLS. This is the opposite result to what was expected and leads me to reject hypothesis 1. The key question is therefore, why did the predictive price comparison condition have a negative causal effect on demand for the TOU tariff? I discuss three plausible explanations below but ultimately argue that the latter two explanations together provide the most compelling rationale for the results.

4.1.1 The price comparison website was less aesthetically pleasing than the control website

One explanation explored in the analysis is that the additional information provided made the predictive price comparison website less aesthetically pleasing than the control condition. Due to the relatively small screen size on mobile phones the price comparison website looked the least aesthetically pleasing on this format so if aesthetics were driving the results then I would expect it to show up in the form of a negative interaction effect between being assigned to the price comparison website and visiting the website from a mobile. However, there is no evidence that this is the case; the results of the heterogeneity analysis found that participants in the price comparison condition who visited the site on a mobile were slightly more likely to get a quote or switch to the tariff and so on, and in the OLS specification this effect was marginally statistically significant. This explanation does not, therefore, provide a compelling rationale for the results.

4.2.2 The savings weren't big enough and the price comparison condition highlighted this

Another potential explanation for the results is that the £300 financial savings promoted on the homepage of the price comparison website were below participants' baseline expectations so correcting these beliefs backfired and reduced their drive to get a quote for the tariff. This explanation is consistent with a number of models of decision making. For instance, it is consistent with a standard economic account of decision making in which consumers are imperfectly informed about the actual savings from switching tariff however a similar outcome would be even more likely to occur under a modified model which either accounts for the possibility that people are overly optimistic when estimating the potential savings or, loss-aversion, whereby the costs of switching are weighted higher than the benefits (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991, 1992), making it less likely that switching would be judged as being net beneficial. Both optimism-bias (Sharot, 2011) and loss-aversion are fundamentally inconsistent with the classical economic model of decision making and either could explain why a price comparison could reduce uptake, although prior evidence already shows that the majority of energy bill payers are loss-averse (M Nicolson et al., 2017).

Another modification to the classical model that is sometimes proposed to explain how highlighting financial rewards can backfire is crowding-out effects: small financial compensation for a task or action (an extrinsic motivation) is worse than offering no financial incentive at all because it undermines individuals' intrinsic motivation to undertake the task or action (see Dellavigna et al. [2017] for a recent review of this literature). However, crowding out is unlikely to be relevant in this context because savings of up to £300 are not negligible and switching tariff is arguably not a very intrinsically rewarding task; although TOU tariffs do have wider societal benefits these were not emphasised on any of the websites and it is unlikely that many participants would be aware of them without being told explicitly.

Meanwhile, a small group of consumers may have judged that savings of up to £300 were sufficiently motivating to get a quote for the tariff. Equally, the results presented in Chapter 5 showed that, of the 50% of British energy bill payers who were unable to correctly identify the cheapest tariff from a menu of three, 20% were willing to admit that they did not when the tariff menu included a TOU tariff. Participants like this may therefore have had little prior expectations about the potential savings and would also have reason and motivation to make use of the get a quote feature that not only performed the calculation on their behalf but, in the predictive price comparison condition, also directly compared their estimated annual bill on the TOU tariff to what they would pay on an average flat-rate tariff based on the appliances they have at home and assumptions about their off-peak usage. This therefore leads me to the third complementary explanation for the results.

4.2.3 The majority of participants were unlikely to save money on the tariff – and the predictive price comparison made it obvious that they would not

The get a quote function provided participants with a different quote depending on whether they owned an EV and/or a heat pump or neither. Participants who reported owning neither were shown that they would be financially worse off by £25, reflecting the fact that these consumers would have less flexibility over their electricity use. As a result, providing participants with price comparison information would have made it clear to website visitors who obtained a quote – whom the descriptive statistics indicate were predominantly not owners of EVs or heat pumps – that the TOU tariff would not save them money and would in fact increase their energy bills. Indeed, this is the logical corollary to the original hypothesis which is that the price comparison would increase demand for the tariff on the basis that the recruitment strategy would result in the majority of website visitors owning an EV or heat pump. Considered in this light, it is no surprise that the largest treatment effect observed across all conditions is the negative impact of the predictive price comparison condition on switching rates.

In summary, I propose that the price comparison reduced the proportion of people who obtained a quote because baseline expectations of the savings to be made from switching to a TOU tariff and making an effort to reduce peak time consumption were higher than the savings advertised on the homepage of the price comparison website. The more numerate participants in the price comparison group judged that the advertised savings would not exceed the costs of switching or the effort required to realise the savings, such as running their appliances overnight. Note that, this does not involve making any assumptions about how people arrived at their beliefs about the expected savings; their beliefs may be rational in the sense of rational expectations or they may be optimistic in the sense of optimism bias (Sharot, 2011) or biased if they weight losses higher than gains.

Meanwhile, the price comparison had a negative impact on switching rates because, amongst those participants who did get a quote (potentially the less numerically confident participants), the quote results in the price comparison condition demonstrated that the tariff would be more expensive than a flat-rate tariff given that the majority of participants did not own an EV or heat pump and the website was hard-coded to display a lower average energy bill on a flat-rate tariff for non-EV and heat pump owners (reflecting the fact that this group has less flexible demand).

By comparison, participants assigned to the control website would have had to find the requisite price information for flat-rate tariffs and compute this themselves, which as the Tariff Decision Making Study suggested, many would not know how to do. The coefficient measuring the impact of the price comparison on switching rates is negative and statistically significant at the 90% confidence level which is consistent with the possibility that, if more people had obtained a quote, this result would surpass conventional thresholds for statistical significance (just 21 participants switched across all conditions). Future research would be required to establish whether this result is statistically robust.

In summary, then, although it is ostensibly surprising that the price comparison website reduced average demand for the TOU tariff, given that I had hypothesised that the price comparison condition would increase demand, the finding is good news because, for the reasons discussed throughout this thesis, the average visitor to the website would have likely increased their energy bills by switching to the TOU tariff.

4.2 Why did tailoring reduce average demand for the TOU tariff in the Flex Trial?

Tailoring reduced average demand for the tariff amongst participants in the Flex Trial relative to the control group that provided no tailored marketing. The hypothesis (hypothesis 2) that tailoring would increase average demand for the TOU tariff was based on the assumption that the targeted advertising would effectively deliver a participant sample comprised mostly of EV and heat pump owners. The descriptive statistics strongly indicate that this is not the case. The results are therefore consistent with the model of decision making proposed in Chapter 3 and with hypothesis 4 that tailoring TOU tariffs towards particular consumer segments will detract consumers who do not belong to these segments.

This explanation is also supported by the results of the Population-Based Survey experiment which also found that tailoring reduced the average survey participants' willingness to switch to a very similar TOU tariff; indeed, baseline willingness to switch to the tariff amongst non-EV owners was 33% and tailoring reduced this by 60%, which means it cut non EV owners' desire to switch to a TOU tariff by more than half. This is a remarkable effect considering that the tariff in the control group and in the tailored group are identical, and stands in complete opposition to a model of decision making which assumes consumers are fully rational and make decisions only on the basis of the costs and benefits of alternative options.

The key question now is, whether or not tailoring can exert a positive influence on intention to switch amongst EV owners, which is the second part of hypothesis 4. To test this, it is necessary to consider the results of the Population-Based Survey experiment, reported in Chapter 7.

4.3 Do tailored tariffs selectively attract EV owners?

The Population-Based Survey experiment indicates that we can be over 95% confident that simply calling a TOU tariff an 'EV tariff' instead of an 'Off-peak tariff' would cut the proportion of non EV owners who would be willing to switch, but also less likely to save, by more than half. The results show that we can be just under 90% confident that this tailored labelling of TOU tariffs would also increase the willingness of EV owners to adopt a TOU tariff, although since this result is not statistically significant at the conventional thresholds, further research is required on a larger sample of EV owners to verify whether this result is robust.

Although these effects cannot be interpreted as causal because EV ownership was not randomly assigned, the results from both the Flex Trial and the Population-Based Survey Experiment provide early evidence that tailoring the marketing of TOU tariffs towards a group like EV owners who are more likely to save money on a TOU tariff may increase the likelihood that TOU tariffs will be adopted by groups who can save money and not adopted by groups who will not save money on them in answer to research question 2.

Developing such a recruitment strategy was demonstrated to be important because the results in Chapter 5 showed that a large portion of British energy bill payers will be unable to determine what tariff is right for them, suggesting that bill payers need a nudge in the right direction. I therefore conclude that, in combination, the Flex Trial and Population-Based Survey Experiment provide promising but not statistically robust evidence that this type of tailored marketing is likely to be an effective but also selective nudge. The relatively small number of participants assigned to the tailored group who also had EVs makes it highly desirable to collect more data on the impact of tailored marketing amongst a larger sample of EV owners.

4.4 Why is there no difference in outcomes across the price comparison and tailored groups?

Contrary to hypothesis 3, demand for the TOU tariff was no different across the tailored and price comparison conditions. Given that the raw data shows only very minimal differences in outcomes across these groups and the p-values are all very large (the p value ranges from 0.611-0.929) it is likely that the null effect is a true null rather than that the tailored condition really would have a better or worse impact on demand amongst the type of people who participated in the trial that the study was merely underpowered to detect.

The lack of difference between the outcomes in the tailored and price comparison groups can therefore be interpreted at face value; showing people they will not save money on a TOU tariff is just as off-putting as being told that a tariff is aimed at a consumer group to which you do not belong. However, what does this mean for the two models of decision making presented in Chapter 3, namely classical and behavioural economics? Moreover, does this mean that a predictive price comparison could be just as good at increasing uptake amongst consumers who could save money on a TOU tariff whilst decreasing uptake amongst those less likely to save? I address each of these questions in turn.

On the one hand this result could be interpreted as meaning that British energy bill payers are just as much affected by the type of information they are given about a tariff as the way in which information is framed. This is consistent with a behavioural economics perspective which assumes that decision making is affected both by rational considerations of the costs and benefits of various alternative outcomes as well as the decision making context and how cost-benefit information is presented to us (Baddeley, 2017). However, the idea that what we are told is just as important a how we are told it goes against the results of the Population-Based Survey experiment as well as a range of other studies which demonstrate that people often make fundamentally different choices when faced with the same information framed in different ways (e.g. Kahneman and Tversky, 1979; Hallsworth et al., 2014; Spence and Pidgeon, 2010). When considering the results of all three studies reported in this thesis, a more nuanced explanation that is consistent with the results of all three studies emerges. I therefore postpone the remainder of the discussion of this question for the global discussion/conclusion at the end of this thesis.

4.5 Price comparisons or tailoring – which is the most appropriate effective and selective nudge?

Based on the results of these trials, it would seem that both price comparisons and tailoring would deter consumers who are unlikely to save money on a TOU tariff from signing up to one. If this is the case, is there any reason to favour one over the other?

There are is one key advantage of tailored marketing over price comparisons. Although price comparisons are likely to be effective, they have limited potential overall impact because only a very narrow sub-group of consumers make use of such tools. According to Ofgem's annual market surveys – the most comprehensive source of data on switching in GB – approximately 14% of consumers switch year on year, of which approximately one third switch through price comparison websites (Ofgem, 2015). For instance, in the Flex Trial, the probability of switching to the TOU tariff having obtained a quote that directly compared the estimated energy bill on a TOU tariff to the average flat-rate tariff decreased by 133% relative to the baseline in the control group ($p>0.10$), most likely because the majority of visitors to the website did not own a heat pump or EV (although I note that, since this result does not meet conventional statistical significance thresholds, it represents an interesting but not statistically robust finding). Therefore the quote results demonstrated that switching to the TOU tariff would increase their energy bills. However, only a handful of participants got a quote.

By comparison, those assigned to the tailored marketing condition were immediately able to see from the homepage that the tariff was best suited to EV and heat pump owners without processing very much information at all. Although it is possible that a predictive price comparison would increase uptake amongst people who would be predicted to save money, the evidence suggests that additional interventions will be required to drive people to price comparison websites in the first place. Tailored marketing could potentially be used to drive people to price comparison websites or it could by-pass them altogether.

On the other hand, a potential downside of tailored marketing is that suppliers could exploit tailoring effects to encourage uptake to tariffs that are not necessarily the best tariffs for people. For instance, suppliers could create expensive tariffs called ‘EV’ tariffs. Moreover, ownership of an EV is never going to be a perfect proxy for being able to save money on a time varying tariff; many other consumer groups may benefit from being on a TOU tariff even though they do not own an EV and it would not be a good outcome for these groups to be deterred. A potentially promising approach could be for utility companies to design tariffs based on different types of households and use tailoring to nudge householders to the right type of tariff. Another limitation of the tailoring approach tested in this experiment is that it will only reach the sub-group of EV owners who are already in the market for switching tariff; it will not reach EV owners who have never considered switching provider, which could be a much larger group of consumers than those who have considered switching.

5 Conclusions

This chapter aimed to present and discuss the results of the Flex Trial, a field experiment to measure the average causal effect of price comparison information and tailoring on demand for a TOU tariff, as well as the results of the Population-Based Survey experiment which tested whether tailoring could increase demand amongst EV owners whilst decreasing demand amongst non-EV owners.

The chapter makes three main contributions to this thesis: first, it provides empirical evidence to answer the research questions and, in so doing, provides evidence for UK policymakers over how to increase adoption of TOU tariffs without using mandates or opt-out enrolment; second, it provides additional evidence in support of the theoretical framework laid out in chapter 3; finally, it generates useful lessons for the design of randomised control trials, some of which inform the design of the final field experiment and others which could help future researchers undertaking field experiments in the energy domain.

5.1 Contribution to the research questions

The results on the impact of tailoring provide evidence in relation to research question 2. In short, the results obtained in the Flex Trial and Population-Based Survey Experiment show that tailoring the marketing of TOU tariffs towards EV owners increases demand for TOU tariffs amongst EV owners, a consumer group that is more likely to save money on a TOU tariff, whilst depressing demand amongst non-EV owners who are less likely to save money (on average) by switching to a TOU tariff. It is therefore an effective and selective nudge.

The results are therefore good news in the sense that EV owners pose one of the greatest threats to the security of the future electricity network (along with new forms of electric heating) so encouraging them to adopt TOU tariffs is very important. On the other hand, it is likely that EV owners will need to be specifically prompted to consider switching tariff. The results in this study suggest that such prompts should be tailored to them as EV owners. The next study tests this hypothesis explicitly.

5.2 Further empirical support for the theoretical model of tariff decision making

Of those who got a quote for the tariff, the majority did not own an EV or heat pump. Many did not even own wet goods which can be run at off-peak times. Of the 21 who switched, 75% did not own an EV or heat pump. This leads me to question the extent to which the consumers who did get a quote and who did switch to the tariff would have saved money from such a switch as opposed to actually increasing their energy bills.

One possible explanation for these results is that these consumers expected to substantially increase their flexible electricity demand in the near future, for example by investing in an EV or an electric heating system with a smart thermostat that permits them to programme their heating schedule in line with the time periods on the tariff. However, an alternative explanation that is supported by the results presented in Chapter 5 is that these people are simply making a mistake; they were unable to identify that the tariff would not save them money so switched.

In total, the results provide suggestive evidence that some consumers will sign up to a TOU tariff who will not save money on one as proposed by the model outlined in Chapter 3. If this is true then the results are more supportive of a behavioural economic model in which decision making is affected by bounded rationality than the standard account in which, in the absence of market failures, all decisions are optimal and just reflect variation in preferences.

5.3 Lessons for research design and next steps for Chapter 7

There are three key limitations to the research presented here that could either be improved in future research through changes to research design or simply through more research testing additional questions.

First, whilst the Flex Trial and Population-Based Survey experiment suggests that tailoring is effective at selectively recruiting EV owners, the data collected is unable to say why tailoring had this effect. Two mutually exclusive explanations for why the tailored marketing could impact decisions were proposed in Chapter 3 and could be tested in future research. The first is that the increased personal relevance of the information for EV owners increased the likelihood of information processing and later behavioural action and vice versa for non-EV owners (Kreuter, 2000).

The second explanation is that visitors to the tailored website were able to engage in some form of heuristic decision making, judging the probability that they would save money on the tariff based on some very easily retrievable information (the label) rather than the more complex information provided on the tariff structure and pricing. Although Tversky and Kahneman (1974) emphasise the way in which decision heuristics lead to poor decision making and errors, there are many examples showing the way in which heuristics can sometimes lead to better decisions given our scarce mental and physical resources (Gigerenzer, 2008; Gigerenzer and Brighton, 2009; Gigerenzer, 2010; Gigerenzer and Gaissmaier, 2011). Testing these causal mechanisms is beyond the scope of this thesis but, given the large effect sizes observed from tailoring, would be a fruitful avenue for future research to help determine whether a similar approach could work in other settings.

Second, as already alluded to above, the approach tested for boosting uptake to TOU tariffs amongst consumer groups who can save money will only capture people who are already shopping around for tariffs, which the majority of people do not do.

Third, the research design of the Flex Trial was not conducive to the collection of baseline data and the trial had to be complemented by additional data collected through the Population-Based Survey experiment in order to test for treatment effect heterogeneity. Many field experiments collect baseline data on participants through surveys administered prior to randomisation however, as argued in Chapter 4, this can lower the external validity of trials by highlighting to participants that their behaviour is under observation and by confining participation to people who are willing to opt-in to participate by completing the survey and signing consent forms and so on.

The limitation of relying on the survey data is that it only measures treatment effect heterogeneity on stated intention to switch to the tariff and it is well known that behavioural intentions are not perfect predictors of future action. Further, the interaction terms which capture the relationship between being an EV owner and being in the tailored condition cannot be interpreted causally and even then the reference category in such interaction terms do not provide the ideal counterfactual. For instance, when interpreting the interaction term between owning an EV and being assigned to the tailored group, the reference group is not just EV owners who were not assigned to the tailored group but a combination of non-EV owners in the tailored group, non-EV owners in the control group *and* EV owners in the control group.

This leads me onto the motivation for the OLEV trial which was designed to address these limitations. The next chapter presents the results of the final study in this thesis, the OLEV trial.

Chapter 7

Results (3):

The OLEV trial – timely, tailored email prompts are an effective and selective nudge

1 Introduction

This chapter presents the method and results of the OLEV trial. This field experiment tests whether EV purchase represents a window of opportunity to prompt EV owners to adopt TOU tariffs that could be exploited through tailored email prompts.

In partnership with the UK Government Office for Low Emission Vehicles (OLEV) and the Energy Saving Trust (EST) an email was delivered to approximately 7,000 private EV owners prompting them to switch electricity tariff and providing them with a link to a webpage hosted on the EST website containing information to help them identify whether a TOU tariff would be right for their household. The outcome measures are open rates to the email and click-through rates to the information webpage, both of which are likely to be correlated with switching (Morwitz et al., 2007; Kormos and Gifford, 2014).

The chapter is structured as follows. Section 2 will present a detailed overview of the method following the CONSORT statement's reporting checklist for randomised control trials (Schulz et al., 2010; Boutron et al., 2010). Section 3 will present the CONSORT diagram of the flow of participants from initial recruitment through to randomisation and the results of a balance check across experimental groups followed by Section 4 which provides descriptive statistics of the participants in my sample. Section 5 will present the average treatment effects of the tailored email on engagement with the email prompt whilst Section 6 will present the results of a regression analysis used to test whether EV owners are more receptive to the prompt shortly after purchasing their EV (the habit discontinuity effect). Section 7 discusses the results in relation to whether tailored, timely email prompts have the potential to increase switching rates to

TOU tariffs, which is the ultimate outcome of interest. Section 8 summarises the key findings of this trial.

2 Method

This study was designed to complement the first field experiment in two ways in terms of its contribution to answering research question 2, namely whether tailored marketing can increase uptake to TOU tariffs amongst consumers who are most likely to save money on one.

The first is that since OLEV has the contact email address and date of purchase of every private purchased EV in the UK, OLEV has the ability to prompt every privately owned EV owner in the UK to switch electricity tariff. This means the email prompts can be delivered to EV owners regardless of their prior probability of switching tariff or willingness to shop around for new tariffs, thereby overcoming the self-selection problems inherent on just relying on price comparison websites or implementing interventions on energy supplier websites, as in the Flex Trial.

The second is that it will involve recruiting amongst a known sample of EV owners to increase the amount of baseline data held on participants whilst avoiding alerting participants to the fact a trial is taking place, as would be the case if I randomised participants to interventions amongst the sub-group who completed a baseline survey. Since all participants are known to be EV owners, the causal impact of tailoring the marketing of TOU tariffs towards EV owners is equivalent to the average treatment effect of tailoring on the outcomes of interest. The advantage of estimating the impact of tailoring on EV owners using an average treatment effect as opposed to a heterogeneous treatment effect is that average treatment effects have a causal interpretation whereas sub-group analyses and interaction terms do not.

2.1 Population of interest

The population of interest for this trial is people in the UK who drive a plug-in EV for personal use and are therefore exposed to the costs of charging their vehicle at home. This excludes people who drive EVs for business purposes (business fleets) and therefore whose businesses are likely to cover charging expenses. However, new vehicles purchased by businesses make up just 1.2% of all new vehicle sales (SMMT, 2017b) and private road users account for 80% of all traffic on the road in the UK (Department for Transport, 2016), making EVs driven for personal use, whether leased from a company or privately owned, the single biggest target market for TOU tariffs.

Although the previous studies in this thesis confined the population of interest to British energy bill payers[83], this trial does not explicitly identify which EV owners identify as energy bill payers and does not exclude EV owners in Northern Ireland. This is for two reasons. Firstly, it will not be possible to exclude EV owners who do not identify as energy bill payers because data is not available on this variable. However, this does not threaten the success of the study because it is unlikely that many people purchasing EVs will not be financially responsible for their household energy bills.

Second, the usual motivation behind excluding Northern Irish energy bill payers from consumer trials on electricity tariffs does not apply to this study. The single

[83] Research on energy tariffs commonly limits participant samples to people who are "at least jointly responsible for their household bills" (Ipsos Mori and Consumer Focus, 2012a, i) by excluding participants who indicate that they are not responsible for paying household energy bills.

market for electricity covering GB is separate from the energy market in Northern Ireland, which means that British energy suppliers do not have a licence to operate in Northern Ireland. The Flex Trial tariff was designed in partnership with a British energy supplier, and therefore it would not have been possible for Irish consumers to adopt this tariff, hence the study was confined to British bill payers. It was for these reasons that the first study was also confined to British energy bill payers. However, OLEV's EV grant is a UK wide policy and Northern Irish EV owners will also have access to TOU tariffs from Irish energy suppliers. It would therefore not have been considered fair or necessary to exclude Northern Irish EV grant recipients from the study considering that they could also potentially save money from switching to a new electricity tariff, including TOU tariffs. Although TOU tariffs will eventually become mandatory in Northern Ireland, the energy regulator intends to encourage voluntary adoption of TOU tariffs in the interim period to minimise any potential consumer backlash (Commission for Energy Regulation, 2015).

2.2 Trial design

This is a two-armed randomised control trial that was designed to test the impact of prompting private purchase EV owners to switch electricity tariff via email using the generic appeal from Government tariff switching campaigns “Switch energy tariff to save money” relative to an email tailored to the target audience of EV owners “Switch energy tariff to cut the costs of charging your electric vehicle”.

Participants were randomly assigned with a 1:1 allocation ratio to receive one of two factually identical emails that framed the benefits of switching in one of two ways:

- Control: Switch to save over £300 on your energy bill

- Tailored: Switch to cut the costs of charging your electric vehicle by over £300

Both emails encouraged recipients to visit the Energy Saving Trust website containing tips on how to either cut the cost of their household energy bills (generic control email) or cut the cost of home charging (tailored email). The tips also included advice on how to work out whether the Economy 7 tariff, the UK's only TOU tariff at the time the trial was conducted, would be right for them. This information is important given that Chapter 5 illustrated that many consumers have difficulty in working this out independently.

The webpage was especially created for the trial, designed by me in collaboration with the UK Government OLEV and the Energy Saving Trust.

The study does not include a no-email control group because it would not have been possible to monitor the potential behavioural outcomes in such a group and because, as demonstrated through the review of the literature in Chapter 3, it is by now relatively well established that any prompt is more effective than no prompt (Haynes et al., 2013; Sanders and Smith, 2016), whereas the evidence on how best to frame the prompt for maximum effect is less clear.

The email was sent from a UK Government OLEV email account, because government emails tend to receive higher open rates[84] and because a key aim of the trial was to test whether such emails could be sent to grant recipients from government as business as usual. Email was chosen because it is low cost and,

[84] The source for this is the online email software management tool Mail Chimp, which publishes its email marketing benchmarks based on millions of emails sent every month from 12 million users. https://mailchimp.com/resources/research/email-marketing-benchmarks/.

unlike letters, provides easy tracking of behavioural outcomes using email campaign tools (see Chapter 3).

Emails are preferable to text messages because more information can be included in them and are preferable to letters because it is easier to monitor recipient engagement with emails than letters.

2.3 Recruiting amongst the population of interest

As noted above, the population of interest is people in the UK who drive an EV for personal use. Trial participants are all recipients of the private purchase UK Government Plug-In Car Grant (PICG) and for which a valid personal email address was held for the driver. The PICG subsidises the upfront cost of purchasing an EV by up to £5,000.

This means the trial includes all people who purchase an EV either outright or using a finance scheme (EV owners), but excludes people who drive a vehicle for personal use by leasing an EV from a company because OLEV only holds the email address for the leasing company that purchased the EV not the driver that goes on to drive it (EV leasers). EV leasers are part of the population of interest since they are likely to be exposed to the costs of charging their EV at home. Unfortunately, there is no reliable way of contacting the drivers of leased EVs. Despite this limitation, OLEV EV grant recipients represents an excellent sampling frame for four reasons.

First, based on unpublished data from OLEV, approximately 60% of private purchase EVs are bought for leasing, so EV owners encompass 40% of the population of interest, a sizeable sub-group of the EV population. Moreover, private purchase EV owners are an important sub-group of the EV population that will represent an increasing share of all vehicles on the road because private road users account for 80% of all motor vehicle traffic in the UK (Department for Transport, 2016) and the sale of internal combustion engine vehicles will be banned in the UK from 2040 (Department for Environment Food and Rural Affairs and Department for Transport, 2017).

Second, since the PICG is automatically applied at the point of purchase and approximately 98% of all EVs sold in the UK for private use are PICG eligible models (Next Green Car, 2017), the effectiveness of sending generic versus tailored email prompts can be tested on a very large sample of EV owners regardless of their prior interest in switching tariff and the extent to which they are willing to identify as EV owners. Recruiting a sample of EV owners through adverts aimed at EV owners then the study could overestimate the effect of tailoring on EV owners because it would only recruit participants who are willing to identify as EV owners or who automatically self-identify as an EV owner, which ex-ante may be correlated with tailoring. Equally, due to the relatively low population prevalence of EV owners, sending out generic adverts with a baseline survey aimed at identifying EV owners is unlikely to deliver a very large sample of EV owners. Indeed, early studies on EV owners have had very low samples despite intensive recruitment efforts, for instance in the region of 40 to 100 EV owners (Phillips et al., 2013; My Electric Avenue, 2015). This sampling frame is known to consist solely of EV owners to provide a very good test of the effectiveness of tailoring.

Third, grant recipients are required to complete a short questionnaire at the point of sale which includes their contact names and email addresses as well as a number of other demographic characteristics, making it relatively easy to contact them directly and prompt them to switch tariff by email, including to tariffs designed to incentivise off-peak charging. This information also includes the date of sale, which is necessary for testing whether EV owners are more receptive to prompts delivered the more recently they purchased their vehicle, to test the habit-discontinuity hypothesis.

Fourth, since this data is routinely collected as part of the administration of the PICG, if the trial is successful – participants open the emails and access the information – these email prompts could be rolled out by OLEV as business as usual. The trial could therefore have a positive impact on EV owners beyond the life of the trial itself.

An overview of this field experiment is provided in Figure *22*.

Figure 22 Overview of the OLEV trial design.

I worked with OLEV and the Department for Transport to draft a data sharing agreement and Privacy Impact Assessment, a document which considers in detail the risks and benefits to the use of this data for the research purposes and mitigation strategies for minimising any potential risks. Formal discussions with OLEV and the Department for Transport began in November 2016 and the agreement was in place by July 2017. The emails were sent to participants on a single day in August 2017.

Since the project would involve me handling personal data, the project was sent to the UCL Data Protection Officer who approved the project (Data protection number ‘Z6364106/2016/05/59 social research’. This trial does not alert participants to the fact that they are taking part in a trial. It was concluded that this does not pose an ethical concern as:

- The precedent has been set by other trials run with UK Government departments in which website or email content is altered
- Participants will not receive different information in any of the intervention arms, it will only be framed differently.
- It was concluded that the content of the email was unlikely to cause any distress to participants.

Based on this, the project received approval from the Head of Research Ethics at UCL’s Bartlett School of Environment, Energy and Resources (BSEER).

2.4 Intervention design

2.4.1 Generic vs tailored email design

The generic email was designed to mirror the type of messaging provided by most tariff switching campaigns in the UK reviewed in Chapter 3, which target the average energy bill payer and encourage them to switch tariff to save an average of £300.

As in the Flex Trial, the tailored manipulation was designed in line with the definition in the health literature, namely that tailoring “is a process of creating individualised communication” (Kreuter et al., 2002, p.272). Tailoring is theorised to enhance information processing through several channels, all of which were exploited in the design of the tailored email: (1) the content was *matched* to the EV owner's needs, by drawing attention to the fact that their energy bill would increase once charging their vehicle from home and pointing out that switching tariff could mitigate this; (2) the method was *framed* in a way that was relevant to the recipient by presenting the savings from switching tariff as a £300 saving to be made on home charging an EV rather than a £300 reduction in their energy bill.

The approach to framing also intends to exploit another finding from the behavioural science literature on mental accounting, that people do not make financial choices in relation to their overall wealth, as assumed by classical economics, but in relation to different mental accounts held for different intended purposes, for instance rent, holidays and energy (Thaler, 1980, 1990, 1999). It is possible that EV owners could have a separate mental account for their energy bills as they do for covering the cost of running their EV. If so, and if the EV mental account is more salient than their energy bill mental account, this provides an additional reason why the tailored email would be more effective than the generic email.

Designing behavioural interventions based on multiple findings from the behavioural science literature is a relatively common approach in nudge studies both because behavioural interventions can often yield relatively small treatment effects (and combining multiple insights could potentially enhance the impact) and because it is often not possible to say on theoretical or empirical grounds what influences will be more important (Thaler and Benartzi, 2004; Volpp et al., 2008). Indeed, since there have been no prior framing studies on EV owners, it is not possible to say a priori whether mental accounting or increased salience will be more important and, moreover, the approach to mental accounting fits the definition of tailored communication used in the health literature, which has undertaken a large amount of research on tailored communications.

Nevertheless, since there is an element of subjectivity in how tailoring could be interpreted, the emails were constructed according to a pre-defined matrix of tailored versus non tailored sentences; in other words, for every sentence of content in the generic email there is an equivalent in the tailored email that is factually identical but 'framed' towards EV owners. These are presented in Table 31, however the full text of the emails as sent to participants is reproduced in Appendix 12. Both emails contained text in a one column format with links to the webpage of tips hosted on the Energy Saving Trust website, a well-respected British organisation providing consumers with accessible advice on energy related matters. This webpage is still in use and can be visited at the following address http://www.energysavingtrust.org.uk/travel/electric-vehicles/electricity-tariffs-electric-vehicles.

Table 31 Example of the messages provided in each experimental group (italicised text is absent in the generic email but present in the tailored email).

	Generic email	**Tailored email**
Email subject lin	Switch your energy tariff to save £300.	Cut the cost of charging your electric car by £300.
Email preview text (appears in inbox)	Dear [First Name], Your current energy tariff may no longer be appropriate. Find out how to choose the right tariff to save £300.	Dear [First Name], Now that you own an electric car, your current energy tariff may no longer be appropriate. Find out how to choose the right tariff for your EV to save £300.

Email body copy – line 1	You could save over £300 by switching your energy tariff.	You could save over £300 by switching your energy tariff, *equivalent to 11,000 free electric miles*.
Email body copy – line 2	We recommend that you consider switching your electricity tariff.	*Now that you've bought an electric car*, we recommend that you consider switching your electricity tariff. *That's because, if you're charging your car at home, your electricity bill will go up.*
Email body copy – line 3	Click here for five top tips on how to choose the right energy tariff.	Click here for five top tips on how to choose the right energy tariff *for your electric car*.
Email body copy – final line	Wondering whether Economy 7, which gives you a cheaper rate overnight, could help lower your energy bills? Visit our online guide today to find out how much money you could save on Economy 7 based on how you use energy at home.	Wondering whether Economy 7, which gives you a cheaper rate overnight, *might help you charge your car for less*? Visit our online guide today to find out how much money you could save on Economy 7 based on how much you *charge your electric car from home*.

At the time of the trial, there were no smart meter enabled TOU tariffs. The email therefore mentioned the savings from switching to flat rate tariffs[85] as well as to the Economy 7 tariff, the only existing domestic TOU tariff in GB. However, emails

[85] The reason for mentioning the savings to be made from switching to the cheapest flat-rate tariff is that, given so few consumers switch tariff, the largest average savings can still be made by switching to the cheapest available flat-rate tariff with further potential savings to be made from switching to an Economy 7 tariff, as is made clear to EV owners in the tips pages.

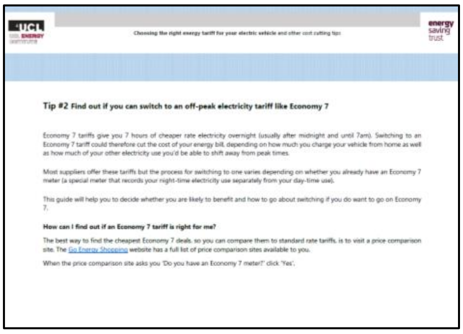
are a generic mechanism by which EV owners could be prompted to switch to any future smart meter enabled TOU tariff.

2.4.2 The webpage on the Energy Saving Trust website

The page on the Energy Saving Trust website created for this trial contained five tips on 'how to reduce the running costs of your EV':

- Save over £300 by switching to the cheapest fixed rate electricity tariff
- Find out if you can switch to an off-peak tariff to benefit from cheap overnight electricity
- Look out for new types of 'smart' off-peak tariffs which could save you even more money
- Discounted electricity tariffs for EV drivers
- Check if you can get a smart meter

Figure 23 The webpage (left) and an example of the downloadable tips (right).



2.5 Outcomes

It is assumed that the tailoring, which affects the content of the email, will play the greatest role in encouraging EV owners to engage with the content and respond to the call to action in the email to consider switching tariff. However, it is assumed that the timing of the email – specifically, how recently the email is sent since the individual purchased their EV – will play the greatest role in encouraging EV owners to open the email in the first place since the habit discontinuity hypothesis should take effect just from reading the word ‘electric vehicle’ and seeing the name of the recipient (OLEV), without having to engage in detail with the content of the message itself.

Therefore, the primary outcome measure used for assessing the average treatment effect of the way in which the email was framed is the proportion of people who click through to the Energy Saving Trust website from the email (binary 1 for YES or 0 for NO).

The open rate to the email (binary 1 for YES or 0 for NO) is the primary outcome of interest for measuring the impact of the timing of sending tariff switching prompts on receptiveness to the prompt.

However, the impact of tailoring will also be measured on open rates and unsubscribe rates to the email (binary 1 for YES or 0 for NO).

2.6 Additional data collection

Data was also collected on the number of downloads of the PDF leaflets on the Energy Saving Trust website. The Energy Saving Trust reported this data to me at the end of the trial period (details on this in section 6.7 below). This data cannot be linked to the interventions so is not used as an outcome measure, but is of general interest for understanding whether email recipients who clicked through to the website did indeed go on to access the information provided.

In addition to the names, email addresses and the date of purchase, the OLEV dataset also contains the following information on PICG recipients which is collected via a survey administered in the dealership at the point of purchase:

- Gender (male, female)
- Age (17-30, 31-40, 41-50, 51-60, >61, prefer not to say)
- Employment status (employed, not working)
- Number of vehicles in household (0, 1, 2, 3 >3)
- Vehicle type purchased (van or car)
- Whether the EV will be used as the main household vehicle (yes, no, don't know)
- Self-reported expected annual mileage (<1600; 1,600-8,000; 8,000-16,000; 16,000-32,000; 32,000-48,000; >48,000; Don't know, Varies too much to say)
- Self-reported top three expected uses for the EV (Visiting family or friends, Commuting to work, Holiday trips, Shopping, Personal business, Business trips, Taking children to school, Commercial use)
- Self-reported expected charging location (Home, Work, Motorway service station, Other public infrastructure, Public car parks, On-street other, On-street residential)
- Vehicle make and model (Categorical variable with multiple categories)
- Purchase cost of the vehicle (Continuous variable)

The survey was designed by OLEV when the grant was launched so is not included in this thesis.

2.7 Sample size

The email contact data was downloaded from the OLEV system in June 2016 in preparation for the trial. Once inclusion criteria were applied (private purchase recipients with valid personal email addresses), there were 8,081 unique email addresses.

Since this trial has two primary outcomes of interest, power calculations were run separately for open rates and click-through rates, conditional on the estimated open rate. In both cases the alpha was set at 0.05 and power at 0.80 the convention for trials in the social sciences (Glennerster and Takavarasha, 2013).

2.7.1 Open rate power calculations

Power calculations run in advance on Stata v.13 indicated that, with a sample size of 8,000 participants (4,000 per arm), the trial would be powered to detect between a 0.02649-0.02802 percentage point difference in email open rates between the control and treatment email from various baseline email open rates (0.22-0.2626). The minimum open rate of 22% was set because this is the average open rate for email marketing although the average for Government emails is 26% so this was set as the maximum likely open rate.[86] The assumptions used in these calculations and its impact on the minimal effect size that the trial will be powered to detect are summarised in Table 32.

Table 32 Ex-ante power calculations on the open rate outcome variable.

N	Delta (percentage point difference)	P1 – control email open rate	P2 – tailored email open rate	Delta (percentage point difference)	Minimum detectable effect size (percentage increase)
8,000	0.02649	0.22	0.2465	0.02649	12%
8,000	0.02802	0.2626	0.2906	0.02802	11%

[86] The source for this is the online email software management tool Mail Chimp, which publishes its email marketing benchmarks based on millions of emails sent every month from 12 million users. https://mailchimp.com/resources/research/email-marketing-benchmarks/. Overall average, regardless of sector, was computed by the authors as Mail Chimp only provides averages by industry sector.

2.7.2 Click-through rate power calculations

Power calculations run in advance on Stata v.13 indicated that the trial would be powered to detect between a 0.02363-0.02933 percentage point difference in click-through rates between the control and treatment arms from various baseline click through rates (0.0271-0.0362) after accounting for various email open rates (0.22-0.2626) – in other words, after accounting for the fact that not all recipients would open the email. The smallest assumed click-through rate of 2.7% was set since this is the average click-through rate for email marketing, however the average for Government emails is slightly higher at 3.6%, so this was estimated to be the maximum likely click-through rate.[87] The assumptions used in these calculations and its effect on the smallest effect size the trial would be powered to detect are summarised in Table 33.

Table 33 Ex-ante power calculations on the click-through rate outcome variable.

	N conditional on open rate	**P1 – control click through rate**	**P2 – click through rate in tailored**	**Delta (percentage point difference)**	**Minimum detectable effect size (percentage increase)**
Open rate: 22%	1760	0.0271	0.05332	0.02622	97%
	1760	0.0362	0.06553	0.02933	81%
Open rate: 26%	2100	0.0271	0.05073	0.02363	87%
	2100	0.0362	0.06269	0.02649	73%

2.7.3 The approach taken to the power calculations

It is considered best practice to select a sample size on the basis of the smallest effect size between a control and treatment group that would make the treatment

[87] Based on the email marketing benchmarks published by Mail Chimp.

more cost-effective than the control[88] (e.g. see Glennerster and Takavarasha, 2013), and this was the method used to arrive at the MDE for the Flex Trial (see Chapter 6). However, the marginal cost of sending an email to a grant recipient is virtually zero so cost-effectiveness is a poor barometer for determining a worthwhile difference in open or click-through rates. It was therefore decided that the trial would be run if the existing size of the EV population was large enough to be able to identify a treatment effect size that is in line with the smaller effect sizes observed in the literature on framing effects in letter, text and email communication (reviewed in Chapter 3) and if these treatment effect sizes would deliver a valuable increase in the number of EV owners exposed to prompts about switching to a TOU tariff once an increasing share of new vehicle sales are electric.

The power calculations noted above demonstrated that a sample size of 8,000 would be sufficient to detect a treatment effect of at least 11% for open rates and at least 73% for click-through rates which is in line with the smaller treatment effects observed in the literature and was judged by the OLEV to be of substantive importance to them. For example, in 2016, approximately 2.6 million new vehicles were registered in the UK each year. By 2030, the target is for 60% (1.6 million at the current rate of sales) of these new vehicle sales to come from EVs and 100% by 2050 (Committee on Climate Change, 2013). An 11% increase in open rates from a baseline of 26% would mean reaching an additional 464,000 – 416,000 = 50,000 new EV owners by 2030 and additional 754,000 – 676,000 = 78,000 new private EV owners by 2050 with a prompt to switch to a TOU tariff at

[88] For example, in clinical trials, the minimum detectable treatment effect between an existing treatment for a disease and a new experimental treatment might be the difference in patient outcomes that would make the new drug more cost-effective relative to the existing drug.

minimal cost. This is the number of additional prompts accessed by EV owners per year and this rough calculation ignores growth in population and growth in new vehicle sales.

Given that the majority of people are unlikely to open the email, the increase in click-through rates resulting from the tailoring email would need to be larger to have a substantive impact on the number of recipients accessing information about tariff switching; an increase in click-through rates of at least 70% from a baseline of 3.6% would mean an additional (754,000 x 0.06) – (754,000 x 0.036) = 18,000 new private EV owners accessing specific information about what TOU tariff to switch to as well as how to switch. That is twice as many private EV owners as currently exist in the UK at present.

2.7.4 Stopping rules for measuring outcomes

I pre-committed in advance to stop recording outcomes when there was a 5 day period throughout which there were fewer than three new unique opens/clicks. This is because, once sent, the email would be stored in recipients' inboxes (unless deleted) so people could open the email and click-through to the link at any time. This stopping rule was pre-specified in the Pre-Analysis Plan.

2.8 Randomisation and blinding

Participants were randomly assigned to either the generic or tailored email message by the email campaign management tool Email Center, from which the emails were sent. Email Center uses simple randomisation.[89] A 1:1 allocation

[89] It randomly sorts the list of intended email recipients and then assigns the top half to the control and bottom half to treatment as is recommended in Glennerster and Takavarasha (2013).

ratio was employed to achieve equal numbers of participants across both groups on average. The unit of randomisation was the unique email address.

Since the intervention is delivered in an email to private email addresses, participants will be unaware of any variations in the treatment and since the allocation was performed by Email Center, treatment assignment was also concealed from me although I sent the emails.

2.9 Analysis plan

The trial and Pre-Analysis Plan was registered with the EGAP trial registry (20160726AA). Below, I outline the analysis method used to test for the average treatment effect and the habit discontinuity effect.

2.9.1 Average treatment effect equation

The second research question asks whether tailored message framing could be used to increase switching rates to TOU tariffs amongst EV owners. In the context of this experiment, this research question is associated with the following hypothesis:

- **Hypothesis 1** Click-through rates to an email prompting EV owners to switch electricity tariff will be higher when the email messaging is tailored towards EV owners than when the email messaging is applicable to the average energy bill payer

This hypothesis will be tested using the following equation estimated using OLS regression:

[1] $\gamma_i = \alpha + \beta_1 T1_i + u_i$

Where:

- γ_i is the outcome measure, a binary variable taking the value of one (1) if the participant clicks through to the EST website and (0) otherwise after the email is sent
- α is the constant
- $T1_i$ is a binary variable that equals one (1) if a participant was sent the tailored email, so that the control (generic email) is the omitted reference category
- β_1 is the coefficients on $T1_i$, which measures the effect of being sent the tailored email rather than the generic email so is the primary coefficient of interest for testing hypothesis 1
- u_i is the error term.

The equation above was also run with the secondary outcome measures identified (open rates, unsubscribe rates) and the following set of baseline covariates to increase the precision of treatment effect estimates by reducing unexplained variation in the outcomes (Gerber and Green, 2012):[90]

- Postcode district, implemented as fixed effects
- Time in months since purchase (continuous)[91]
- Price of vehicle
- Time email opened (continuous)

[90] Three additional control variables specified in the Pre-Analysis Plan but which were not ultimately included are (controls for whether or not the electric vehicle had been delivered to the owner (dummy) as well as the email client and the device the email was opened on, as it was expected that this could affect the way the email displayed and therefore click-through rates. However, there was less than 95% variation in the delivered dummy so in line with the Pre-Analysis Plan, this was excluded from all analyses. Although Email Center provides a breakdown of what email client and device recipients used to open the email, this data is provided on aggregate and not linked to each individual recipient as the marketing team had originally said. These variables were therefore not included.

[91] This variable was created using the date of purchase.

- A dummy variable to control for change to the maximum grant value awarded (March 2016)

2.9.2 Testing the habit discontinuity effect – the regression equation

The habit discontinuity hypothesis states that the receptiveness to the prompt is affected by when the prompt is delivered in relation to when the EV owner purchased their vehicle, however it is not known whether the effect is linear. In the context of vehicle users, it was found that people with strong environmental attitudes have lower self-reported car use, but only after recently moving home (<12 months ago) but also that this effect decays as the time since moving home increases (Thomas et al., 2016). In the case of people who have recently moved home, the effect has been found to last for up to three months (Verplanken and Roy, 2016). It was therefore theorised in Chapter 3 that in the same way that this prior research suggests "moving into a new home [is] a potential 'window of opportunity'" (Thomas et al., 2016, p.1) to influence people's use of their vehicles, purchasing one's first EV may also present a window of opportunity to introduce EV owners to a new positive habit of enrolling on a TOU tariff and charging their vehicles at off-peak times.

However, unlike with moving home, it is not so obvious when EV owners would be most receptive to tariff switching prompts. For example, we could imagine that people who have recently purchased an EV will be particularly receptive to information that relates to their household electricity use, especially any information that specifically addresses them as EV owners. If so, we expect engagement rates with an email prompt to decrease linearly as time since purchasing the vehicle increases (a negative correlation).

Alternatively, engagement may decrease as time since purchasing increases but only up until some time point beyond which people are accustomed to owning their EV (a negative correlation with an extreme positive skew) if there is cut-off point for this window of opportunity e.g. as people become accustomed both to their EV and to the increased amount of their monthly electricity bill. On the other hand, we might hypothesise that, having just spent thousands of pounds on a new vehicle, the prospect of saving £300 on their electricity bills will seem relatively unsubstantial – until they receive their first electricity bill after having received delivery of their new EV. Two thirds of energy bill payers pay for their electricity on a monthly basis (Ofgem, 2015) so it may not be until they receive their first few energy bills after buying an EV that they start to take notice of their increased electricity use and therefore feel interested in reducing it.

To avoid the risk of cherry-picking particular values that support the habit discontinuity hypothesis, I pre-specified the way in which the analysis would be undertaken to test for both a linear and non-linear effect of time on email open rates. Firstly, there are therefore two pre-specified hypotheses[92]:

- **Hypothesis 2** Demand for email information about electricity tariffs will decrease as time in months since the EV was purchased increases (the habit discontinuity hypothesis)
- **Hypothesis 3** Demand for email information about electricity tariffs will initially decrease as time in months since the EV was purchased increases

[92] The Pre-Analysis Plan specified that I would also test for differences based on weeks since purchase however such an analysis became less valuable given that there was a delay in time between the data being extracted from the Government's database system and the start of the trial (a three month delay).

and then trail off (the habit discontinuity hypothesis with a window of opportunity)

These hypotheses will be tested using the following equation estimated using OLS regression:

[2] $\gamma_i = \alpha + \beta_1 T1_i + \beta_2 time_i + \chi_i + u_i$

Where, in addition to the model set out in Equation [1] $time_i$ is a variable that aims to test for the presence of a correlation between the time since the recipient purchased their EV and demand for information about switching electricity tariff as proxied by click-through rates and open rates.

Secondly, the way in which the variable $time_i$ will be coded was also pre-specified:

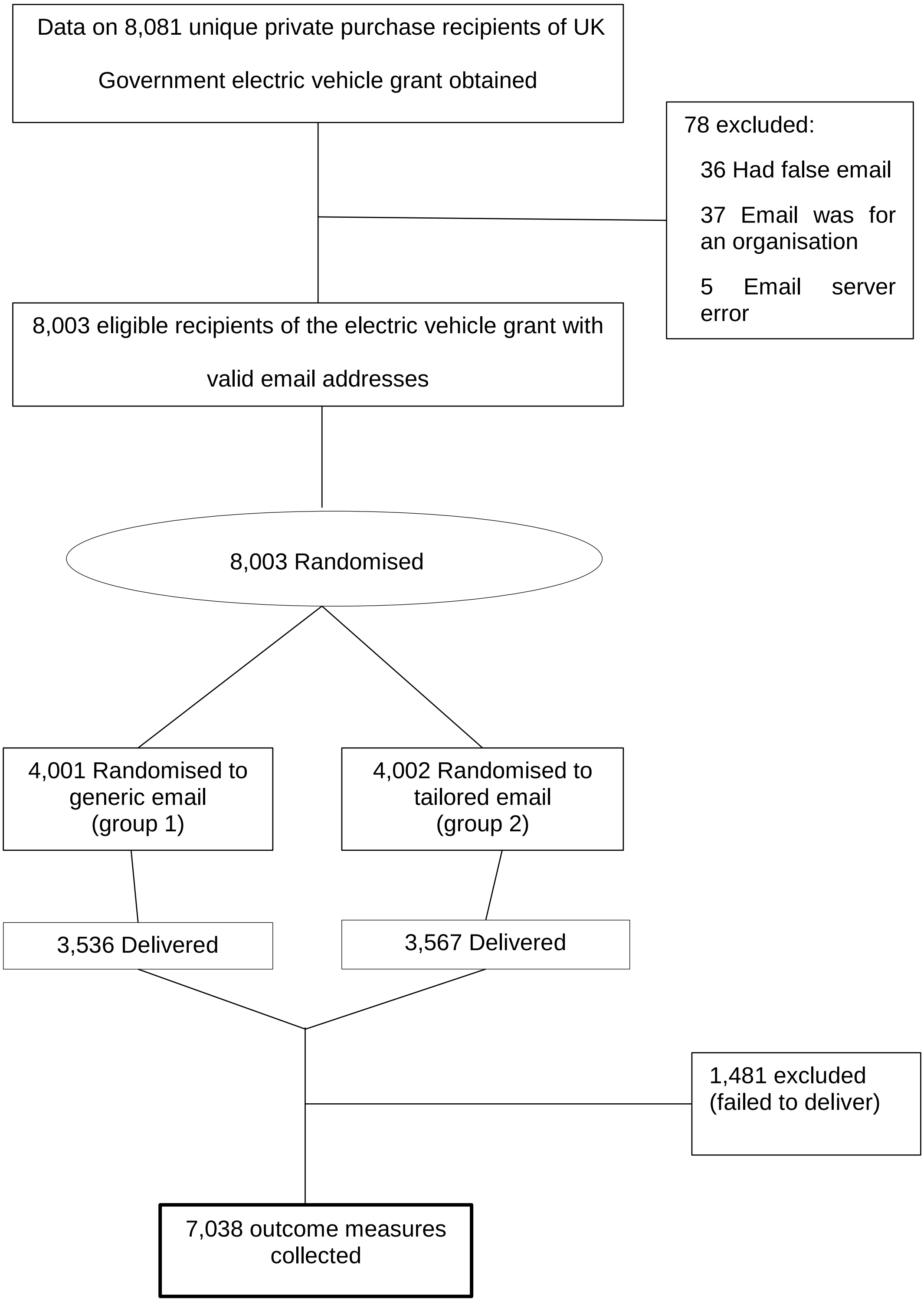
- To test hypothesis 2, $time_i$ will be coded as a continuous variable which measures the time in months since the recipient purchased their vehicle and where β_2 is the coefficient on $time_i$ which tests the hypothesis that email open rates decline as time in months since purchasing the EV increases (a classic habit discontinuity)
- To test hypothesis 3, as a categorical variable in which the sample was split into equal quartiles according to the time in months since the vehicle was purchased and where β_2 is the coefficient on $time_i$ which tests the hypothesis that email open rates decline as time in months since purchasing the EV increases but then stagnates (habit discontinuity with a window of opportunity)

The reason the time variable is coded based on quartiles is that it makes it possible to pre-specify the type of non-linear relationship that may be expected without having access to the dataset; quartiles were chosen following a recent study on the habit discontinuity hypothesis (Thomas et al., 2016).

3 Implementation of trial

In August 2016 an email was sent to 8,003 private EV owners in the UK prompting them to switch electricity tariff. Figure 24 describes the flow of participants from the receipt of email address data, to randomisation, delivery of emails and collection of outcomes. The final sample for analysis consisted of 7,038 participants because some participants were excluded due to having invalid or company email addresses or because, after randomisation, some emails failed to send (however this was not statistically significantly different across the two email conditions).

Figure 24 Participant flow diagram.



4 Descriptive statistics of sample

4.1 Participant characteristics and baseline randomisation checks

Table 34 presents the characteristics of the participants in the entire sample and for the treatment and control group separately as measured by OLEV through a survey administered to grant recipients at the point of purchase in the dealership. Balance checks on baseline characteristics indicate that the randomisation was successful. The final column presents the p-values associated with a statistical significance test for whether there are any significant differences in the characteristics of the participants in the control group and those in the tailored group for each of the baseline variables. Out of 50 significance tests, only one variable is statistically significantly different between the control and treatment group at the 5 percent level and a further three variables are statistically significantly different across the treatment and control group at the 10 percent significance level, which is fewer than would be expected by chance alone.

There are some statistically significant differences between the characteristics of participants who successfully received the email compared to those for whom the email was undelivered. However, assuming that the characteristics of individuals who do not report valid email addresses to OLEV is the same for future grant recipients as for the grant recipients in this trial, these differences will not substantively alter the policy implications of any results.

It is often asserted that EV owners will do the majority of their charging from home, due to its convenience (e.g. see Knight et al., 2015), and the data overwhelmingly supports this conclusion; 90% of EV owners in the UK who purchased their vehicle outright intend to charge their vehicle at home whereas just 25% say they intend to charge at work and less than half (45%) indicate that they would use locations that are likely to be equipped with public charge points (e.g. public car parks, motorway service stations).[93] This has important implications for the importance of TOU tariffs since, if EV owners do most of their charging from home rather than public service stations, this means that a large portion of their charging could potentially be influenced by their household electricity tariff.

Another feature of the dataset worth noting is that there is also a large range in terms of when EV owners purchased their vehicle. At the time of the trial, some participants had purchased their EV as recently as three months prior to receiving the email whereas others had owned their vehicle for over five years. This is important since hypotheses 2 and 3 are that receptiveness to the email will vary depending on how recently the recipient purchased their vehicle.

Finally, it is also worth considering the profile of the average private purchase EV owner, because it could affect their likelihood of responding to the tailored email and also because the profile of the average EV owner may change as EVs become more mainstream in a way which could affect the generalisability of the findings to future EV owners. According to the data, the average private purchase EV owner in the UK is male and, if we assume that non-response for age is equally distributed across all age brackets, aged 40 and above. The majority already have two vehicles at home when they purchase their EV compared to a population average of one vehicle per household. This is not surprising given that the purchase price of EVs is significantly higher than traditional combustion

[93] In the survey, which was designed by OLEV, recipients are able to select multiple responses when answering this question, which is why the percentages do not sum to 100. The sample size for some of these questions is smaller than the full sample size of 8,003 because new questions were introduced into the survey part way through the grant scheme.

engine vehicles, even after considering the grant, so are presumably purchased by people who are wealthier than average.

Given that the results of chapter 5 suggested that bounded rationality was more likely to affect energy bill payers in lower social grades than bill payers in higher social grades, the current profile of EV owners provides a particularly stringent test of the tailoring intervention which, according to a classical economic model, will have no effect on the outcomes since the incentive to switch (the potential £300 plus saving) is the same in both groups.

Table 34 Descriptive statistics of sample and randomisation balance checks on baseline characteristics

	Summary statistics (%)			P value (2)=(3)
Variable name	Entire sample	Control	Tailored email	
	(1)	(2)	(3)	(4)
	N=8,003	N=4,001	N=4,002	
Owner demographics				
Gender:				
Female	22	22	21	0.930
Male	76	77	76	0.604
Not reported	2	2	2	**0.082**
Age:				
17-30	2	2	2	0.442
31-40	8	9	8	0.622
41-50	21	21	21	0.963
51-60	27	26	28	0.121
> 61	26	26	25	0.372
Prefer not to say	16	16	16	0.851
Not reported	10	10	9	0.042*
Employment status:				
Employed	31	31	31	0.641
Not working	9	10	9	**0.095**
Not reported (dummy)	60	59	60	0.155
Number of vehicles in househo				
0	0	0	0	-
1	21	21	20	0.258
2	46	46	46	0.567
3	17	16	17	0.168
>3	8	8	8	0.868

Not reported	8	8	8	0.285
Self-reported usage of vehicl				
EV will be the main household vehicle:				
Yes	91	90	91	0.315
No	6	7	6	0.168
Don't know	3	3	3	0.891
Expected average annual mileage: †				
<1,000	0.7	0.8	0.6	0.592
1,000-4,999	10	10	10	0.737
5,000-9,999	52	51	53	0.222
10,000-19,999	32	33	32	0.562
20,000-29,999	3	3	3	0.494
>30,000	1	1	0.4	0.189
Don't know	1	1	1	0.665
Varies too much to say	0.4	0.5	0.4	0.643
Expected charging location: ‡				
Home	92	92	92	0.562
Work	25	24	26	**0.092**
On-street residential	5	5	6	0.266
On-street other	5	4	5	0.509
Public car parks	15	15	16	0.341
Other public infrastructure	15	15	15	0.925
Motorway service station	15	14	15	0.395
Expected purpose for travel:‡				
Commuting/getting to work	63	62	64	0.308
Business trips	19	20	18	0.200
Visiting family or friends	67	66	66	0.761
Holiday trips	43	43	44	0.528
Shopping	42	42	42	0.829
Personal business	23	23	23	0.882
Education/taking children to scl	7	7	8	0.562
Commercial use	0.3	0.4	0.3	0.610
Vehicle characteristics				
Car	99	99	99	0.257
Van	0.2	0.2	0.3	0.257
Basic price (mean £)	38,130 (20,224)	38,154 (20,079)	38,106 (20,370)	0.917
Characteristics of claim				
Purchase date (range)	12/2010-05/2016	02/2011-05/2016	12/2010-05/2016	0.584
Time since vehicle purchased in months (mean)	21 (13)	21 (13)	21 (13)	0.584

Notes: The p-values in column 5 were obtained by regressing the treatment dummy against each baseline characteristic using logit regression for binary variables and OLS linear regression for continuous variables. Covariates found to be significant at the 95% level are marked with an asterix. Covariates which are marginally significant at the 10% level are highlighted in bold. The symbol † means the total sample size for each cell in this category is 3233 rather than 8003 because this question was not added to the customer survey until May/June 2015 although the first survey was run in December 2010. The symbol ‡ means the total sample size for each cell in this category is 3220 because this question was not added to the customer survey until May/June 2015 although the first survey was run in December 2010.

Table 35 Comparing the characteristics of participants with valid and invalid email addresses

	Group		P value (1)=(2)
Variable name	Included participants	Excluded participants	
	(1)	(2)	(3)
	N=7,038	N=1,481	
Owner demographics			
Gender:			
Female	0.22	0.21	0.818
Male	0.76	0.73	0.011*
Not reported	0.02	0.05	0.000*
Age:			
17-30	0.02	0.02	0.771
31-40	0.08	0.08	0.429
41-50	0.21	0.21	0.929
51-60	0.27	0.27	0.782
> 61	0.26	0.25	0.626
Prefer not to say	0.16	0.18	**0.088**
Not reported	0.09	0.17	0.000*
Employment status:			
Employed	0.32	0.23	0.000*
Not working	0.09	0.08	0.342
Not reported (dummy)	0.59	0.69	0.000*
Number of vehicles in household:			
0	0	0	-
1	0.21	0.22	0.238
2	0.46	0.45	0.253
3	0.17	0.15	0.235
>3	0.08	0.09	0.989
Not reported	0.08	0.10	**0.058**
Self-reported usage of vehicle			
EV will be the main household vehicle:			
Yes	0.90	0.88	0.002*
No	0.06	0.08	0.028*
Don’t know	0.03	0.04	**0.056**
Expected average annual mileage:			
<1,000	0.01	0.01	0.328
1,000-4,999	0.10	0.11	0.917

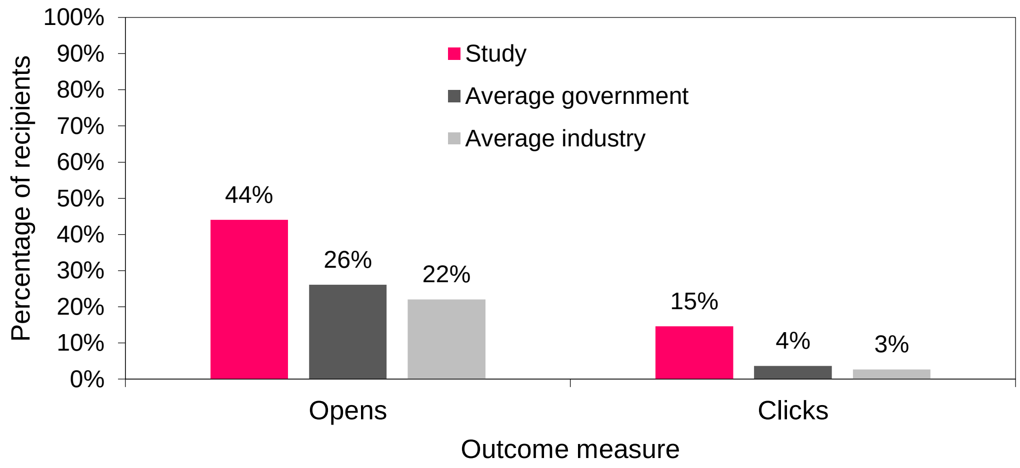
5,000-9,999	0.52	0.49	0.280
10,000-19,999	0.32	0.32	0.963
20,000-29,999	0.03	0.02	0.397
>30,000	0.01	0.01	0.733
Don’t know	0.01	0.04	0.000*
Varies too much to say	0.004	0.01	0.496
Expected charging location:			
Home	0.92	0.91	0.578
Work	0.25	0.26	0.592
On-street residential	0.05	0.07	**0.094**
On-street other	0.05	0.06	0.315
Public car parks	0.15	0.18	**0.060**
Other public infrastructure	0.15	0.13	0.235
Motorway service station	0.15	0.14	0.806
Expected purpose for travel:			
Commuting/getting to work			
Business trips	0.63	0.62	0.545
Visiting family or friends	0.19	0.15	0.027*
Holiday trips	0.66	0.65	0.832
Shopping	0.43	0.41	0.370
Personal business	0.42	0.45	0.175
Education/taking children to school	0.23	0.23	0.957
Commercial use	0.078	0.07	0.725
Vehicle characteristics			
Car	0.99	0.99	0.673
Van	0.002	0.002	0.673
Basic price (mean £)	38,695	34,969	0.000*
Characteristics of claim			
Time since vehicle purchased in months (mean)	21	23	0.000*

Notes: The p-values in column 4 were obtained by regressing a dummy variable indicating whether an individual received the email (1) or whether they did not receive the email (0) against each baseline characteristic using logit regression for binary variables and OLS linear regression for continuous variables. Covariates found to be significant at the 95% level are marked with an asterix. Covariates which are marginally significant at the 10% level are highlighted in bold.

4.2 Outcome variables

Figure 25 presents a diagram of the two outcome measures in this trial, open rates and click-through rates, compared to the average open and click through rates to emails sent by Government bodies and the average for any type of email marketing (see footnote 86 for source). As can be seen, email open rates and click through rates are both much higher in this trial than on average.

Figure 25 Outcome variables in the OLEV trial compared to average email campaign outcomes



Note: Bars represent the average email open and click-through rate in the study (pink) compared to the average open and click-through rate for government emails (dark grey) and the average for email marketing as a whole (light grey).

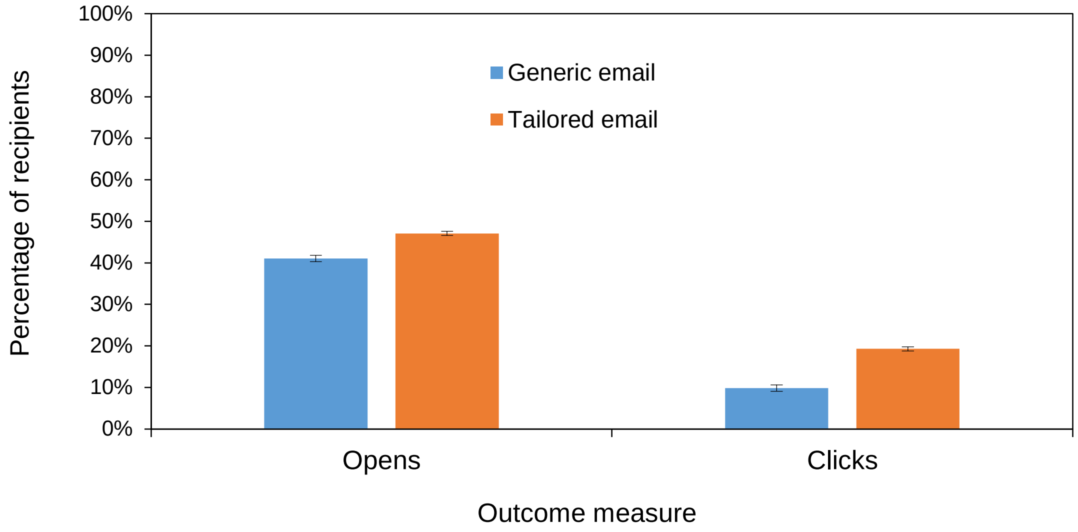
5 Results – average treatment effects

Hypothesis 1 proposed that the tailored email would increase open rates and click-through rates relative to the generic email. This hypothesis is first explored by looking at the outcomes graphically followed by a presentation of the results of the regression model outlined in Section 2.9.1 to test whether any differences are statistically significant.

5.1 Outcomes by experimental group visually

Figure 26 is a bar chart of email open and click-through rates across the control and tailored group. It shows that both outcome measures are higher in the tailored group which framed the benefits of switching in terms of a potential £300 reduction in charging their EV from home compared to the control group which framed this benefit as a £300 reduction in household energy bills. Open rates are 15% higher and click-through rates are 90% higher in the tailored condition.

Figure 26 Email open and click through rates by experimental group



Note: Bars represent the average email open and click-through rate for the generic email and the tailored email with standard error bars.

5.2 Outcomes regression model and results

Table 36 reports the results of the pre-specific regression analysis testing whether the differences in open and click-through rates observed in Figure 26 are statistically significant. Looking at the first two columns, the results show that the difference in email open and click-through rates is statistically significant at the 99.9 percent level, which is consistent with hypothesis 1 that a tailored email would be more effective than a generic email.

The model estimates that the open rate was 6 percentage points higher and the click-through rate 10 percentage points higher in the tailored group than the generic group, which is consistent with the percentage difference in the raw data. Moreover, although recipients could unsubscribe from future emails by clicking a link at the bottom of the email, very few did so (n=59) with significantly fewer unsubscribing in the tailored email relative to the generic email condition ($p<0.05$). The statistical significance levels are identical in a robustness check in which the equation is estimated using logit with marginal effects reported that are also almost identical to the OLS coefficients reported here (see Appendix 13).

Table 36 The impact of tailored emails on open rates and click-through rates

	(1)	(2)	(3)
Outcome measure:	Opened	Clicked	Unsubscribed
Treatment dummy (1=tailored; 0=generic)	0.060***	0.095***	-0.005*
	(0.000)	(0.000)	(0.012)
Observations	7038	7038	7038
R^2	0.004	0.018	0.0009

Note: All models are estimated using robust standard errors with *p*-values in parentheses.
$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
^ p-value is greater than the 5 percent significance threshold once correcting for multiple comparison testing using the Benjamini and Hochberg (1995) method.

6 Results – habit discontinuity effect

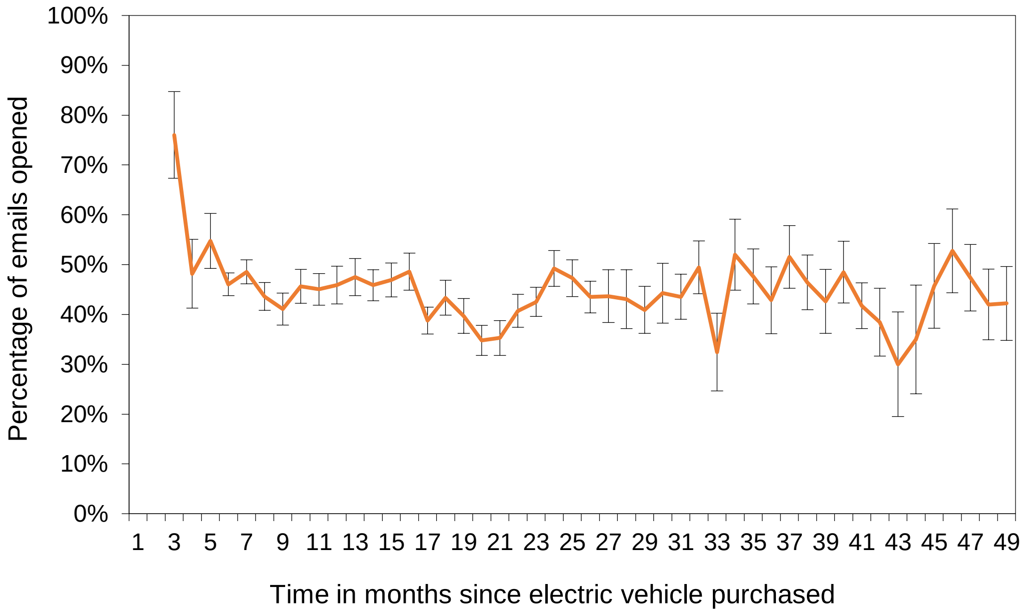
Some participants had purchased their EV as recently as three months prior to receiving the email whereas others had owned their vehicle for over five years. Hypothesis 2 proposed that open rates would decline in a linear fashion based on how recently the recipient had purchased their EV, which is the basis of the habit discontinuity effect (Verplanken and Wood, 2006; Verplanken et al., 2008; Verplanken and Roy, 2016).

Hypothesis 3 proposed that open rates would decline after a particular point in time and then stagnate, in line with the habit discontinuity hypothesis with a discrete window of opportunity. As noted above, it was decided in advance that this hypothesis would be tested by splitting the sample into quartiles based on the time since purchase to avoid cherry picking particular values that support the concept of a window of opportunity. Nevertheless, before presenting the results of these tests, the next section will provide a graphical overview of the data to help gauge whether the pre-specified models are likely to be a good fit for the data.

6.1 Outcomes by experimental group visually

Figure 27 presents a line graph plotting the average email open rate by the time in months since the email recipient had purchased their EV and it reveals a marked non-linearity in the relationship between open rates and time since purchase, with outlying values removed.[94] Email open rates decline from over 70% to 40% between those who had purchased their EV three months ago (the most recent group of EV owners in the dataset) and those who had purchased their EV four months ago or more.

Figure 27 Average email open rate by time in months since EV purchased



[94] Vehicles purchased more than 50 months ago were excluded because the sample size in each of the intervening months is too small (average sample size = 12) to obtain a statistically significant estimate of the open rate. This reflects the fact that uptake of the EV grant was relatively slow to begin with, as can been seen in Supplementary Fig. 2 reported in the supplementary information that accompanies the journal paper (Moira Nicolson et al., 2017). The same graph is reported with outliers included in Supplementary Fig. 3 of the journal paper (Moira Nicolson et al., 2017).

Notes: Error bars represent standard errors on the mean. Outliers removed (See footnote 94).

6.2 Outcomes regression model and results

The results of the regression analysis are presented in Table 37. Consistent with the habit discontinuity hypothesis, the model estimates that email open rates decrease very slightly, by just 0.1 percentage points per month since the recipient purchased their EV (*b*=-0.001, p=0.026). To account for the rightwards skew in EV sales, a further robustness check was run using the log transformation of time since purchase in months, which also revealed a mild statistically significant correlation indicating that open rates decline the longer ago the recipient received their EV (*b*=-0.026, p=0.005). When the sample was split into quartiles based on the time in months since purchase and regressed this against open rates, there is also a statistically significant negative coefficient (*b*=-0.012, p=0.028), in support of the habit discontinuity effect.

To test whether the sharp decrease in open rates between the third and fourth month since purchase is statistically significant – i.e. whether this represents the length of the 'window of opportunity' for encouraging EV owners to switch tariff – an additional model that was not pre-specified was run in which the independent variable is a dummy indicating whether the recipient received their EV three months since the email was sent (1) or more than three months since it was sent (0). The model estimates that receiving a prompt within three months of owning an EV (n=30) is correlated with a 32% increase in email open rates (*b*=0.320, p=0.000). A further robustness check is run including a battery of control variables collected at the time of purchase: vehicle price, vehicle type, gender, age, employment status, number of vehicles in the household, whether the EV will be the main vehicle and expected annual mileage; the point estimate is almost unchanged, with the model estimating that receiving a prompt within three months of purchasing an EV is associated with a 28% increase in the likelihood of opening the email (*b*=0.275, p=0.002).

As outlined in Nicolson et al. (2017), since the decline in open rates is so marked, there is little risk that I am selecting an arbitrary point in the data to conduct this analysis. Indeed, all of the analyses methods used, including those pre-specified in the analysis plan, are supportive of the habit discontinuity effect, including the p-value on the dummy variable indicating an EV owner received their vehicle within three months, even after controlling for multiple comparisons testing using the Benjamini and Hochberg (1995) procedure and in further robustness checks in which the equation is estimated using logit with marginal effects reported at the mean of the independent variables (Appendix 14).

Table 37 Explaining email open rates by time since EV purchased

	(1) Continuous	(2) Log transformed	(3) Quartiles linear	(4)	(5) Dummy	(6) Dummy with controls
Time since vehicle purchased in months	-0.001* (0.026)					
Log of time since purchase in months		-0.026** (0.005)				
Quartiles of time since purchase in months (linear)			-0.012* (0.028)			
Quartile 1				0.111 (0.103)		

Quartile 2				0.044		
				(0.519)		
Quartile 3				-0.089		
				(0.196)		
Quartile 4				Omitted		
Purchased vehicle three months ago					0.320***	0.275**
					(0.000)	(0.002)
Individual and vehicle control variables						X
Observations	7038	7038	7038	7038	7038	2891
R^2	0.001	0.001	0.001	0.001	0.001	0.019

Notes: The sample size in Model 5 is smaller because there are missing observations for the covariates, however a further robustness check which includes only controls for missing variables provides similar results (see Appendix 15). All models are estimated using robust standard errors with *p*-values in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
^ p-value is greater than the 5 percent significance threshold once correcting for multiple comparison testing using the Benjamini and Hochberg (1995) method.

7 Discussion

This chapter sought to test the hypothesis that EV owners are more likely to respond to tariff switching messages that frame the savings as a reduction in the cost of charging their vehicle than to the typical message used in national tariff switching campaigns which frame the savings as a reduction in household energy bills, even though the savings are financially equivalent. It also tested the hypothesis that EV purchase may constitute a significant life change that is subject to a window of opportunity during which EV owners could be prompted to adopt a TOU tariff, rather than to follow the approach used by most tariff switching campaigns which are timed to coincide with the start of the heating season and therefore the seasonal peak in energy bills. These hypotheses were tested in the context of a field experiment run with OLEV in which approximately 7,000 emails were sent to recipients of the Government's EV grant.

The results show that reframing the £300 savings on household energy bills that can be made from switching electricity tariff as a £300 saving on charging an EV caused a 15% increase in email open rates and a 90% increase in the proportion of people who clicked-through to an information webpage that provided tips to help them determine whether a TOU tariff was right for them. The results also show that the timing of the message is also crucial; an overwhelming 70% of recipients who had purchased their vehicle within the past three months opened the email whereas this number dropped to 40% amongst those who had owned their vehicle for over three months.

The crucial questions now are: how effective would such prompts be at increasing actual switching rates to TOU tariffs amongst private EV owners in the UK and beyond; and why did the tailored message work better than the generic message when the two emails were factually identical? The possible answers to these questions are discussed below.

7.1 The relationship between open rates, click-through rates and switching

Although the study was unable, for practical reasons, to track whether EV owners went on to switch tariff as a result of the prompts, theory (Ajzen, 1991) and empirical evidence (Kormos and Gifford, 2014) suggest that the intermediate outcomes measured (open rates, click-through rates, downloads) will be correlated with switching. By 2050, the target is for 100% of new vehicle sales to come from EVs, a target which is increasingly realistic given that the UK Government has just announced that the sale of internal combustion engine vehicles will be banned in the UK from 2040 (Department for Environment Food and Rural Affairs and Department for Transport, 2017). This would mean an EV market size of approximately 2.6 million vehicles at the current rate of sales or 25 million under the National Grid's (2017, p.41) high adoption 'Two Degrees' scenario.

If these email prompts were sent in the first three months of purchase when open rates are approximately 70%, then even if just 5% of those who open a tariff switching email go on to switch tariff, that could translate into an additional 90,000 EV owners switching tariff by 2050 at the current rate of sales or nearly 1 million extra switchers at high adoption levels, at almost zero cost (Moira Nicolson et al., 2017). Given that recipients who open the email are likely to be more engaged with tariff switching messages than the average recipient, a higher switching rate may be achievable and, if it reaches 50%, this would translate into an extra 9 million EV owners switching tariff under a high EV adoption scenario, which would represent 40% of all plug-in EVs in 2050 (National Grid, 2017, p.41).

Although this email promoted both flat-rate and TOU tariffs, future emails could exclusively promote TOU tariffs. Considering that the National Grid estimated that at least 85% of EV owners would need to participate in off-peak charging to avoid the worst possible increase in peak electricity demand from EV uptake (National Grid, 2017, pp.43–44), a 40% uptake of TOU tariffs by EV owners as a result of a single email would be very substantive contribution indeed. However, unlike default enrolment (the most common 'nudge' (Thaler and Sunstein, 2008)), prompts do not succeed by encouraging choice without awareness (Smith et al., 2013b) and therefore increase the likelihood of active rather than passive participation in DSR, whereby people defaulted onto time of use tariffs do not substantially alter their energy consumption patterns (Cappers et al., 2016; S. A. Fenrick et al., 2014).

7.2 Wider applications – the international EV market and electric heating

Since the study was run on the full population of private EV owners in the UK, approximately 10% of all UK EV owners, it is reliable to conclude that the treatment effects observed here would transfer if OLEV rolled this email messaging out to grant recipients as business as usual, as they intend to. Private purchase EV owners are those who purchased their EV outright or through hire purchase, and excludes vehicles purchased by leasing companies or for commercial use (e.g. for company fleets). Other methods would be required to reach people who lease their EV, since this group is also likely to be charging their vehicles from home and thus presenting a risk to the electricity network.

Although this study was run on recipients of the UK Government's EV grant, a number of countries (e.g. India, China, South Korea, Sweden, Germany, Netherlands, Portugal) run similar EV subsidy schemes for which contact data is also likely to be collected to enable the sending of timely, tailored email prompts, if further research shows they are effective in these countries too. Moreover, the same approach could also be tested in the context of other new low carbon technologies such as the installation of new electric heating systems, which are also expected to place a great strain on the future electricity network (Frontier Economics, 2011) but which are also subject to similar government incentive schemes. A key contribution of this study is to demonstrate how additional value can be obtained from this administrative data.

7.3 Why did tailoring work so well?

Although this study does not provide evidence on why the tailored message worked best, the literature reviewed in Chapter 3 identifies three potentially mutually overlapping mechanisms that are most likely to explain the effectiveness of tailoring. The first is inattention to insalient costs, or myopia as proposed in Gabaix and Laibson's (2006) model. According to this model, 'add on' costs are less salient than purchase costs and consumers do not rationally gather information about 'shrouded' costs. As argued elsewhere (Allcott, 2011), fuel costs (e.g. the cost of charging an EV) are analogous to 'add on' costs in that, unlike the purchase price, they are not explicitly presented upfront. The tailored email specifically pointed out that their household electricity bills would increase having bought an EV, making it particularly important for EV owners to be on the right electricity tariff. Many new EV owners may not have otherwise perceived themselves as having higher than average electricity consumption and, unlike the generic email, the tailored email 'unshrouds' (Gabaix and Laibson, 2006) the insalient costs of owning an EV, thereby encouraging EV owners to act to lower these costs.

A second potential mechanism is found in Thaler's (1980, 1990, 1999) concept of mental accounting which describes the way in which people have been found to evaluate their finances. Standard economic theory implies that re-framing the savings to be made from switching tariff as a saving on home-charging an EV rather than on total household energy bills should make no difference to the appeal of switching energy tariff since the financial values are identical and all income is fungible; a saving of £300 has the same value in terms of what it can subsequently be spent on regardless of how that money was saved or earnt. However, experimental evidence suggests that, when evaluating their finances, rather than making financial decisions based on its effect on their total wealth or consumption, people engage in what is called narrow framing (Barberis and Huang, 2001; Dupas and Robinson, 2015) whereby they create separate mental accounts (e.g. an account for spending on rent, an account for spending on food and possibly an account for the running costs of their EV) and make financial decisions in relation to its isolated effect on each relevant account. The finding that EV owners were more motivated by the message that framed the savings as a reduction in home charging costs than a reduction in home energy bills may suggest that they may be engaging in a form of mental accounting whereby household energy bills and the running costs of their EV are accounted for separately in their minds but that the 'EV account' is more salient to them. The concept of mental accounting has been used to explain why people may be more likely to spend government transfers on their children when the transfer is labelled Child Benefit (Kooreman, 2000; Blow et al., 2010) or on fuel when the transfer is labelled a Winter Fuel Payment (Beatty et al., 2014).

A third related mechanism proposed in the literature on tailored health communication (Rimer and Kreuter, 2006) is that tailoring increases the perceived relevance and salience of information, thereby increasing motivation to process and act on it, in this study, by visiting information about how to reduce the costs of charging an EV.

These explanations are not mutually exclusive but a future study could attempt to isolate the impact of 'unshrouding' (Gabaix and Laibson, 2006) from the impact of appealing to a more salient mental account by running an email trial in which participants are either told that switching electricity tariff is a good way of mitigating the increase in electricity bills owing to buying an EV (unshrouding) and another in which the savings from switching electricity tariff are framed in terms of the reduction in home charging costs rather than household energy bills.

8 Conclusions

This chapter sought to test whether recipients of the UK Government EV grant could be prompted to consider switching tariff by sending them an email reminder shortly after purchasing their EV, when they are already likely to be thinking about the costs of running their new vehicle.

This chapter makes two contributions to answering the second research question, which is whether tailored marketing messages could be used to increase uptake to TOU tariffs amongst consumers most likely to save money on one. The first is that yes, tailoring tariff switching campaigns towards EV owners is likely to be a much more effective way of boosting switching rates to TOU tariffs amongst EV owners than relying on generic broadcast campaigns like the DECC Power to Switch campaign, which also risk increasing uptake amongst groups who would be financially better off by staying on a flat-rate tariff.

Most tariff switching campaigns emphasise the energy bill savings from switching tariff, however, this study shows that EV owners are much more receptive to prompts which frame the savings as a reduction in home-charging costs, even though the monetary value of the savings presented (over £300) were identical. This effect may be reflective of the tendency people have to evaluate their finances within separate mental accounts, whereby the costs of charging an EV are accounted for independently to the costs associated with household energy bills but which, for EV owners, the EV account is more mentally salient. Alternatively, it could be that the tailored email unshrouded the hidden costs associated with running an EV. Regardless of the mechanism at work, the study shows that, rather than relying on EV owners to adopt TOU tariffs of their own accord, mass unsolicited emails represent a simple but low cost mechanism of actively prompting EV owners to adopt TOU tariffs or potentially other smart charging programmes regardless of their prior interest in switching tariff or likelihood of visiting price comparison websites.

The second contribution to the second research question is that governments need to act soon, in the early days of the transition towards EVs. Consistent with the habit discontinuity hypothesis (Verplanken and Wood, 2006; Verplanken and Roy, 2016; Thomas et al., 2016) (that people are more susceptible to information delivered in the context of life changes), email open rates decline from over 70% to 40% for recipients who have owned their EV for over three months, equivalent to missing out on reaching an extra one million people once EVs reach 60% market penetration. In doing so this study demonstrates that the habit discontinuity effect applies beyond life changing events such as moving house (Verplanken et al., 2008; Verplanken and Roy, 2016; Thomas et al., 2016).

The practical implications of these findings are important because repetitive behaviours, such as EV charging, could become habitual and evidence to date shows that EV owners have got into the routine of charging their vehicles when they get home from work (Zarnikau et al., 2015; My Electric Avenue, 2015; Capova et al., 2015), when electricity demand is at its peak and, in many countries, the least efficient and therefore most polluting power plants are brought into operation to meet peaks in demand (Ma et al., 2012). By intervening in the early stages of EV ownership, such email prompts could deter EV owners from getting into the habit of charging at peak times.

Moreover, sending prompts encouraging the adoption of TOU tariffs to EV owners specifically will help to minimise the risk that other consumer groups who are not suitable for TOU tariffs will also adopt them. A key argument of this thesis is that, whilst the Government's target to have 30% of domestic consumers on a time of use tariff by 2030 is unlikely to be met without some intervention by Government or third parties to help boost switching rates, a recruitment approach is needed which encourages uptake to TOU tariffs amongst consumers who will save money that does not also increase uptake amongst consumers who are likely to be made worse off from switching to a TOU tariff. Since charging an EV uses substantially more electricity than most household electrical appliances and the vehicle can be set to charge overnight on a timer, EV owners can stand to save more money a lot more easily than the average British household. Tailored email prompts are therefore an 'effective and selective' nudge.

This concludes Chapter 7 and therefore also the presentation of the empirical results of this thesis. Chapter 8 will discuss the results of all three results chapters in the context of the wider literature on behavioural science and the overall aim of this study, which is how to increase uptake to TOU tariffs amongst consumers who stand to save money on one but not amongst consumers who could be made worse off. This will be followed a conclusion that summarises the key findings of this thesis as well as its potential policy implications and avenues for future research.

Chapter 8

Global discussion:

The pros and cons of opt-out enrolment and tailored marketing for recruiting domestic consumers onto TOU tariffs

1 Introduction

This chapter discusses the results of each of the four empirical studies presented to show how they achieve the two overarching aims of this thesis. The first aim was to synthesise, for the first time, the various measures of uptake to TOU tariffs in GB and internationally to provide a robust estimate of consumer adoption of TOU tariffs in GB. This aim was motivated on the basis that policymakers and electricity network operators need an accurate picture of how many domestic consumers will participate in DSR to verify the assumptions in the UK smart meter cost benefit analysis (BEIS, 2016b) and to understand the likely contribution of domestic DSR to overall DSR in GB. However, since TOU tariffs are not widely commercially available in GB, it is necessary to look beyond GB for market-based measures of demand that can be synthesised with the available survey evidence from GB.

The second aim was to provide evidence on how the adoption of TOU tariffs amongst British consumers could be increased without making them mandatory, as in Ireland (Commission for Energy Regulation, 2015), or the default tariff as proposed by some US researchers (Faruqui et al., 2014; S. A. Fenrick et al., 2014; Cappers et al., 2016). The motivation behind this aim is that voluntary uptake to TOU tariffs could be lower than the 30% required by the UK Government to realise its business case for smart meters (BEIS, 2016b) and lower than optimal to realise the system benefits of DSR envisioned by Government. However, there is a lack of evidence as to how to increase uptake whilst also protecting consumer welfare. As argued throughout this thesis, evidence suggests that not all consumers will save money on a TOU tariff (see the energy bill impacts documented in Chapter 2) but both mandated and default enrolment will enrol consumers regardless of their likelihood of saving money (Chapter 3).

This research was conducted in several stages to achieve these two aims. I discuss each of them in turn.

2 Aim 1: synthesise the evidence on UK consumer demand for TOUs

To achieve the first aim, this thesis presented the results of a systematised review and meta-analysis of enrolment rates to TOU tariffs combining the results of 66 measures of uptake to TOU tariffs across 27 studies conducted in six OECD countries. The two strongest determinants of uptake were the method by which uptake had been measured, notably willingness to switch from surveys or adoption rates of a commercially available tariffs, and whether recruitment to the tariff was opt-in or opt-out. The model in Chapter 2 estimated that these two variables explained 85% of the variation in the measures of uptake to TOU tariffs.

It was therefore recommended that demand for TOU tariffs is expressed as a range, accounting for the standard deviation around the mean, for opt-in and opt-out methods separately but with strong consideration given to the possibility that survey measures of demand may be highly optimistic. Under opt-in recruitment, it was found that the lowest lower 95% confidence limit for uptake to commercially available tariffs was 1%; the highest upper 95% confidence limit was based on mean willingness to switch obtained from surveys and was 43%. Under opt-out recruitment, the lower 95% confidence limit was 57% and the upper 95% confidence limit was 100%.

The difference in average uptake to TOU tariffs across survey studies and commercially available tariffs cannot be causally attributed to the method of measurement for reasons discussed in Chapter 2. However, wider evidence suggests that there is a strong risk that uptake is more likely to fall at the lower rather than higher end of the range presented above unless action is taken to engage consumers with TOU tariffs.

Surveys measure willingness to switch to a TOU tariff however it is well known that behavioural intentions are a relatively poor predictor of future behavioural action (Sheppard et al., 1988; Sheeran, 2002; Van Hooft et al., 2005; Whitehead and Blomquist, 2006). Consumer inertia is a major feature of the energy market with the majority of consumers around the world having never left their home supplier since the privatisation of the retail electricity markets over two decades ago (Defeuilley, 2009). Therefore, an adoption rate of 43% is unlikely to be achieved in reality unless substantial efforts are made to close the intention-action gap.

Although prior to this research it was hard to say whether the inconsistency in uptake obtained in surveys compared to commercially available products was due to cross-country differences in demand (see Chapter 2), the Flex Trial had a switching rate of 0.3%, which is 100 times lower than stated intention to switch elicited in surveys of British energy bill payers. Although Flex is an unknown supplier and uptake to a TOU tariff offered by a large supplier could be higher, it would need to be substantially higher to approach anywhere near the volume suggested by the surveys.

On the other hand, it is also possible that opt-in uptake could exceed 43% if new recruitment approaches are tested since, after all, the interval of 1%-43% is based on the existing literature which has only tested a limited number of ways of increasing opt-in uptake, namely small upfront cash payments and bill protection.

I therefore conclude that, if consumers are left to opt-in to TOU tariff rates, uptake could be as low as 1% (or closer to 0.3% if only offered by unknown suppliers) unless effort is made to close the intention-action gap, in which case enrolment rates could be as high as 43% or potentially higher. If consumers are automatically enrolled onto a TOU tariff unless they opt-out, enrolment should exceed 57% and approach 100%.

Although the opt-in estimate covers a wide range of possible uptake measures, it carries three main implications for the UK Government in terms of meeting the enrolment target required for the smart meter cost-benefit analysis (BEIS, 2016a). First, the estimate indicates that uptake to TOU tariffs could either be substantially lower or moderately higher than the UK Government's target to have 30% of domestic consumers enrolled onto a TOU tariff by 2030 if recruitment is opt-in. I therefore strongly suggest that research is conducted to increase the precision of these estimates. Second, it implies that the Government target could be achieved without using opt-out enrolment; the next crucial step is to undertake research into how to encourage consumers to adopt TOU tariffs to avoid the risk of enrolment rates being closer to the lower bound confidence limit of 1%. Third, this research needs to obtain measures of uptake based on behavioural actions taken by real consumers in the market rather than based on stated intentions to switch obtained in surveys (specific suggestions for how this research could be carried out are reserved for Chapter 9).

This takes me to the discussion of the second research aim, which was to identify a method for closing the potential gap between behavioural intentions and behavioural action amongst consumers who are more likely to save money on a TOU tariff.

3 Aim 2: identify a method of increasing uptake to TOUs without using defaults or mandates

Energy consumers rarely switch their energy tariff despite the large annual savings on offer (Defeuilley, 2009; CMA, 2016b). In their seminal paper *Libertarian Paternalism* Thaler and Sunstein (2003) proposed that the same shortcomings that lead consumers to make poor decisions could be used to guide, rather than force, them into making better ones. This approach was popularised through their later book *Nudge: Improving Decisions about Health, Wealth and Happiness* (2008). However, as pointed out in a recent review article (Benartzi et al., 2017), in some situations, such as preventing violent crime, conventional policy tools such as laws will nearly always be more effective than nudges; the comparative advantage of nudge is highest in situations in which consumers are making “biased, rushed or otherwise imperfect decisions, in which imperfection is judged by reference to the welfare of those same individuals” (Benartzi et al., 2017, p.11). Therefore, before regulators intervene to influence consumer decision making, it is first necessary to determine whether energy consumers really are likely to be making poor choices and, depending on the nature of the poor decision making, what type of nudge is likely to be the most welfare enhancing.

Moreover, although nudge has been used to increase average uptake of beneficial products or services such as workplace pensions (Wells, 2014), national organ donor registers (E. Johnson and Goldstein, 2003) and exercise programmes (Royer et al., 2015), there are many occasions when increasing average uptake could pose significant harms on some consumers because the best course of action varies across people (Carroll et al., 2009; Keller et al., 2011; Sunstein, 2013b). In the case of TOU tariffs, a nudge that increases average uptake could harm those consumers who are unable to shift a large enough amount of their electricity use away from peak times to be better off rather than worse off on a TOU tariff. As shown in Chapter 2, although trials find that most people are made financially better off on a TOU tariff, 20%-40% have also been made financially worse off, in one trial by nearly £200 a year (Sidebotham, 2014a), presumably because they are unwilling or possible unable to adjust their consumption patterns significantly enough to avoid bill increases.[95] A nudge which selectively increases uptake amongst those consumers most likely to save money may be more desirable and political acceptable than opt-out enrolment because it could minimise the possible negative distributional impacts from the launch of TOU tariff rates.

Therefore, to achieve the second aim, this programme of research set out to answer two research questions: (1) Is consumer decision making over electricity tariffs affected by bounded rationality to justify intervening using nudge? and; (2) If consumers are not very good at making these decisions, would tailoring the marketing of TOU tariffs towards consumers groups who are more likely to save money on one increase uptake amongst these groups whilst reducing enrolment amongst consumers who could be made financially worse off from switching? I

[95] Based on the design of the price comparison intervention in Chapter 6, it can be hard to save money on a TOU tariff unless a high proportion of household electricity use is consumed on the super off-peak rates – 60% in the case of the TOU tariff tested in the Flex Trial.

now discuss the results presented in this thesis in relation to both of these research questions.

3.1 Research question 1: is consumer decision making over electricity tariffs substantially affected by bounded rationality?

3.1.1 Are most energy consumers fully rational?

Identifying whether energy consumers are making economically sub-optimal decisions over their electricity tariff is difficult because, as discussed in Chapter 3, many of the costs and benefits of switching tariff are unobserved (Wilson and Price, 2010). This makes it hard to rule out the possibility that people do not switch tariff more frequently because they care more about customer service or other features of a tariff or supplier than just the price. As noted throughout this thesis, classical economics does not imply that the cheapest tariff is the optimal tariff, so if people are not switching tariff despite the savings on offer, this is perfectly consistent with a model of a rational decision maker who is prioritising non-price attributes. It is also consistent with the rational model of decision making in which consumers would like to switch to the cheapest tariff, but does not because they do not have easy access to accurate energy consumption information to get a reliable quote on a price comparison website.

Moreover, like most models, the purpose of the classical economic model is not to perfectly predict every individuals' choice but to provide a general analytical framework that predicts the average persons' choice and therefore aggregate market phenomena (Friedman, 1953). The important question is therefore not whether some energy bill payers do not behave in line with the model of full rationality but whether a significant portion of energy bill payers fail to meet the standard of full rationality so that classical economics is unlikely to be a useful way of modelling decision making (Box, 1976).

Instead of testing whether consumers are currently making optimal choices regarding their tariff, this thesis first set out to test whether consumers are able, in principle, to identify the optimal energy tariff from a menu of options when given all the information required, a key assumption of EUT, the dominant model used to explain how consumers making decisions under uncertainty (Barberis, 2013). To test this I presented 811 British energy bill payers with two vignettes in which they were asked to identify the cheapest of three tariffs, one vignette in which all three tariffs were flat-rate tariffs and another in which one of the tariffs was a TOU tariff (Chapter 5). This exercise does not assume that the cheapest tariff is the optimal tariff; it tests people's abilities to undertake costs-benefit analysis since if consumers cannot undertake a cost-benefit analysis based on one variable, in this case price, then it is unlikely that they will be able to undertake a cost-benefit analysis in which they also need to make trade-offs between multiple factors such as price, customer service, green energy, online account management and so on, particularly given that people would have to assign a fictional financial value to these individual items to undertake the analysis.

I found that approximately half of the participants surveyed failed to identify the cheapest tariff even though they were given all the information required, including total household electricity use and its distribution across the day, the type of information available through a smart meter. Although there was no statistically significant difference in the decision making quality of consumers in the lowest compared to the highest three social grades in British society when the tariff menu only included flat-rate tariffs, consumers in the lowest three social grades (C2-E) performed significantly worse when the menu included a TOU tariff.

Although there are limitations to the method – chiefly that consumers facing this choice in real life may expend more effort to identify the cheapest tariff than survey participants facing no financial consequences from the choice – the results are still informative because effort provision is unlikely to explain why all consumers failed to identify the cheapest tariff considering that prior research (Department for Business Innovation & Skills, 2012) confirms what this survey also implies which is that many British consumers have poor numeracy skills. Moreover, survey participants faced a much easier task than would the average energy bill payer; if half of all survey participants choosing between just three energy tariffs when only asked to consider price, then consumers faced with choosing between several hundred tariffs whilst potentially trying to consider many other non-price factors are unlikely to perform substantially better solely because their choice has financial consequences. Given that so many energy bill payers failed to identify the cheapest tariff and arguably most people will have been taught the maths required at primary school, the findings are more consistent with a model of bounded rationality than full rationality. Future research could definitively disentangle the two models by testing whether performance is similarly poor even after people have been given additional training in how to undertake the calculation.

Whilst chapter 5 discussed a number of implications of these results, the two most important implications are that: (1) Government cost-benefit analyses which rely on the collective decisions of British energy bill payers, such as the one for the smart meter roll-out (BEIS, 2016b), should account for the fact that approximately half of energy bill payers struggle to optimise; (2) if many British energy bill payers are unable to discriminate between tariffs when provided with all the information required to do so, then neither opt-in nor opt-out enrolment are likely to be viable recruitment strategies for TOU tariffs. The second implication will now be discussed in more detail below.

3.1.2 Sub-optimal switching

The policy debate on consumer switching focuses on how to “engage the disengaged” (Ofgem, 2016d; CMA, 2016a), taking for granted that the small percentage of consumers who switch tariff each year constitute the sub-group of rational, optimal decision makers. The results of this study, as well as the wider evidence on adult numeracy skills (Department for Business Innovation & Skills, 2012), suggest that this assumption should be questioned.

That consumers could actively switch to more expensive energy tariffs is consistent with the results of the only other known study of consumer decision making over energy tariffs which estimated that 17-32% of British consumers who reported leaving their incumbent supplier after the privatisation of the energy markets in the 1990s moved to a more expensive supplier, despite indicating that they switched to reduce their bill (Wilson and Price, 2010).

This is an interesting result because it suggests that, rather than solely worrying about adverse selection to TOUs (Baladi et al., 1998; Hartway et al., 1999; Charles River Associates, 2005; Herter, 2007; Ericson, 2011; Qiu et al., 2017), whereby TOU tariffs selectively attract consumers who already have favourable consumption profiles, we should also be concerned that opt-in enrolment could result in adoption of TOU tariffs by consumers who will not save money on them due to consumers’ inabilities to determine whether they are suitable for the tariffs and low use of price comparison websites. Although previous research has suggested that TOU tariffs could create negative distributional impacts if vulnerable or low income groups are less likely to adopt TOU tariffs (Spence et al., 2015), to my knowledge this is one of the first projects to find evidence that these groups could be disadvantaged precisely because they may sign up to a TOU tariff that may end up costing them money.

This thesis explored two potential ways of helping guide consumers onto TOU tariffs who would save money on one. The first method was to use price comparisons to help people make informed choices for themselves, a solution implied by the classical economic framework. The Flex Trial provided evidence that a price comparison could indeed lower uptake to TOU tariffs amongst consumers who are less likely to save money on one. However, much more research is required into how to develop accurate and transparent price comparisons for TOU tariffs.

This is because, to be effective, price comparisons for TOU tariffs would need to be built on some assumptions about the households' ability to shift their electricity use into off-peak times; if price comparisons were simply based on historical consumption patterns, then a price comparison would simply show that the majority of people would be significantly financially worse off, given that most people do have peaky load profiles. However, given that people do not have the energy literacy skills to identify the cheapest out of three energy tariffs, it is also possible that they would struggle to determine the extent to which any in-built load shifting assumptions are realistic for them. Future research could test whether consumers would be able to accurately predict how willing or able they would be to run their washing machine or charge their EV overnight, for example, using a series of questions added to the additional survey given to people who use price comparison websites.

The second method was to use tailored marketing. The potential advantage of tailored marketing is that it could influence the decisions of people regardless of whether they use price comparison websites. Ofgem's (2015) most recent annual survey finds that approximately one third of people report having used a price comparison website to help them switch tariff, which still leaves at least two thirds who are potentially making this decision without much additional help.

3.1.3 'Green' defaults could sometimes be bad defaults

There is a large literature on the use of 'green' defaults, whereby people are automatically given the most environmentally friendly product or service unless they explicitly opt-out (Pichert and Katsikopoulos, 2008; Sunstein and Reisch, 2013; Broman Toft et al., 2014; S. A. Fenrick et al., 2014; Faruqui et al., 2014; Ebeling and Lotz, 2015). However, the literature and empirical results presents in this thesis highlight some potential limitations of opt-out enrolment that warrant serious consideration before it is adopted as a recruitment strategy for TOU tariffs.

In particular, with so many British consumers unable to identify whether a TOU tariff is right for them even in a relatively simple scenario where they are choosing between just three tariffs which they are being paid to take the time to consider, then how can we expect consumers in the real world who are facing other demands on their time to opt-out of being enrolled onto a TOU tariff if one is unsuitable for them? The result is particularly worrying given that: (1) Consumers in the lowest three social grades in society performed significantly worse in the Tariff Decision Making study when a TOU tariff was included in the menu of tariffs relative to those in the top three social grades and; (2) Bad defaults are just as sticky as good defaults (see Chapter 5)[96] so consumers who are inappropriately defaulted onto a TOU tariff may not dis-enroll once or if they notice the impact on their energy bill.

Although opt-out enrolment could result in a greater overall reduction in peak electricity consumption and lowering of future energy system costs and carbon emissions[97], these efficiency savings will only be transferred to the consumers who are on TOU tariffs and able to adjust their consumption patterns; those who do not adopt a TOU tariff or adopt one but cannot adjust their consumption patterns, could pay significantly more for their electricity than they do currently. In previous GB trials of TOU tariffs, whilst the majority of consumers were financially better off on a TOU tariff, a sizeable minority of approximately 20%-40% were made financially worse off on a TOU tariff (Chapter 2).

The key concern is that these 'losers' from TOU tariffs may be disproportionately represented by consumer groups who are in most need of reducing their energy bills. This is for two reasons. First, the results in Chapter 5 suggest that consumers in the lowest social grades, some of whom are likely to be at higher risk of living in fuel poverty, are more likely to struggle to identify whether a TOU tariff will increase or decrease their energy bill.[98] Whilst annual savings of

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[96] US consumers defaulted onto a TOU reduced their peak electricity use by 50% less than those who actively enrolled and in one case did not reduce their peak consumption at all, but retention rates were identical across both groups (US Department of Energy, 2016). Retention rates were in excess of 70%-90% (US Department of Energy, 2016).

[97] This follows from the fact that, although average peak load shifting is lower amongst opt-in than opt-out customers, the total amount of electricity shifted into off-peak hours under an opt-out policy is greater because default enrolment results in much higher enrolment rates (S. A. Fenrick et al., 2014; Cappers et al., 2016).

[98] A household is defined as being in fuel poverty if they are on a low income whilst also living in a dwelling that is expensive to heat, due to its thermal performance (Hills, 2012). It seems likely that energy bill payers in the lowest social grades are likely to be living across both the social and private rental sector, the latter of which has the highest proportion of homes that fail to meet the 'decent housing' standard and also a relatively high proportion of housing benefit recipients (25%) (DCLG, 2012, p.50), a benefit which is mostly given to people on a low income.

switching to the cheapest flat rate tariff of £300 – or losses of £120 from being on a TOU tariff (Chapter 2) – may not seem much to some people, it could make a big difference to the welfare of those in the lowest income groups in society. Energy bills are the second highest item of expenditure after housing and, for those in the bottom income decile, energy bills represent 9% of total household expenditure compared to 3% for those in the highest income decile (Office for National Statistics, 2017). Second, there is no guarantee that the benefits of a smarter energy system – which would be higher under opt-out enrolment – would be shared out equally across all consumers or whether it will accrue disproportionately to groups who own high consuming flexible electrical appliances that offer the greatest potential for financial savings. The only comprehensive GB study to assess the distributional implications of cost-reflecting electricity pricing used a model to estimate whether TOU tariffs would particularly disadvantage vulnerable groups (Cambridge Economic Policy Associates, 2017), however there is not sufficient empirical data to inform the model assumptions. Even then, the authors conclude that any potential energy bill increases are not a problem because "Currently customers must make an explicit choice to be put on a TOU tariff. They would not be likely to make that choice if they expected a higher bill. So they are unlikely to suffer this loss as long as it remains an explicit choice." (5). Even with the Renewable Heat Incentive and the OLEV EV car grant, these high consuming technologies are not – at least not currently – technologies accessible to all consumers, regardless of ability to pay.

Another option is personalised defaults. However, as pointed out in Chapter 3, to avoid adverse selection, a personalised default will have to be based on a lot more than just historical electricity consumption alone. Moreover, if defaults are effective because people do not notice what option was pre-selected for them (inattention), consumers will not know they have been enrolled on a seemingly suitable TOU tariff and thus make the assumed changes to their electricity consumption patterns.

This discussion suggests that opt-out enrolment to TOU tariffs, whether personalised or not, is unlikely to be compatible with the Government's other responsibilities to protect consumers from harm. It may also be possible to design TOU tariffs that reduce prices at off-peak times but do not increase the price at peak time, to which consumers could be automatically enrolled without any adverse consequences. However, whether these tariffs would reduce peak time electricity demand rather than just increase off-peak consumption is unknown.

Alternatively, automated DSR services such as DLC could eliminate any impact on the consumers' energy bill from such 'choice without awareness' (Smith et al., 2013a). For instance, if an EV owner was automatically defaulted onto a controlled charging scheme, in which a third party remotely adjusted the current going to their smart home charging point, the owner would accrue financial savings whilst helping ease the strain on the electricity network without ever having to know that such a service was taking place. As long as temperature variations on DLC of heating services are minimised, they may have no effect on householders' thermal comfort and thus go entirely unnoticed, especially given that worldwide trends in smart thermostat sales[99] suggest that suppliers may not even need to install a smart thermostat in consumers' homes to undertake DLC. If all electrical appliances were manufactured to permit DLC, companies could theoretically extract DSR services from consumers by virtue of the appliances

[99] In the US, smart thermostats have already reached 70% market penetration and global sales increased by over 120% in 2015 alone (IoT Analytics, 2016).

and technologies that consumers have already adopted or will adopt, since then consent could in theory be obtained at the point of purchase through additions to standard product terms and conditions. This is a relatively common commercial practice known as 'bundling' (Bakos et al., 2014), and Ofgem has indeed recently relaxed its rules on bundling (Ofgem, 2016b). An opt-out recruitment policy to automated DSR schemes could therefore potentially be highly effective at increasing adoption and energy system flexibility, particularly given that evidence suggests that only a tiny minority of people read terms and conditions.[100]

On the other hand, automatically enrolling electricity consumers onto DLC or vehicle-to-grid services, potentially without their knowledge, raises strong ethical concerns. It could also backfire. For example, covertly enrolling EV owners on controlled charging schemes risks leaving EV owners with their vehicles half charged when they need them so could results in many exiting such schemes (Moira Nicolson et al., 2017). It may not even be permitted under the Smart Energy Code. The Smart Energy Code is the document outlining the rights and obligations of organisations involved in the end-to-end management of smart metering in GB and which comes into force under the Data and Communications Company Licence. In it, it provides a definition for what it calls 'User Unambiguous Consent':

> *…means the explicit and informed consent of an Energy Consumer given to a User to undertake a specified action, and that consent shall not be treated as having been given explicitly unless the Energy Consumer has:*
>
> *(a) of his or he own volition, communicated to the User a request for it to undertake that action or;*
>
> *(b) in response to a specific request by the User for him or her to indicate consent to it undertaking that action, taken a*

[100] One of the most comprehensive studies of online purchases finds that less than 0.02% even access standard terms and conditions (Bakos et al., 2014), a prerequisite for full informed consent.

> *positive step amounting to a clear communication of that consent (SECAS, 2017, p.92).*

Whilst the Smart Energy Code does not currently specify what types of actions will require Unambiguous Consent, it is clear that, if Unambiguous Consent was required for DSR services, opt-out enrolment would not be a permissible recruitment method for any DSR services. This is because opt-out enrolment fails to satisfy clause (a) and, would only satisfy clause (b), if the consumer undertakes some positive action to indicate that they consent, which therefore still requires some active choosing on the part of the customer.

Therefore, at least for the moment, personalised defaults are not a viable option for recruiting customers onto TOU tariffs. If the Government decides that companies must obtained informed consent from consumers before enrolling them onto TOU tariffs or DSR services, then opt-out enrolment will not be a permissible recruitment strategy at any point in the future either. Consumers would then need to be left to make an active choice whether to adopt TOU tariffs, vehicle-to-grid or DLC services. Since opt-in enrolment usually comes at the cost of much lower enrolment rates – but given that not all consumers will save money on a TOU tariff – the UK Government needs evidence for opt-in strategies that are both effective and selective by increasing the likelihood of “getting people into the right box” (Johnson, 2016). In this context, this means finding a recruitment method that increases enrolment to TOU tariffs amongst consumers who can save money and contribute towards reducing peak demand or exploiting renewable energy supplies whilst detracting enrolment amongst consumers for whom TOU tariffs are likely to increase their energy bills relative to flat-rate tariffs. However, as noted in Chapter 3, there is a scarcity of evidence on effective and selective nudges, leading me to research question 2, discussed below.

3.2 Research question 2: can tailored marketing increase uptake to TOUs amongst consumers who are most likely to benefit?

3.2.1 Yes – tailoring shows promise with EV owners

Overall the results show that it may indeed be possible to use tailored marketing to increase uptake to TOU tariffs amongst consumers most likely to save money. The results of the randomised control trials presented in chapter 6 found that TOU tariffs tailored towards EV owners substantially reduced demand amongst non-EV owners who are less likely to save money on a TOU tariff. The results in chapter 6 also produced evidence that naming a TOU tariff “electric vehicle tariff” could increase the willingness of EV owners to adopt a TOU tariff, however there were relatively few EV owners in the sample and, potentially because of this, the result was not even statistically significant at the 10 percent level, making it strongly desirable to look to other evidence to substantiate its statistical robustness. The results of chapter 7 showed that tailored marketing in an email could increase demand for TOU tariffs amongst EV owners relative to generically worded emails at the 95% confidence level. EVs are expected to place one of the greatest burdens on the future electricity network and, compared to the average energy bill payer, have greater potential to save money on a TOU tariff by charging their vehicles at home at off-peak times (Frontier Economics & Sustainability First, 2015).

The first field experiment (N = 6000) run on a website for a fictional energy supplier called “Flex” showed that tailoring communication about TOU tariffs towards EV owners reduces demand for a TOU tariff amongst the average consumer shopping around for electricity tariffs online, who are less likely to be able to save money from switching to it. The tailored marketing treatment was implemented on the Flex website by calling the tariffs ‘Electric Vehicle’ and ‘Heat Pump’ tariffs relative to the control group websites where they had the generic name of ‘Off-Peak Saver 3-Rate tariff’ and with any other information about the tariffs framed in terms of their relevance to electric vehicle and heat pump owners.

In the Population-Based Survey Experiment, the tailored marketing treatment was implemented in a very similar manner to the Flex Trial (the tariff was called an ‘Electric Vehicle’ tariff in the tailored condition but the ‘Super Saver’ tariff in the control condition) but was administered to a broadly nationally representative sample of British people who identified as energy bill payers in the context of a hypothetical survey experiment in which the outcome measure was intention to switch to the tariff. This study showed that the EV tailored messaging decreases willingness to switch amongst non EV owners and provides some early but not statistically robust evidence that the tailored labelling increases demand amongst EV owners.

The final field experiment showed that a tariff switching prompt sent by email to nearly every private EV owner in the UK (N=8,000) was much more likely to be opened and acted on when the email messaging was tailored towards EV owners compared to when the messaging was broadly applicable to all energy bill payers. In this OLEV experiment, tailoring was implemented slightly differently from the other two trials. Instead of describing TOU tariffs as electric vehicle tariffs, the tailored email framed the potential £300 saving from switching electricity tariff in terms of a reduction in the costs of charging their electric vehicle from home rather than as a reduction in their household energy bills.

The relative consistency in the findings across these studies is reassuring as it suggests that the effectiveness of tailoring the marketing of TOU tariffs towards EV owners is unlikely to be isolated to particular settings, specific ways of wording the tailored messaging or to the experimental subjects of this thesis rather than the wider population of energy bill payers in GB. As noted in Athey and Imbens (2016), most concerns about external validity relate to treatment effect heterogeneity, with replication of treatment effects across multiple settings, intervention delivery and participants providing greater evidence that the treatment effect will generalise beyond the specific study in which the effect was measured and therefore to the real-world context which initially motivated the study.

Further research is required to test whether tailored marketing could be effective on other high electricity consuming groups, such as households with electric heating who are also likely to run their heating during existing peak times unless incentivised to do otherwise (Frontier Economics, 2012; National Grid, 2017). In particular, research is required which tests the impact of tailored marketing on actual switching rates to commercially available TOU tariffs and also DLC of home heating services and home EV charging as well as vehicle-to-grid services. This study tested the impact of tailored marketing on behavioural pre-cursors to switching such as obtaining a quote for a TOU tariff on a fictional energy supplier's website and clicking-though to information about TOU tariffs from an email prompt. These outcome measures are likely to be more closely related to switching than surveys which measure stated intention to switch to a TOU tariff (Arrow et al., 1993; Diamond and Hausman, 1994; Whitehead and Blomquist, 2006), which forms the bulk of the evidence on consumer demand for TOU tariffs (Chapter 2). However, since the ultimate outcome of interest is still switching rates, it is necessary to establish precisely what proportion of EV owners or other high electricity users would switch to a TOU tariff or controlled charging scheme in response to a tailored marketing message relative to a generic message. Although the tailored marketing effect may not differ across types of DSR, it is still useful to conduct the research to verify this assumption.

In addition, policymakers need to identify the level of domestic consumer uptake of TOU tariffs required to realise its flexibility strategy. Although the flexibility strategy says that DSR could save consumers a total of £40 billion off their energy bills from now until 2050 (Ofgem & BEIS, 2017), it does not specify what level of adoption this figure is based on or what level of adoption is required to meet system demands, after accounting for non-domestic DSR as well as other strategies for balancing electricity supply and demand such as storage and interconnectors which also form part of the Government's energy security strategy (DECC, 2012a). Although the smart meter cost-benefit rests on 30% uptake to static TOU tariffs by 2030 (BEIS, 2016b), this is not necessarily the same as the level of uptake required to meet system benefits.

Once this evidence is obtained, policymakers can make a fully informed decision over how recruitment to TOU tariffs or the other automated DSR services should be conducted.

3.2.2 Should tailored marketing be used to recruit customers onto TOU tariffs?

The final question for debate is therefore whether tailored marketing should be employed as a strategy to recruit customers to TOU tariffs. There are two main considerations involved in making this decision. The first is whether tailoring the marketing of TOU tariffs towards particular consumer groups could itself harm consumers. The second is whether tailored marketing would be more effective than some other alternatives at realising the optimal level of domestic consumer uptake to TOU tariffs. I address each in turn.

One potential criticism of tailoring the marketing of TOU tariffs towards high electricity users such as EV owners is that, given that EV owners tend to be wealthier than the average consumer (Knight et al., 2015), tailored marketing could have regressive impacts by increasing the likelihood that the benefits of TOU tariffs will disproportionately accrue to the wealthiest members of society. Another possibility is that tailoring could be used for harm as well as good if suppliers exploit tailoring effects to attract consumers to more expensive tariffs. For instance, a two-tiered TOU tariff that operated with a smart meter that one of the Six Large Energy Suppliers marketed as an 'electric vehicle tariff' had a much higher peak time rate and off-peak rate than the most competitive Economy 7 tariff, a legacy TOU tariff. However tailored marketing is unlikely to disproportionately benefit the rich once EVs infiltrate the second-hand market. Moreover, regulation could be introduced to prevent unscrupulous suppliers from creating 'Electric Vehicle' tariffs that are more expensive than identical TOU tariffs that are not marketed under such labels.

Therefore the main consideration over whether tailoring should be adopted as a key strategy by the UK Government to boost uptake to TOU tariffs is how tailoring is likely to perform relative to a range of alternative approaches which also do not involve making a TOU tariff mandatory or the default tariff. One such alternative would be to create tailored tariff structures which are particularly favourable for EV owners or those with electric heating or to offer one-off financial incentives to such consumers to sign up to TOU tariffs. Another alternative discussed in Chapter 2 would be to offer small upfront cash payments for switching to a TOU tariff, an incentive which could even be targeted at EV owners or households with electric heating. Whilst both these approaches could help to selectively attract EV owners or other consumer groups, tailoring the marketing of TOU tariffs to EV owners, as tested in this thesis, would be lower cost so could generate a higher impact per pound spent, which is important given that the marginal cost savings to suppliers from having a domestic consumer participating in DSR are reportedly modest.[101] However, until a cost-effectiveness analysis is undertaken for all three approaches, based on actual switching rates, it is hard to say conclusively which approach would deliver the most additional sign-ups to a DSR programme for each £1 spent.

Although opt-out enrolment is also likely to be a very low-cost but effective recruitment strategy, it is not clear to what extent enrolment rates and changes to electricity consumption patterns would vary under an opt-out compared to an opt-in system with TOU tariff marketing tailored at high consuming electricity users. For instance, it could be imagined that tailored email prompts could boost uptake to TOU tariffs significantly in future, and that it could therefore have a high potential impact on reducing peak electricity demand. As discussed in Chapter 7, if half of all EV owners prompted to switch tariff via email do go on to switch to a TOU tariff, this would translate into an extra 9 million EV owners switching tariff under a high EV adoption scenario, which would represent 40% of all plug-in EVs in 2050 (National Grid, 2017, p.41). Considering that the National Grid estimated that at least 85% of EV owners would need to participate in off-peak charging to avoid the worst possible increase in peak electricity demand from high EV uptake

[101] The author attended a number of conferences between 2013-2017 at which representatives from energy supply companies reported that the per customer savings from having a half-hourly settled domestic customer enrolled on a TOU tariff were too small to make the tariff commercially viable.

(National Grid, 2017, pp.43–44), a 40% uptake of TOU tariffs by EV owners as a result of a single email would be very substantive contribution indeed.

The first field experiment also found that price comparisons, in which people get a quote for a tariff based on what appliances they own and the price comparison website does the maths for people, could also effectively deter consumers who are unlikely to save from switching tariff. It is possible that price comparisons could also increase uptake to TOU tariffs amongst those who could save; unfortunately it was not possible to robustly test this in the Flex Trial because there were many more non EV and heat pump owners.

If future research identifies methods of providing transparent and accurate price comparisons for TOU tariffs then combining price comparisons with tailored tariff marketing to create tailored price comparisons could be an even better approach. This is because, a key potential limitation of tailoring tariff marketing to consumers based on a single household characteristic such as whether the household owns an EV is that such characteristics will never be perfect proxies for being able to save money or delivering demand-response relief to the electricity network. More research is certainly required to investigate what characteristics provide good proxies or indicators for being a flexible electricity consumer who could save money on a TOU tariff. Whilst it is beyond the scope of this thesis to develop indicators for what could be called ‘flexibility capital’ (Powells and Bulkeley, 2013), the next chapter points to this as a fruitful area for future research.

3.2.3 Message framing debates

The findings help to add nuance to the debate over the success of message framing and nudge as a tool for effecting behaviour change. As was discussed in Chapter 3, the literature on framing effects has recently been criticised in a number of domains from health psychology (Gallagher and Updegraff, 2012; Updegraff et al., 2012) to climate change communication (Bernauer and McGrath, 2016b) for providing inconsistent results. Some studies show large average effects (e.g. Bolderdijk et al., 2012) whilst others show very small average effects (Spence and Pidgeon, 2010; Spence et al., 2014; Schwartz et al., 2015) or no effect at all (e.g. Toll et al., 2007; Nicolson et al., 2017). Given publication bias, it is possible that a large unpublished body of null results framing studies exist.

Indeed a wider criticism of nudge is that researchers are not always able to predict when it will work, for whom and why (Harford, 2014; Collins, 2015; Dellavigna et al., 2017). What the studies in this thesis collectively show is that tailored framing – or at least tailored marketing of TOU tariffs – is a particularly *effective* type of framing but that *diagnosis* of the population for whom it is effective is crucial (Wydick, 2016).

The *effectiveness* of tailoring is demonstrated by the large effect sizes observed across all three studies. In the Flex Trial tailoring reduced the proportion of website visitors who obtained a quote for the tariff by 40%. In the OLEV trial, tailoring increase average open rates and click-through rates to the email prompting them to switch tariff by 15% and 90% respectively. In the Population-Based Survey experiment, statistically significantly reduced demand amongst non-EV owners by 60% and increased demand amongst non EV owners by 20%, although this latter result was not statistically significant so is interesting but not robust.

The importance of *diagnosis* is demonstrated by the fact the direction of the effects varied depending on the study's participant population. When looking only at the results from the Flex Trial and the OLEV trial the framing effects appear inconsistent: in the Flex Trial the average causal effect from tailoring is negative whilst in the OLEV trial the average effect is positive. It was only by running the Population-Based Survey experiment, which provided higher quality baseline data than could be obtained in the highly naturalistic field experiment, that I was able to understand why the average effect in the Flex Trial was negative rather than positive.

Although the type of tailored framing employed in this study makes it relatively easy to form predictions about which groups will respond to treatment, the results still have implications for other contexts in which framing has been employed but to varying success. For instance, Bernauer and McGrath (2016) argue that simply framing climate change mitigation strategies in terms of either helping the planet for the long term good of future generations versus protecting economic growth or our health is unlikely to be effective given that these frames will likely have conflicting effects on different people which could negate any positive average impact from a universal re-framing of climate change. Instead, Bernauer and McGrath (2016) suggest that future research should test whether it may be possible to change peoples' attitudes and actions to combat climate change by matching climate change communication strategies with peoples' political affiliation. This trial matches a frame to consumer groups based on appliance ownership and demonstrates that it is highly effective.

4 Weighing up the limitations

There are five key limitations to the research conducted in this thesis, which are now discussed in turn.

4.1 Using economics as a benchmark

The thesis examined uptake to TOU tariffs using a classical economic framework as the benchmark against which interventions informed by behavioural science were tested. The reasons for using economics as a benchmark were outlined in detail in Chapter 3 however this does not mean that there are not potentially strong limitations to this approach.

The first key limitation is that a range of evidence from other social sciences suggests that economics is an oversimplified, but also potentially widely inaccurate, model of individual behaviour (Chapter 3). The second is that the standard model of economics sees no other role for Government or the energy regulator than correcting economic inefficiencies (Stiglitz, 2000). Economics therefore has nothing to say about the distributional impacts of the recruitment methods used for TOU tariffs even though policymakers are expected to ensure that the benefits of a smarter energy system are shared out across all taxpayers.

This thesis tried to address these limitations in a number of ways. First, by using behavioural economics it was able to account for a wider range of potential drivers of decision making towards TOU tariffs, including psychological drivers such as the way tariffs are framed to consumers. By testing whether energy bill payers were able, in principle, to make optimal choices over their energy tariff, the thesis did not take for granted the assumption made by classical economics which is that consumers are approximately fully rational decision makers. However, nor did it take for granted that, since empirical evidence shows that many consumers are foregoing large financial savings by not switching tariff (CMA, 2016b) and struggle to make rational choices over their finances (Lusardi and Mitchell, 2006a, 2008; van Rooij et al., 2011), they must also be failing to make rational choices over their energy tariff because the former does not guarantee the latter.

Second, the thesis took the stance that the distributional impacts of TOU tariffs – and how consumers are recruited – is of prime importance. This is markedly different from most analyses of uptake to TOU tariffs which, as pointed out in Verbong et al. (2013) are mostly performed by classically-oriented economists who “can semantically be divided between a group who claims that users should reap the benefits of participation and a group who claim that users who refuse to adapt should be punished with higher costs” (122).

Nevertheless, using economics as a benchmark still has its downsides in respect of considering the distributional impacts of TOU tariff recruitment methods. Economics defines efficiency in terms of Pareto optimality, namely that changes to existing resource distributions are only optimal if they can make someone better off without making anyone else worse (Stiglitz, 2000). Classical economics is therefore inherently biased towards the status quo and some may argue that the status quo in the electricity market is itself inequitable because people who consume more electricity at peak times are being subsidised by off-peak users. From this perspective, opt-out enrolment onto tariffs which more closely reflect the true cost of electricity generation *is* more equitable, if adopting a ‘user pays’ definition of equity.

Nevertheless, the status-quo is an important benchmark because evidence suggests that this is likely to be what people refer to when considering whether TOU has made them better off (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991, 1992). As noted in Verbong et al. (2013), a more flexible electricity system may indeed save consumers money relative to a future world in which average electricity prices are higher but in which there are no TOU tariffs. However, people are unlikely to compare their bills on a TOU tariff to a counterfactual world in which electricity prices are higher but there are no TOU tariffs; rather, they are likely to compare whether they are better off on a TOU tariff relative to what they are paying now because the counterfactual is unobserved. Moreover, the evidence suggests that TOU tariffs could substantially increase the electricity bills of a sizeable minority of consumers relative to what they pay now (Star et al., 2010; Carmichael et al., 2014; Sidebotham, 2014a; Long Island Power Authority, 2015). These perceptions matter because policymakers are selling DSR to people on the basis that it will save them money and, as argued in Verbong et al, “An overly positive approach could be very harmful to public acceptance when smart grids have been introduced and prices do still rise” (Verbong et al., 2013, p.122).

Finally, whilst it may be inequitable that high peak time users are currently being subsidised by those with flatter electricity profiles, by getting EV owners and heat pump owners who will have higher than average peak time use to sign up to TOU, tailored marketing could reverse this trend by getting the highest users to subsidise the lowest users.

4.2 The limitations of changing individual behaviour

A second limitation is that by only focusing on individual theories of decision making that emphasise consumer choice, this thesis may underestimate the extent to which choices are constrained by important institutional and cultural factors. For instance, energy sociologists have argued that encouraging individuals to make more sustainable consumption choices may not be the most effective way of tackling climate change because public and private organisations structure and restrict the choices available for people to develop more sustainable ways of living and working (Spaargaren and Vliet, 2000; Uzzel, 2009; Shove, 2010). In a review article, Wilson and Dowlatabadi (2007) point out that our society and technology has co-developed over many years in ways that has embedded us into a high energy consuming future. Since these developments are strongly path dependent, they are not legitimate targets of interventions since they cannot be easily changed.

A good example of the path dependency of energy consumption, given by Wilson and Dowlatabadi (2007), is the installation of central air conditioning in the United States which increased from being present in 12% of homes in 1962 to 64% of homes in 1992, which in turn affected the way homes were designed since air conditioning meant that other means of passive cooling such as verandas, eaves and thermal mass were no longer required to keep people comfortable. However, another example is that encouraging people to replace their internal combustion engine vehicles with EVs is helpful but not as impactful as if people had never become accustomed to travelling by car and if cities had not therefore been built across such extensive areas of land that it becomes infeasible to walk or cycle between home and work.

According to this line of argument, interventions targeting individual behaviours will only have a limited effect and substantial changes to energy use can only be achieved “not through behaviour change by individuals but through government-led interventions, the targeted delivery of public services or upstream solutions” (Darnton, 2004, p.9). For instance, implementing interventions to boost EV uptake may only have a limited effect on the uptake of EVs until the public infrastructure is available to permit drivers to charge their vehicles on the move if necessary. These major infrastructure investment decisions are the domain of government departments, not individual consumers.

Nevertheless, whilst behavioural interventionists could learn from the ambition of the sociological perspective, if these regimes are strongly path-dependent (based on their historical development), then all intervention designers, regardless of their theoretical background, will be able to exert the most impact by implementing interventions at “critical moments when sociotechnical regimes are openly changing and can be most easily influenced” (Wilson and Dowlatabadi, 2007, p.188). Intervening at a point of change, in collaboration with a government department that has the potential to exert much greater change, is precisely what the study described in Chapter 7 did and showed could be effective.

Moving from combustion engine vehicles to a system of EVs represents a major disruption to the existing socio-technical regime and therefore to the existing choice architecture, the term coined by Thaler and Sunstein (2008) to describe the set of organisational rules and conventions which structure and influence consumer choices. The transition towards EVs is creating a host of new systems and services including new infrastructure (e.g. public charging points, home charging points), institutions (e.g. OLEV, Go Ultra Low, EV public charge point car clubs) and therefore new choices and potentially new behaviours. Whilst Darnton (2004) may be right in saying that sustainability goals are highly unlikely to be met without such government programmes, the lesson from behavioural science and nudge (Thaler and Sunstein, 2008), is that the way in which these programmes are designed and structured could have an important influence on take up of these programmes (Hillier et al., 2016, p.2), and, in the case of this study, on the other choices people make when they purchase their EV.

This study demonstrates that OLEV, as the institution responsible for administering the EV grant, could take advantage of the window of opportunity created when people adopt their first EV to prompt an entire and growing sub-group of the population to participate in DSR before they get into the habit of charging their vehicle at peak times which would put an increasing strain on the electricity network and reduce the environmental benefits of EVs. Given the success and low cost of the intervention, OLEV intends to send this email to new grant recipients as business as usual with the future intention for this email to contain links to specific TOU tariffs that are suitable in structure for home charging. If such prompts become part of the normal fabric of designing government programmes, they can help to create a lower carbon ‘choice architecture’ that means the choices people make, whether conscious or not, are more likely to lead to low energy consuming lifestyles, a goal emphasised strongly in Shove (2010). Indeed, a recent review article concluded that, despite the marked differences in the theoretical and epistemological underpinning of behavioural theories and social practice theories, these “tensions…fall into less sharp relief when designing interventions and making policy recommendations” (Kurz et al., 2015, pp.124–125).

At the same time, it is also acknowledged that nudge will not have as large an impact on behaviour as a carbon tax or major cultural shifts in the expectations people have over the size of the homes they live in (Wilson and Dowlatabadi, 2007) or the way they travel to and from work or holiday destinations. However, the topic of this thesis is DSR and most of the policy changes required for enabling DSR outlined in Chapter 2, including electricity settlement reform and the smart meter roll-out, are already underway. Therefore, a key missing link in realising domestic participation in DSR *is* changing individual consumer behaviour and this thesis shows that nudge is a valuable tool for influencing peoples’ choices over their energy tariff, beyond just using nudges such as opt-out enrolment.

4.3 Recruitment strategies

A third limitation is that the participant recruitment methods employed in this thesis are likely to have excluded some of the most vulnerable members of society. As noted in Chapter 5 and 6, online surveys tend to recruit a higher proportion of younger people who are more likely to have Internet access. Naturally, both the online field experiments would only cover people with Internet access. Although nearly 90% of British people have Internet access (Office of National Statistics, 2015), for 10% of the population to be without access encompasses 6.5 million people whose views are excluded from the research conducted. The key risk is that it cannot be known whether the treatments tested would work on these groups and that by excluding their views, their interests would not be accounted for in the conclusions and recommendations of this thesis.

With regards to the latter concern – of failing to consider the interests of vulnerable consumers – it is my view that the case made in this thesis against opt-out enrolment for TOU tariffs (a case that I have not seen taken anywhere else) does consider and align with the interests of vulnerable consumers. Vulnerable groups may be even less likely to pay attention to default settings because other aspects of their lives mean that they may have less time and mental bandwidth to meticulously analyse the details of all correspondence from their energy supplier. Future research would be required to test whether tailoring the marketing of TOU tariffs towards EV and heat pump owners would also detract vulnerable consumers who may also be less likely to save money on a TOU tariff.

4.4 Generalising to future consumers

The fourth potential limitation is that the energy market is evolving rapidly and will continue to evolve whereas the data collected in this thesis started in 2016 and concluded in 2017. This raises potential issues regarding the applicability of the results to future energy consumers. For example, the study sampled early adopters of EVs and it is possible that early adopters of EVs will not respond in the same way to tailored marketing messages as would future adopters when EVs become mass market. It also raises issues over the generalisability of the results to future scenarios in which, for example, TOU tariffs are not the key mechanism by which domestic consumers will be incentivised to engage in DSR.

Regarding the first point, it seems unlikely that tailored marketing would be less effective on later adopters because early adopters of EVs may be more rational than later adopters; study 5 suggested that bounded rationality was higher amongst consumers in low socio-economic grades and study 7 showed that EV owners are likely to much wealthier than the average bill payer. Regarding the second point, as noted elsewhere, the results of this study are generally applicable to any type of DSR not just TOU tariffs. Assuming that consumers will always need to provide their consent for DSR, it will be necessary to consider whether consent will be assumed unless people opt-out or whether it will have to be actively given. For the same reason that it may be unethical to automatically enrol people onto TOU tariffs if they do not have the energy literacy skills to work out whether they would be better off opting out and because they may not notice that they have been defaulted onto a TOU tariff, it may also be unethical to automatically charge and discharge someone's electric vehicle as part of a vehicle-to-grid service without the EV owners' knowledge.

Equally, automatically enrolling a consumer onto a DLC programme and remotely turning up or down their thermostat in line with real-time availability of electricity supply may also be considered highly unethical unless it is done with the persons' knowledge. Unfortunately, opt-out enrolment is not a good method for obtaining peoples' informed consent because defaults are effective, not only because of status-quo bias, but because people do not pay attention to what option was pre-selected as the default (Keller et al., 2011). Further, this debate does not only apply to DSR: the Smart Energy Code has a general definition of what it calls User Unambiguous Consent, which if it was applied to DSR or any other customer service, would mean opt-out enrolment would be forbidden. The results of this thesis – which demonstrate the effectiveness of tailored marketing – could be relevant in a range of future consumer scenarios.

4.5 Commercial availability of TOU tariffs

As noted in Chapter 4, TOU tariffs of the type required to meet the challenges of the future electricity grid are not widely commercially available in most European countries including in GB. Only two smart-meter enabled TOU tariffs emerged in the GB market just shortly after data collection for this thesis was either completed or already significantly underway. Although the Flex Trial simulated in a very realistic environmental what it might be like for a consumer to visit an energy supplier's website to switch to a TOU tariff, participants were not actually enrolled onto the tariff. Even those who switched without knowing the study was part of a trial, in reality may have left the tariff in a cooling off period. Retention rates to TOU tariffs or other DSR services are also an important consideration when evaluating recruitment methods. This is an inescapable limitation of the thesis which I tried to overcome by measuring as many behavioural outcome variables as possible in the present circumstances. Other possible ways of conducting research in the absence of a large market for domestic DSR are discussed in Section 4 of Chapter 9 which discusses future research.

4.6 Summary of limitations

Although there can be strong limitations to exclusively using economic theoretical frameworks, this thesis tried to overcome the two most important ones by accounting for psychological influences on decision-making and accounting for the distributional implications of recruitment methods used for TOU tariffs. Although the behavioural sciences may assign greater agency to human decisions than would a sociological model, evidence suggests that there are strong merits in trying to change individual behaviour at a time when the institutional frameworks in which individual choices are embedded are also changing (Verplanken et al., 2008; Verplanken and Roy, 2016; Thomas et al., 2016).

At the same time, this thesis acknowledges that nudging people into making more environmentally friendly choices will in no way be sufficient on its own to address climate change. Both government and industry have a major role to play in setting and meeting carbon emission targets, raising fossil fuel prices to reflect their environmental cost as well as creating the opportunities for people to make environmentally friendly choices. Although there are many more psychological influences to decision making than were employed in this thesis – framing is the main one adopted – it would be beyond the scope of the thesis to test others. Although the thesis focused on TOU tariffs, the debate over opt-in vs opt-out enrolment is generally applicable to almost any other energy service, such as vehicle-to-grid or DLC. Ideally, future research would measure the impact of a range of different recruitment strategies on switching rates to a range of DSR services onto which consumers could be enrolled in reality.

5 Conclusions

This chapter set out to discuss the results of each of the empirical studies presented in this thesis to answer the research questions, whilst also considering the limitations of each study and the wider literature reviewed in chapters 2 and 3.

The conclusions of the thesis as a whole are summarised in the next chapter along with their implications for the regulation of the GB electricity market and the UK Government's cost-benefit analysis for the National Smart Meter Implementation Programme. The next chapter also includes specific recommendations for future areas of research.

Chapter 9

Conclusion and future research:

Minimise opt-outs and market TOU tariffs at high consuming electricity users

1 Introduction

This thesis had two aims: (1) to provide the first robust estimate of likely British consumer adoption of TOU electricity tariffs and; (2) to generate evidence on how adoption rates could be increased without making TOU tariffs mandatory or automatically enrolling people unless they opt-out.

These aims were motivated on the basis that an accurate understanding of likely consumer adoption rates of TOU tariffs is important for the success of the UK's energy security and decarbonisation strategies (DECC, 2012a; BEIS, 2016c; Ofgem & BEIS, 2017) and the UK Smart Meter Implementation Programme which is premised upon 30% of domestic consumers adopting a static TOU tariff by 2030 (BEIS, 2016b).

Moreover, given that consumers rarely switch tariff or supplier (Defeuilley, 2009; CMA, 2016b), there was a legitimate cause for concern that uptake to TOU tariffs would be lower than optimal if methods for increasing enrolment rates were not identified which, unlike mandates or opt-out enrolment, would respect the fact that TOU tariffs will not be right for all consumers.

This chapter summarises the key findings in relation to the aims of the thesis and outlines the original contribution of this thesis to the literature on DSR and nudge. This is followed by a brief outline of how the results have or could be used to inform policies around DSR in GB and avenues for future research.

2 Summary of key findings and main argument of thesis

To achieve aim 1, this thesis provided evidence that if consumers are left to opt-in to TOU tariffs, uptake could be as low as 1% unless effort is made to close the intention-action gap, in which case enrolment could be around 43% or above; if consumers are enrolled onto a TOU tariff by default, unless they opt-out, enrolment could exceed 57% and approach 100%.

To achieve aim 2, the thesis provides evidence that tailored marketing could be an *effective,* but also potentially *preferable,* alternative recruitment method for TOU tariffs than opt-out enrolment. The evidence for this is now summarised below.

There are obvious advantages to using opt-out enrolment. Although people who actively sign up to TOU tariffs reduce their peak electricity use by significantly more than consumers who are enrolled by default (Chapter 3), the evidence suggests that opt-out enrolment would result in higher overall reductions in peak electricity demand than if recruitment was opt-in because of the much higher enrolment rates on an opt-out system (S. A. Fenrick et al., 2014; Cappers et al., 2016). This greater reduction in peak demand would lower electricity system costs overall, savings which will accrue to those who are on TOU tariffs and can adjust their consumption patterns.

However, the evidence reviewed in Chapter 3 of this thesis and also the new evidence presented in Chapter 5 suggests that these efficiency gains will come at a price. In the case of TOU tariffs, opt-out enrolment, whether personalised or not, presents a real risk that millions of consumers could be signed up to tariffs that substantially increase rather than decrease their energy bills, particularly vulnerable consumers.[102] This is based on the findings from study 1 which showed that approximately half of all British energy bill payers are unable to

[102] Half of the domestic electricity customer base of 28 million customers (Ofgem, 2016d) is 13.5 million people. If the survey overestimated the proportion who would correctly identify whether a TOU tariff would be right for them by 50%, this is still 6.7 million customers. If all of these people were enrolled onto a TOU tariff by default, and assuming that at least 40% would be financially worse off as was the case in the CLNR TOU tariff trial (Sidebotham, 2014a), this would mean harming 2.6 million bill payers.

identify the cheapest tariff even when given all the information required to do so and that this ability declines when the menu of tariff options includes a TOU tariff, particularly for consumers in the lowest three social grades (C2-D) who are more likely to be in fuel poverty because they are more likely to have below average incomes and may also face high energy costs if they are living in poorly insulated homes (Hills, 2012).

Further, since even bad defaults are 'sticky' (Keller et al., 2011) – retention rates amongst consumers automatically enrolled onto TOU tariffs exceed 70% regardless of whether the household shifts their electricity use away from the expensive peak times (US Department of Energy, 2016) – there is no guarantee that consumers would dis-enroll from an unsuitable tariff once it had started to negatively impact their energy bills.

Defaulting consumers onto TOU tariffs on the basis of their electricity consumption history (personalised defaults) will not necessarily prevent this problem either; for a TOU tariff to change consumption patterns – the aim of any DSR programme – people would first need to know that they have been put on a TOU tariff. However, one of the key reasons opt-out enrolment is thought to work is precisely because people do not realise what option was pre-selected for them (Keller et al., 2011), which is why opt-outs often end up with people enrolled onto receiving unwanted marketing communication (Carroll et al., 2009).

Automation could avoid the negative financial implications of being unknowingly enrolled onto a TOU tariff. However, if the Government decides that companies must obtain *informed* consent from people before enrolling them on TOU tariffs, vehicle-to-grid or DLC of home heating services – what the Smart Energy Code refers to as User Unambiguous Consent (Smart Energy Code Company, 2017)

– then opt-out enrolment will not be an option for automated services either because opt-out enrolment does meet the criteria for User Unambiguous Informed consent laid out in the Smart Energy Code (2017).

However, without opt-out enrolment, we are left with opt-in, a strategy which would result in substantially lower enrolment rates. Further, the same bounded rationality that means consumers would not know whether to opt-out of being automatically enrolled onto a TOU tariff would also affect consumers opting in. The first study effectively forced consumers into making an active choice between three tariffs and 50% still did not identify the cheapest tariff, implying that opt-in enrolment will not prevent consumers from adopting inappropriate tariffs either.

This thesis therefore tested the effectiveness of tailored marketing, a strategy which aims to overcome the disadvantages of both opt-in and opt-out enrolment by being both 'effective' and 'selective' (Johnson, 2016). That tailored marketing can be *effective* and *selective* is demonstrated by the results from two field experiments and one survey experiment which show that, compared to marketing appeals which address the average energy bill payer, tailoring the marketing of TOU tariffs towards high peak-time electricity users, could reduce uptake amongst lower consuming groups who are more likely to face increases in their energy bills from switching to a TOU tariff. One of the field experiments, the OLEV trial, also produced evidence from a large sample of EV owners that tailored marketing messages presented in emails could increase demand amongst EV owners, who are higher than average peak time electricity users. The survey experiment provided similar, but not statistically robust evidence of this effect too.

In this thesis, the high consuming group is EV owners, who use approximately double the amount of electricity as households without EVs[103] (National Grid, 2017) and who mostly charge their vehicles during the existing peak times (Capova et al., 2015; Zarnikau et al., 2015), when the marginal carbon intensity of electricity is at its highest (Ma et al., 2012).

That tailored marketing can be *effective* on EV owners was shown by the results in Chapters 6 and 7: tailoring the marketing of TOU tariffs to EV owners using appeals such as “Switch to this EV tariff” or “Switch to cut the costs of charging your EV”, increased demand for these tariffs amongst EV owners relative to generic marketing appeals such as “Switch to save money on your energy bills” and “Switch to the Off-Peak Saver tariff”; however, tailored marketing was also *selective* because these tailored marketing messages also decreased demand amongst other consumers who are likely to have lower electricity use and who are also more likely to face higher electricity bills on a TOU tariff because, unlike EV owners, they do not have a single large electricity load that they can shift into the off-peak times.

The effect sizes are large (up to 90% relative to the baseline) and consistent in direction and magnitude across one survey experiment and two field experiments, including one performed on nearly every privately owned EV driver in the UK (Chapter 7). The latter experiment, for example, demonstrated that unsolicited mass emails could effectively engage an additional one million people with TOU tariffs once EVs reach 60% market penetration if the message is tailored to EV owners and sent within the first three months of vehicle purchase.

[103] See Appendix 3.2.

Further research is required to test whether tailored marketing could be effective on other high electricity consuming groups, such as households with electric heating who are also likely to run their heating during existing peak times unless incentivised to do otherwise (Frontier Economics, 2012; National Grid, 2017). In particular, further research is required to test the impact of tailored marketing on actual switching rates to a range of commercially available DSR services relative to opt-out enrolment. At present, opt-out enrolment may indeed perform better however once more EVs and heat pumps enter the market, tailored marketing towards these groups may be able to rival opt-out enrolment for recruitment numbers. Once this evidence is obtained, policymakers can make a fully informed decision over how recruitment to TOU tariffs or the other automated DSR services should be conducted.

Nevertheless, by starting this discussion and providing evidence of the promising role that tailored marketing could play, it is hoped that this thesis will provide nuance to the debate on opt-in versus opt-out enrolment in the context of consumer participation in the smart grid. Without this discussion and evidence, a policymaker may dismiss calls for TOU tariff enrolment to be opt-in on the basis of their knowledge of the effectiveness of opt-out enrolment in the contexts of pensions or on the basis that there is no viable alternative. However, TOUs are not like pensions because not everyone will benefit from TOUs and the study shows that tailored marketing is a very promising alternative that respects the fact there is no one-size fits all energy tariff.

3 Original contribution of this thesis

The introduction to this thesis set out four original contributions that this research intended to make. The following sections review to what extent the research succeeded in doing so.

3.1 Substantive contribution to the literature on consumer participation in DSR

The first was a substantive contribution to knowledge over how many British consumers could be expected to adopt TOU tariffs and how to increase uptake if it was lower than optimal. This thesis made this contribution by synthesising the available empirical evidence on uptake to TOU tariffs to find that uptake could be as low as 1% but that tailoring the marketing of TOU tariffs towards consumer groups such as EV owners could help to increase uptake so that it is closer to the 43% who say they would be willing to adopt a TOU tariff in surveys (of which prior research shows EV owners are likely to form a disproportionate number [Nicolson et al., 2017]).

In doing so, this thesis takes forward both the academic and policy literature on domestic DSR in two key ways. First, it progresses the debate on how to increase uptake to TOU tariffs away from an exclusive focus on the average energy bill payer to how to increase uptake amongst particular consumer groups. Whilst this thesis started out by highlighting that a key challenge for the success of domestic DSR is how to encourage an additional 30% of domestic consumers to adopt the kinds of tariffs and programmes that expose consumers to DSR signals, the thesis has demonstrated that an even greater challenge is how to make sure that the right 30% of consumers sign up.

Prior to this research there was no discussion or empirical research testing ways of achieving targeted uptake of TOU tariffs. The only concern that had been expressed was that TOU tariffs would be adopted by people who already have low peak time energy consumption (Baladi et al., 1998; Hartway et al., 1999; Charles River Associates, 2005; Herter, 2007; Ericson, 2011; Qiu et al., 2017), so-called 'free-riders' who would "provide little to no load relief during load-control events, but still benefit as much as do those providing significant load reductions" (Herter, 2007, p.2122). This thesis provided evidence to suggest that a different type of adverse selection problem is possible, whereby TOU tariffs attract customers who do have peaky electricity demand profiles but who, for a variety of reasons, may be unable to change this but also unable to process the information required to determine whether switching to a TOU tariff would increase or decrease their energy bill. These consumers will provide no benefits to the electricity network and will just face higher energy bills.

The Government needs to decide whether the increase in overall TOU tariff adoption rates from using opt-out rather than opt-in enrolment (S. A. Fenrick et al., 2014; Cappers et al., 2016) is more important than protecting the sizeable minority of energy bill payers who are unwilling or unable to alter their electricity consumption patterns from being enrolled onto TOU tariffs. If the Government decides that the benefits to society as a whole from having a more flexible energy system cannot justify significantly increasing the energy bills of ~40% of British consumers, then opt-out enrolment for TOU tariffs would need to be ruled out.

A second way in which this thesis takes forward the literature on consumer participation in DSR is that it highlights an important distinction between consumer adoption and consent. Unlike the former, consent is usually characterised in the health domain as being voluntary, informed and given by a person with the capacity to understand the information given to them to make an informed choice.[104] The Smart Energy Code has a similar definition called "User Unambiguous Consent" which is defined as a request by the consumer to a third party (the 'User') to undertake a particular action or when the consumer takes a positive action agreeing showing that they agree to a third party's request to undertake an action on their behalf (SECAS, 2017, p.92). The Government now needs to decide whether it will require energy suppliers and other DSR companies to obtain User Unambiguous Consent from customers before enrolling them onto DSR services. If it does, then opt-out enrolment, whether personalised or not, will not be a viable recruitment option.

As pointed out in the last chapter, the distinction between consumer adoption and consent will become increasingly pertinent in a world where electrical appliances are increasingly being made both Internet connected and 'DSR-ready'[105], i.e. where an appliance could be remotely controlled by a third party, such as a third party turning up or down the set-point on a smart thermostat for a heat pump (a type of DSR called DLC). In my experience many new technology companies, including those intending to enter the domestic DSR market in Britain, express the view that consumers only care about saving money and do not need to know how so-called 'smart' savings are achieved. Given that Ofgem has recently decided to remove prohibitions on tariff bundling (Ofgem, 2016e) and there is nothing in the European Commission's Smart Energy Code (SECAS, 2017) to

[104] See, for example, the NHS' definition of consent http://www.nhs.uk/conditions/consent-to-treatment/pages/introduction.aspx#definition.

[105] The European Commission has worked with industry to create a set of standards to ensure the interoperability and DSR readiness of smart appliance and home energy management systems including ETSI/OneM2M and the SAREF (Smart Appliances REFerence Ontology) ontology for smart appliances.

prevent non-energy suppliers from undertaking such practices, regulators may need to consider this as an area for future regulation.

3.2 Theoretical contribution

The second contribution that this thesis makes is to the theory of bounded rationality. Herbert Simon proposed that humans are not fully rational, in the sense of processing all available information before making a decision, but are rather boundedly rational; people selectively search through information, terminating their search with “the discovery of satisfactory, not optimal, courses of action” (Simon, 1985, p.295). The finding that only 50% of energy bill payers were able to identify the cost-minimising tariff when given all the information required may be of no surprise to psychologists. However, “empirical validation and precision are particularly critical for policy-relevant behavioural research” (Nature Energy, 2017, p.1) because it is only if a large proportion of consumers fail to select the cost-minimising tariff that energy companies will be able to charge what they want (Varian, 1980). The first study provides empirical evidence to support the intuition that many, not just a small minority of, consumers would struggle to work out whether or not they should opt-out of being enrolled onto a TOU tariff if their supplier wrote to them to say this was going to happen and gave them information to help them make an informed choice. This also rules out the common “as if” argument used to defend the rationality paradigm (Friedman, 1953) and suggests that bounded rationality should be incorporated into economic cost-benefit analyses used by Government that rest of the decisions made by domestic energy bill payers, such as the smart meter cost benefit analysis.

Although a prior study suggested that consumers may struggle to identify the cost-minimising tariff (Wilson and Price, 2010), it was not able to rule out the possibility that unobserved non-price factors or imperfect information could have been influencing people's decisions; the study in this thesis eliminated the influence of those possible confounding factors by asking people to identify the cheapest tariff and providing all the information required.

3.3 Contribution to the small evidence base on effective and selective nudges

The third contribution is to take forward the literature on nudge by contributing to the small literature on what Johnson (2016) called "selective and effective" nudges. As noted in Chapter 3, there are many contexts in which there is a need to influence consumer decisions without manipulating default options. In some cases, choice architects may lack the information required to identify a suitable default, such as in the case of credit cards, mortgages, health insurance schemes (Johnson, 2016) and the decision over at what age to retire (Knoll et al., 2015). In other cases, success relies on maintaining on-going engagement in a particular behaviour such as enrolment in a course of antibiotics or a weight loss programme (Keller et al., 2011). There are also some decisions for which the public or policymakers feel that automatic enrolment would unethical even in cases where it has been shown to save lives; many countries have rejected calls to make registration to their national organ donor register an opt-out rather than opt-in choice (A Spital, 1995; Spital, 1996) despite the evidence that opt-out enrolment results in much higher registrations and organ donations (E. Johnson and Goldstein, 2003).

However, much of the literature on nudge has tested ways of influencing the average individuals' behaviour, for example using opt-out enrolment or social norms messaging to encourage people to save energy or enrol in a pension. However, in the case of TOU tariffs as in the case of mortgages, credit cards and many other consumer goods, the best option will vary across people and in these cases a more targeted approach is required (Keller et al., 2011). Although commitment devices aimed at encouraging weight loss (Volpp et al., 2008; John et al., 2011) or smoking cessation (Giné et al., 2010) are targeted, the targeting is achieved by deliberately implementing these interventions on exclusively obese or smoking populations. However, in many cases, it will not be possible to selectively expose nudges to particular sub-groups, for example, because there is no mailing list or existing institutions (such as weight loss groups) by which only the right individuals can be nudged. In these cases the nudge will need to be administered to an entire population and, to avoid it nudging the wrong people, the nudge will need to be designed to be selectively effective, in the way that tailored EV messaging is in the case of TOU tariffs. The Flex Study combined with the Population-Based Survey experiment (Chapter 6) showed how an energy supplier could market their tariffs as 'EV tariffs' on their website, with the knowledge that doing so would increase uptake amongst EV owners without also attracting non EV owners who may be less appropriate for a TOU tariff.

3.4 Methodological contribution

The fourth contribution is that thesis shows how innovative research methods can be used to measure consumer behaviour rather than just relying on stated preferences obtained from surveys, even in cases where the behaviour in question is difficult to measure because it requires access to industry (e.g. energy suppliers) or because there is an absence of data (e.g. in the case of TOU tariffs which do not exist commercially in the UK). To my knowledge, this is one of the first times that intermediate outcome measures such as click-throughs, opens of emails and other so-called “digital footprints” (Lambiotte and Kosinski, 2014; Kosinski et al., 2016) have been used to measure demand for future energy products for which an understanding of consumer appetite is vital.

This thesis also demonstrates how government data can be used to overcome many of the barriers involved in sampling amongst populations of interest to energy researchers, in this case EV owners. Past research on EV owners has struggled to recruit as many as 100 EV owners (My Electric Avenue, 2015) because EVs are still in the minority. This thesis was able to reach over 7,000 private EV owners – 10% of all EV owners in the UK – by partnering with the UK Government OLEV, the department responsible for administering the UK’s EV grant scheme. This is important for ensuring that interventions tested in academic research or piloted in industry trials are likely to generalise if and when the intervention is introduced on a national scale. For example, My Electric Avenue found that the majority of its trial participants were “comfortable or very comfortable with [a controlled charging technology] being able to curtail their charging”(My Electric Avenue, 2015, p.10). However, this information cannot be generalised to the wider population of EV owners since we cannot expect that people who volunteer to try out new technologies in experimental trials – and who complete feedback surveys – will have the same views as the average EV owner. As Government’s increasingly administer services electronically, such databases will make it easier for researchers to access traditionally hard-to-reach audiences, including, for instance, heat pump owners through the UK Government’s

Renewable Heat Incentive. Another advantage of conducting research in this way is that it enables researchers to increase the policy relevance of the results:

> *…in the absence of this behavioural evidence, policy decisions could be subject to the whims of a policymaker's assumptions about how they think they would behave in similar circumstances or how they have behaved in the past. A policymaker could dismiss a proposal for such an e-mail scheme because they would never open such e-mails, or endorse the proposal because they routinely open promotional e-mails. Critically, the results of research like that of Nicolson and colleagues are important regardless: either the data are surprising and violate assumptions, or they provide empirical confirmation that intuitions are valid* (Nature Energy, 2017, p.1).

The results have already been used to advise policymakers and other industry stakeholders on how to engage consumers with TOU tariffs (see Annex 1). The results of all four studies reported in this thesis could potentially inform future research by OLEV and Ofgem to test the impact of interventions on actual switching rates through a new domestic licence condition (SLC 32A) that requires energy suppliers to participate in tariff switching trials. These existing and future contributions to policy are described in full in Annex 1.

4 Future research

The thesis also identifies many research gaps which could provide useful avenues for future research. These are summarised in Table 38 but described in full in Annex 2.

Table 38 Avenues for future research (see Annex 2 for details).

What research?	Why and how?

Increase the precision of estimates of uptake to TOU tariffs and identify what is optimal level of uptake to DSR services amongst domestic users	• Why: To inform the BEIS smart meter cost benefit analysis (2016a) and Ofgem's Flexibility strategy (2017b). • How: Ofgem's programme of trials or a Virtual Energy Company[106] funded by the EPSRC-funded Smart Meter Research Portal[107] (SMRP) (grant number: EP/P032761/1).
Test whether tailored marketing could increase switching rates to TOU tariffs and other DSR services amongst electric heating owners	• Why: The electrification of heat is a major driver for domestic DSR (Ofgem & BEIS, 2017). • How: Running a similar trial to the OLEV trial using the Government's database on Renewable Heat Incentive Recipients.
Test why tailored marketing is effective: mental accounting (Thaler, 1980, 1985, 1999), de-shrouding (Gabaix and Laibson, 2006) or personalisation leads to increased information processing (Rimer and Kreuter, 2006)	• Why: to help inform the design of tailored marketing strategies and develop behavioural economic theory. • How: a trial in which each item is manipulated individually (see Annex 2), although information processing is likely best studies at the neural level, as in neuroscientific studies on loss-aversion (Tom et al., 2007; Canessa et al., 2013).

[106] This idea is being developed by Michael Fell at the UCL Energy Institute. For more information see section 1 of Annex 2.

[107] For more information on SMRP see http://gow.epsrc.ac.uk/NGBOViewGrant.aspx?GrantRef=EP/P032761/1 and http://cee.ac.uk/smart-meter-research-portal-smrp/.

Test methods of identifying consumers with 'flexibility' capital	- Why? A person's ability to be flexible over the timing of their electricity use is unlikely to be driven by a single factor such as being an EV owner but rather could be determined by a number of overlapping variables such as appliance ownership, working patterns, dwelling characteristics and so on. If identified as being causally related to flexibility in empirical research, such markers could be used to create a 'flexibility capital' index for each individual household in the population, which suppliers and third parties could use to match energy bill payers to suitable DSR services, to increase the 'winners' and reduce the 'losers' from DSR. - How: Machine learning techniques on smart electricity meter data via the SMRP.
Test the impact of non-punitive TOU tariff structures such as critical peak rebates (where people get paid for being demand-responsive rather than charged more for failing to be demand-responsive)	- Why? To minimise the negative distributional impacts of TOU tariffs (as above) but identify whether payments are less effective at generating demand-responsiveness than penalties, as would be expected given that energy bill payers are loss-averse (M Nicolson et al., 2017). - How? Ofgem's trials or a Virtual Energy Company.
Test whether disaggregated energy billing for EV owners	Why? In putting together the advice for EV owners in the OLEV trial I identified that EV

can maximise the consumer savings of TOU tariffs	owners' abilities to save money on TOU tariffs is likely to be strongly affected by their ability to shift their non-EV demand away from peak times. Creating TOU tariffs which only charge EV owners on a time-of-use basis for their charging demand, but allowing the rest of their household use to be charged at a flat-rate, could increase the proportion of EV owners for whom TOU tariffs would save money and thus be the optimal tariff. • How? Ofgem's trials or a Virtual Energy Company.
Test the consumer acceptability of EV controlled charging schemes with/out vehicle-to-grid services	• Why? To identify whether voluntary uptake will be sufficient to avoid mandating controlled charging, as recommended by the Smart EV Options Group (Cross et al., 2016). • How? Ofgem's trials or a Virtual Energy Company.
Develop an accurate method for comparing TOU tariffs	• Why? This thesis suggested that price comparisons could potentially improve consumer decisions, when used; if TOU tariffs are not on price comparison websites, people will be less likely to adopt them. There are many ways in which TOU tariffs could be compared to other TOU tariffs and flat-rate tariffs e.g., based on historical use (but this risks only enrolling consumers onto

	TOUs who already have favourable consumption profiles, defeating the purpose of DSR which is to change patterns of use) or by predicting the consumers' potential to change consumption patterns e.g. using machine learning, for which there is no precedent and testing is required to test the accuracy of such predictions which, without automation, will be dependent on human behaviour change. • How? Ofgem's trials or a Virtual Energy Company.
Test tailored marketing in other consumer goods markets for which opt-out enrolment is inappropriate due to heterogeneity	• Why? Switching rates are low across mortgages, credit cards, mobile phone contracts etc. (Costa et al., 2016); however, in all these cases, opt-outs are not suitable because there is no one-size fits all best credit card, mortgage type (fixed vs. variable), mobile phone contract etc. • How? Trials in partnership with the relevant commercial organisations.

5 Concluding remarks

The Irish energy regulator has made TOU tariffs mandatory to ensure that enrolment rates are high enough to realise its business case for smart meters (Commission for Energy Regulation, 2015). In the US, researchers are advocating for a policy of opt-out enrolment (Faruqui et al., 2014; S. A. Fenrick et al., 2014; Cappers et al., 2016).

In contrast, the UK Government has yet to propose any alternative to the status quo which is to wait for consumers to switch between tariffs of their own accord on the basis that these tariffs will attract all consumers who can save money from switching to one (DECC, 2014; BEIS, 2016b). However, prior to this study, there was no robust estimate of the number of consumers who would voluntarily adopt a TOU tariff once they do become commercially available; an earlier draft of the Government's cost-benefit analysis states that it is based on international evidence of uptake to such tariffs but no studies or measures of uptake were cited (DECC, 2014). In addition, no methods had been identified for how to successfully increase uptake if recruitment rates were lower than required, apart from automatically enrolling consumers onto a TOU tariff unless they explicitly opted-out, an approach which poses a number of ethical concerns.

This thesis therefore aimed to provide the first robust estimate of likely British consumer adoption of TOU tariffs as well as evidence on how adoption rates could be increased without making TOU tariffs mandatory or automatically enrolling people unless they opt-out. Three main conclusions were drawn from the results:

1. The UK Government's target to have 30% of domestic consumers enrolled onto a TOU tariff by 2030 in addition to those who are already enrolled on legacy TOU tariffs such as Economy 7 (BEIS, 2016b) is optimistic in the absence of a recruitment strategy to motivate consumers to switch tariff in higher numbers as currently switch tariff. Estimates obtained from consumers in national surveys measuring willingness to switch to a TOU

tariff should not be used to predict uptake given that, across 27 existing studies, survey measures of uptake is more than twice as high (2.2 times higher) as uptake to internationally available TOU tariffs.

2. Opt-out enrolment and simple opt-in enrolment may not be viable recruitment strategies for TOU tariffs or DSR services, depending on whether it is considered ethically permissible to enrol customers onto automated DSR services potentially without their knowledge.
3. Tailoring the marketing of TOU tariffs towards high electricity users could help nudge consumers towards actively signing up to tariffs, whilst also helping to reduce peak electricity demand. Johnson (2016) calls this an 'effective' and 'selective' nudge. Specifically, the results of this thesis show that:
    - Labelling a TOU tariff an 'EV tariff' could increase uptake to TOU tariffs amongst EV owners without simultaneously attracting other consumers who may be less likely to save money on a TOU tariff. EV owners consume about double the amount of electricity as an average household and usually charge their vehicles at existing peak times.
    - Although some EV owners may never visit energy supplier's websites or pay attention to such marketing, another study showed that this self-selection problem could be overcome by actively prompting EV owners to switch to a TOU tariff via email, especially if this email is sent within the first three months of purchase and is tailored to EV owners in particular ("switch to save £300 on charging your EV") rather than the average energy bill payer ("switch to save £300 on your energy bills"). In my estimation, this low cost and easy

to implement intervention could encourage an additional 1 million people to switch to a TOU tariff once EVs reach 60% market penetration.

- Although tailored marketing is unlikely to yield enrolment rates as high as those under an opt-out scheme which can deliver recruitment rates of almost 100% (Chapter 2), future research run in partnership with energy suppliers through Ofgem's new domestic licence condition (SLC 32A) could help determine whether tailored marketing could yield domestic consumer enrolment rates in line with what Government requires to realise the business case for smart meters (BEIS, 2016b) and its flexibility strategy (Ofgem & BEIS, 2017).

The results of this thesis have implications for all types of consumer participation in the smart grid, whether that is signing up to TOU tariffs, selling surplus solar to the grid, having the set-point on their thermostat adjusted in line with the real-time price of electricity (DLC of heating) or giving electricity back to the grid via the battery in their EV (vehicle-to-grid). In each case, if it is agreed that consumers must give their consent to provide these services, a decision will need to be made about whether consumers will consent by default, unless they opt-out, or whether it will be opt-in – and to what extent it matters that consent is informed.

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Appendices:

Supplementary information and robustness checks

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1 Questionnaire used in the Tariff Decision Making Study

We are now going to describe two scenarios involving people who are trying to choose a new electricity tariff.

There are two main types of electricity tariff in the UK:

• **Flat-rate tariffs**, where you pay one price for each unit of electricity you use (e.g. you might pay 14p per unit of electricity no matter when you use it) and a yearly standing charge (a fee for having electricity delivered to your home)

• **Off-peak tariffs**, where you might pay two or more different prices for electricity according to the time of day you're using it, a bit like peak and off-peak train tickets (e.g. you might pay 20p in the day and 10p at night)

Click next to read the scenarios.

Q1 ASK ALL, SCENARIO 1

Selin lives with her partner. Their current tariff has come to an end and they're trying to choose a new one.

Take a look at the three tariffs they've got to choose from and then decide which tariff you think would be cheapest for them considering that they use **2,000 units** of electricity a year and they're happy to switch to paperless billing.

	(1) Flat-rate tariff 1	(2) Flat-rate tariff 2	(3) Flat-rate tariff 3
Unit rate	15p/unit	14p/unit	13p/unit
Standing charge	£68/year	£60/year	£95/year

Discount for switching to paperless billing	£30/year	None	None

Please select the tariff that you think would be <u>cheapest</u> for Selin and her partner. You may want to use a calculator to help you.

1. Flat-rate tariff 1
2. Flat-rate tariff 2
3. Flat-rate tariff 3

Q3 ASK ALL, SCENARIO 2

Stephanie lives with her partner. Her current tariff has come to an end and she's trying to choose a new one.

Take a look at the three tariffs she's got to choose from and then decide which tariff you think would be cheapest for her considering that her family uses **3,100 units** of electricity a year at the following times of the day:

- 50% between 4pm-8pm
- 40% between 7am-4pm
- 10% overnight (between 8pm-7am)

		(1) Off-Peak tariff 1	**(2)** Flat-rate tariff 2	**(3)** Flat-rate tariff 3
Super off-peak:	**Overnight** 8pm-7am	10p/unit	14p/unit	13p/unit
Off-peak:	**Day** 7am-4pm	14p/unit	14p/unit	13p/unit
Peak:	**Evening** 4pm-8pm	30p/unit	14p/unit	13p/unit
Standing charge		£70/year	£60/year	£95/year

Please select the tariff that you think would be <u>cheapest</u> for Stephanie and her family. Use a calculator to help you.

1. Off-Peak tariff 1
2. Flat-rate tariff 2
3. Flat-rate tariff 3

2 Keywords for Google advert targeting in the Flex Trial

Keyword	Population target[108]
Electricity supplier	(1)-(3)
Electric tariff	(1)-(3)
Compare electricity suppliers	(1)-(3)
Energy tariff comparison	(1)-(3)
Cheap overnight electricity	(1)-(3)
Cheap energy tariff	(1)-(3)
Energy tariff	(1)-(3)
Energy supplier	(1)-(3)
Economy 7 alternatives	(1)-(3)
When is electricity cheaper to use	(1)-(3)
Economy 7 tariff	(1)-(3)
Economy 7 meter	(1)-(3)
Economy 7 times	(1)-(3)
Economy 7 heaters	(2)
Controls for heat pumps	(2)
Heat pump smart thermostat	(2)
Heat pump controls	(2)
Heat pump	(2)
EV charging stations	(1)
Electric vehicle charging cable	(1)
Electric vehicle tariff	(1)
Electric car tariff	(1)
EV charging cable	(1)
Electric car charging point	(1)
Electric car charging station	(1)
Electric car charging	(1)
Electric car charging point	(1)
EV charging tariff	(1)
EV tariff	(1)

[108] (1)=EV owners; (2)=heat pump owners; (3)=all energy bill payers.

3 Assumptions used to estimate electricity demand of a heat pump and EV

3.1 Heat pump

#	Assumption and the data source	Value
1	Average UK domestic heat demand: DECC (2012, p.4)	450 TWh/year
2	Number of UK households: Office for National Statistics (2016)	27 million
3	Air Source Heat Pump Seasonal Performance Factor[109]: Summerfield et al. (2016, p.65)	2.56
Equation used to compute electricity demand of heat pump using assumptions (1), (2) and (3): $$\text{heat pump electricity demand} = \frac{heat\ demand/no.of households}{SPF_{H2}}$$		
Electricity demand estimate used in quote:		**6,300kWh**[110]

[109] A heat pump delivers more heat than it uses in electricity and is therefore more than 100% efficient (DECC, 2012b). To account for the relative efficiency of a heat pump, the average heat demand in the UK can be adjusted using the Seasonal Performance Factor, which is a measure of how efficiently a heat pump is operating (Ofgem, 2016a) taken from the most recent UK heat pump field trials for air source heat pumps at the system boundary level 2 (Summerfield et al., 2016). Air source heat pumps were chosen because, based on installation data obtained by the author from the Microgeneration Certification Scheme, approximately 80% of heat pumps installed in the UK are air source, a figure which is corroborated by data from the European Heat Pump Association cited in (Hannon, 2015) citing (Nowak et al., 2014) . The system boundary level 2 includes “the heat pump unit and the equipment to make the source energy available for the heat pump” (Zottl et al., 2012, p.5) but excludes the back-up heater and all auxiliary drives.

[110] Based on the assumed values, this should be 6,500kWh but a calculation error was made and so 6,300kWh was used to create the quote. However, this will make only a very minimal difference to the energy bill under the tariff and will have no impact on the energy bill difference between a flat-rate and the TOU tariff.

3.2 EV

#	**Assumption and the data source**	**Value**
1	Battery capacity of Nissan Leaf (most popular EV model in 2015): Manufacturer's website in 2015	30kWh
2	Battery range of Nissan Leaf: Manufacturer's website in 2015	100 miles
3	Average annual mileage driven in UK in 2014: Department for Transport (2015)	7,900 miles
4	Proportion of charging done from home: Based on rapid evidence assessment which indicated that the majority of charging is done at home Knight et al. (2015)[111]	60%
Equation used to compute electricity demand of EV using assumptions (1), (2), (3) and (4): $$\text{EV electricity demand } = \frac{UK\ mileage}{\left(\frac{range}{capacity}\right)} * 0.60$$		
Electricity demand estimate used in quote: **4,200 kWh**		

[111] The figure of 60% was chosen because it represents one possible interpretation of the term 'majority'. Ideally, the quote would have varied depending on different possible home charging behaviours but this would have added substantial extra development work for the website without being necessary for answering the overall research question. However, even if vehicle owners use their home charge point for more than 60% of their charging needs, the impact on electricity demand would, at the time of writing, be relatively small because of the increase in EV efficiency, represented by the range/capacity term in the equation in the table above.

4 Electricity prices used to provide quotes in the Flex Trial

	Flat rate tariff (p/kWh)	TOU tariff (p/kWh)	TOU tariff in UK CLNR trial[112] (p/kWh)
Low	14	11.3	8
Medium	14	14.9	11
High	14	30.6	23
Standing charge	69	Zero	91
Tariff comparison rate[113]	14.02	15.39	11.3

5 Survey questions embedded in the Flex website

Please fill in a few more details below and then click Confirm and Switch.

[1] How many bedrooms does your property have?

Drop down menu: 1 bedroom, 2 bedrooms, 3 bedrooms, 4+ bedrooms

[2] Do you have any of the following in your house? Select any that you have in your home.

[112] Source Figure 25 from (Frontier Economics, 2012). Prices read from graph by eye so actual amounts may not be exact.

[113] The tariff comparison rate was developed by Ofgem and it provides a single figure accounting for standing charges, the unit rate and any discounts based on average electricity consumption.

Radio buttons: Heat pump, electric vehicle – leased, electric vehicle – owned, Washing machine, Tumble dryer, Washer dryer, dishwasher, Electric shower, Solar panels with a home battery (for storage)

[3] What is your main method of heating your home?

Drop down menu: Gas central heating, Electric night storage, Heat pump, Underfloor heating, Other gas, Other electric, Other, Don't know.

[4] Do you have a smart meter fitted at this address?[114]

Radio buttons: Yes, No, Don't know

[5] Do you have an Economy 7 meter?[115]

Radio buttons: Yes, No, Don't know

[ ] Tick this box if you have read and are happy with the terms and conditions.[116]

Confirm and Switch [button]

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[114] This question had a '?' icon adjacent to it that explained what a smart meter is as follows: ""Smart meters can only be installed by an energy supplier. Smart meters send your meter readings directly to your energy company."

[115] This question had a '?' adjacent to it that explained what an Economy 7 tariff is as follows: ""If you pay less for the electricity you use overnight or if your meter has two dials on it, marked 'low'/'high' or 'day'/'night' then you have an Economy 7 meter."

[116] The word 'terms and conditions' was hyperlinked to a document containing the standard terms and conditions for an energy tariff provided by the energy supplier that designed the TOU tariff used in the Flex trial.

6 Average treatment effect of price comparison and tailoring on all binary outcomes in the Flex Trial (logit robustness check)

	Control vs. Price			Control vs. Tailored			Price vs. Control		
Outcome=	(1) Get quote	(2) Switch to us icon	(3) Switched	(4) Get quote	(5) Switch to us icon	(6) Switched	(7) Get quote	(8) Switch to us icon	(9) Switched
Price comparison	-0.013** (0.004)	-0.002 (0.185)	-0.002+ (0.082)						
Tailored				-0.011** (0.008)	-001 (0.463)	-0.002* (0.030)	0.001 (0.873)	0.001 (0.610)	-0.001 (0.407)
Returning visitor	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
Mobile visitor	-0.032*** (0.000)	-0.012*** (0.000)	-0.001*** (0.000)	-0.034*** (0.000)	-0.013*** (0.000)	-0.005*** (0.000)	-0.022*** (0.000)	-0.010*** (0.000)	-0.003* (0.013)
Observations	4288	4288	4288	4276	4276	4276	4280	4280	4280
Pseudo R^2	0.037	0.097	0.140	0.042	0.102	0.188	0.021	0.060	0.045

Notes: Logit model estimated with robust standard errors in which the coefficients represent marginal effects estimated at the mean value of the treatment dummy variables. *p*-values in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 Treatment effect of price comparison on mobile visitors in the Flex Trial (logit robustness check)

Outcome=	(1) Got a quote	(2) Switch to us icon	(3) Switched
Price comparison	-0.023*	-0.01^{+}	-0.004*
	(0.015)	(0.071)	(0.022)
Mobile visitor	-0.037***	-0.014***	-0.010***
	(0.000)	(0.000)	(0.000)
Mobile visitor*Price comparison	0.013	0.005	0.004^{+}
	(0.225)	(0.211)	(0.081)
Observations	4303	4303	4303
Pseudo R^2	0.039	0.101	0.154

Notes: Logit model estimated with robust standard errors in which the coefficients represent marginal effects estimated at the mean value of the treatment dummy variables.
p-values in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

8 Questionnaire used in the Population-Based Survey Experiment

D_sex_age_working	D1_gender	**What is your gender?** Male Female
	D2_age	**Please state your age.** ----------

<table>
<tr><td>D_region</td><td>

Where do you currently live? The map below may help you.

<table>
<tr><td>D4_region</td><td>

I live in...

<table>
<tr><td>◌ North East</td><td>◌ South East</td></tr>
<tr><td>◌ North West</td><td>◌ South West</td></tr>
<tr><td>◌ Yorkshire & Humberside</td><td>◌ Wales</td></tr>
<tr><td>◌ East Midlands</td><td>◌ Scotland</td></tr>
<tr><td>◌ West Midlands</td><td>◌ Northern Ireland</td></tr>
<tr><td>◌ East of England</td><td>◌ Do not live in the UK</td></tr>
<tr><td>◌ London</td><td></td></tr>
</table>

</td></tr>
</table>

</td></tr>
<tr><td>Q1</td><td>

Are you financially responsible or jointly financially responsible for paying the gas and/or electricity bills in your household?

Please select one response only.

◌ Yes, solely responsible
◌ Yes, jointly responsible
◌ No

</td></tr>
<tr><td></td><td></td></tr>
<tr><td>Q2</td><td>

Which of the following companies supplies your electricity?

Please select one response only.

◌ British Gas
◌ Bulb
◌ Co-operative Energy
◌ Ebico
◌ E.ON

</td></tr>
</table>

	◯ Ecotricity ◯ EDF Energy ◯ First Utility ◯ Flow Energy ◯ Good Energy ◯ Green Energy UK ◯ Green Star Energy ◯ LoCO2 Energy ◯ M&S Energy ◯ npower ◯ Ovo Energy ◯ Places for People Energy ◯ Sainsbury's Energy ◯ Scottish Hydro ◯ Scottish Power ◯ Spark Energy ◯ SSE ◯ Utilita ◯ Utility Warehouse ◯ Other (please specify) ____ ◯ Don't know
Info	**The next two pages will show you details of a number of electricity tariffs. Some of these tariffs charge a different price for electricity depending on the time that you use it.** **Tariffs like these might become more common when more people have smart meters, because these meters can record electricity use every half hour and show you your usage in real time on an in-home display.** **At the moment, the average electricity tariff in Great Britain charges about 14p per unit of electricity.** **Please read the descriptions imagining the tariffs are on offer to you now, and answer the questions.**
Random_BlockCopy1	This is the block respondents will be allocated to. Please select one response only. ◯ BLOCK_1Copy1 ◯ BLOCK_2Copy1 ◯ BLOCK_3Copy1 ◯ BLOCK_4Copy1

	○ BLOCK_5Copy1 ○ BLOCK_6Copy1
Block1_control **Include: Random_BlockCopy1 IS BLOCK_1Copy1**	**Q5a Imagine this new electricity tariff was available to you today...** **The *SuperSaver* tariff charges three different rates for electricity: super off-peak, off-peak and peak.** **• Super off-peak rate is 6p per unit, and applies 11pm-6am on weekdays and all weekend.** **• Off-peak rate is 12p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.** **• Peak rate is 24p per unit, and applies 4-8pm on weekdays.** **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **Based on the information you have read, please indicate whether you would like to switch to the above tariff, or stick with the tariff you are currently on. Please select the option reflecting your true preference even if you don't think you would be able to switch in reality (such as if you are on a fixed term contract).** Please select one response only. ○ Switch to the tariff shown above ○ Stick with the tariff I am currently on **Q6a Compared to your current tariff, what level of annual savings would be enough to persuade you to switch to this tariff? Please type a number (using digits) in the box.** **The *SuperSaver* tariff charges three different rates for electricity: super off-peak, off-peak and peak.** **• Super off-peak rate is 6p per unit, and applies 11pm-6am on weekdays and all weekend.** **• Off-peak rate is 12p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.**

		• **Peak rate** is 24p per unit, and applies 4-8pm on weekdays. **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **I would have to save...per year** Please enter a numeric response in £ only.
Block2_Fate_rate_tariff **Include: Random_BlockCopy1 IS BLOCK_2Copy1**	Q5aCopy1	**Imagine this new electricity tariff was available to you today...** **The *SuperSaver* tariff charges a single rate of 12p per unit for electricity, which is amongst the lowest on the market.** **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **Based on the information you have read, please indicate whether you would like to switch to the above tariff, or stick with the tariff you are currently on. Please select the option reflecting your true preference even if you don't think you would be able to switch in reality (such as if you are on a fixed term contract).** Please select one response only. ○ Switch to the tariff shown above ○ Stick with the tariff I am currently on
	Q6aCopy1	**Compared to your current tariff, what level of annual savings would be enough to persuade you to switch to this tariff? Please type a number (using digits) in the box.** **The *SuperSaver* tariff charges a single rate of 12p per unit for electricity, which is amongst**

		the lowest on the market. **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **I would have to save...per year** Please enter a numeric response in £ only.
Block3_Bill_protection **Include: Random_BlockCopy1 IS BLOCK_3Copy1**	Q5aCopy2	**Imagine this new electricity tariff was available to you today...** **The *SuperSaver* tariff charges three different rates for electricity: super off-peak, off-peak and peak.** **• Super off-peak rate is 6p per unit, and applies 11pm-6am on weekdays and all weekend.** **• Off-peak rate is 12p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.** **• Peak rate is 24p per unit, and applies 4-8pm on weekdays.** **This tariff comes with a six month bill protection guarantee. We will automatically refund you if you spend more on this tariff than your old one - so you can't lose out.** **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **Based on the information you have read, please indicate whether you would like to switch to the above tariff, or stick with the tariff you are currently on. Please select the option reflecting your true preference even if you don't think you would be able to switch in reality (such as if you are on a fixed term contract).** Please select one response only. ◯ Switch to the tariff shown above

		○ Stick with the tariff I am currently on
	Q6aCopy2	**Compared to your current tariff, what level of annual savings would be enough to persuade you to switch to this tariff? Please type a number (using digits) in the box.** **The *SuperSaver* tariff charges three different rates for electricity: super off-peak, off-peak and peak.** **• Super off-peak rate is 6p per unit, and applies 11pm-6am on weekdays and all weekend.** **• Off-peak rate is 12p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.** **• Peak rate is 24p per unit, and applies 4-8pm on weekdays.** **This tariff comes with a six month bill protection guarantee. We will automatically refund you if you spend more on this tariff than your old one - so you can't lose out.** **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **I would have to save...per year** Please enter a numeric response in £ only.
Block4_ElectricVehicleTariff **Include: Random_BlockCopy1 IS BLOCK_4Copy1**	Q5aCopy3	**Imagine this new electricity tariff was available to you today...** **The *Electric Vehicle* tariff charges three different rates for electricity: super off-peak, off-peak and peak.** **• Super off-peak rate is 6p per unit, and applies 11pm-6am on weekdays and all weekend.** **• Off-peak rate is 12p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.** **• Peak rate is 24p per unit, and applies 4-8pm on weekdays.** **This tariff is particularly suited to people with**

		<u>electric vehicles, who use more electricity than the average household (that mostly just use electricity for lighting and kitchen appliances) and could therefore save more money by charging their vehicle during the cheap off-peak or super off-peak times.</u> **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **Based on the information you have read, please indicate whether you would like to switch to the above tariff, or stick with the tariff you are currently on. Please select the option reflecting your true preference even if you don't think you would be able to switch in reality (such as if you are on a fixed term contract).** Please select one response only. ○ Switch to the tariff shown above ○ Stick with the tariff I am currently on
	Q6aCopy3	**Compared to your current tariff, what level of annual savings would be enough to persuade you to switch to this tariff? Please type a number (using digits) in the box.** **The *<u>Electric Vehicle</u>* tariff charges three different rates for electricity: super off-peak, off-peak and peak.** **• <u>Super off-peak rate</u> is 6p per unit, and applies 11pm-6am on weekdays and all weekend.** **• <u>Off-peak rate</u> is 12p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.** **• <u>Peak rate</u> is 24p per unit, and applies 4-8pm on weekdays.** **<u>This tariff is particularly suited to people with electric vehicles, who use more electricity than the average household (that mostly just use electricity for lighting and kitchen appliances) and could therefore save more money by charging their vehicle during the cheap off-</u>**

		<u>peak or super off-peak times.</u> **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **I would have to save...per year** Please enter a numeric response in £ only.
Block5_Labelling **Include: Random_BlockCopy1 IS BLOCK_5Copy1**	Q5aCopy4	**Imagine this new electricity tariff was available to you today...** **The *<u>SuperSaver</u>* tariff charges three different rates for electricity: super off-peak, off-peak and peak.** **• <u>Super off-peak rate</u> is 6p per unit, and applies 11pm-6am on weekdays and all weekend.** **• <u>Off-peak rate</u> is 12p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.** **• <u>Peak rate</u> is 24p per unit, and applies 4-8pm on weekdays.** **<u>This is a *GoodGrid Approved* tariff as certified by the GB energy regulator. Approved trials have shown that most people who sign up save money, and that it helps the electricity grid to run more efficiently.</u>** **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **Based on the information you have read, please indicate whether you would like to switch to the above tariff, or stick with the tariff you are currently on. Please select the option reflecting your true preference even if you don't think you would be able to switch in reality (such as if you are on a fixed term contract).** Please select one response only. ○ Switch to the tariff shown above

	◌ Stick with the tariff I am currently on **Q6aCopy4** **Compared to your current tariff, what level of annual savings would be enough to persuade you to switch to this tariff? Please type a number (using digits) in the box.** **The *SuperSaver* tariff charges three different rates for electricity: super off-peak, off-peak and peak.** **• Super off-peak rate is 6p per unit, and applies 11pm-6am on weekdays and all weekend.** **• Off-peak rate is 12p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.** **• Peak rate is 24p per unit, and applies 4-8pm on weekdays.** **This is a *GoodGrid Approved* tariff as certified by the GB energy regulator. Approved trials have shown that most people who sign up save money, and that it helps the electricity grid to run more efficiently.** **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **I would have to save...per year** Please enter a numeric response in £ only.
Block6_Disaggregation **Include: Random_BlockCopy1 IS BLOCK_6Copy1**	**Q5aCopy5** **Imagine this new electricity tariff was available to you today...** **The *SuperSaver* tariff charges three different rates for electricity: super off-peak, off-peak and peak.** **• Super off-peak rate is 6p per unit, and applies 11pm-6am on weekdays and all weekend.** **• Off-peak rate is 12p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.** **• Peak rate is 24p per unit, and applies 4-8pm on weekdays.**

	<u>When you sign up to this tariff you will also get access to a service showing your household electricity use broken down by appliance (e.g. washing machine, oven, etc.). This will show you exactly how much electricity your washing machine (for example) is using in a day or week, and what times you have used it. This makes it easier to decide what to use when to save money.</u> **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **Based on the information you have read, please indicate whether you would like to switch to the above tariff, or stick with the tariff you are currently on. Please select the option reflecting your true preference even if you don't think you would be able to switch in reality (such as if you are on a fixed term contract).** Please select one response only. ○ Switch to the tariff shown above ○ Stick with the tariff I am currently on
Q6aCopy5	**Compared to your current tariff, what level of annual savings would be enough to persuade you to switch to this tariff? Please type a number (using digits) in the box.** **The *<u>SuperSaver</u>* tariff charges three different rates for electricity: super off-peak, off-peak and peak.** **• <u>Super off-peak rate</u> is 6p per unit, and applies 11pm-6am on weekdays and all weekend.** **• <u>Off-peak rate</u> is 12p per unit, and applies on 6am-4pm and 8pm-11pm on weekdays.** **• <u>Peak rate</u> is 24p per unit, and applies 4-8pm on weekdays.** **<u>When you sign up to this tariff you will also get access to a service showing your household electricity use broken down by appliance (e.g.</u>**

	washing machine, oven, etc.). This will show you exactly how much electricity your washing machine (for example) is using in a day or week, and what times you have used it. This makes it easier to decide what to use when to save money. **There is a standing charge of 22p per day, which is amongst the best on the market. Unit prices are fixed for a year, but you can switch away at any time without paying a fee.** **I would have to save...per year** Please enter a numeric response in £ only.
Manipulation check	**We'd now like you to consider the following statements and indicate whether they are true or false based on the information you've received about the tariff that you just saw.** 1. The tariff you just saw charged one price for your electricity regardless of what time of day you're using it 2. The tariff came with a six month bill protection guarantee, meaning you would be automatically refunded if you spend more on this tariff than your old one. 3. The tariff was described as particularly suitable for people with electric vehicles. 4. The tariff was GoodGrid Approved by the GB energy regulator. 5. Signing up to the tariff would give you access to a service showing your household electricity use broken down by appliance. Please drag each item to a category or click on the category header. You can change your choice by dragging the statement into the other box.
	[INTERVENING ADDITIONAL INTERVENTIONS ADMINISTERED – THESE WERE REMOVED BECAUSE THEY ARE NOT RELEVANT TO THIS THESIS]
Q11	**The following questions are about your present electricity tariff and supplier.** **In which of the following ways do you pay for the electricity you use?** Please select one response only.

	◌ Monthly direct debit ◌ Quarterly direct debit ◌ Cheque, cash, card or bank transfer on receipt of your bill ◌ Prepayment meter ◌ Other [ ] ◌ Don't know
Q12	**Are you currently on a 'time of use' tariff such as Economy 7 or Economy 10 (i.e. you pay less for electricity at certain times of the night or day)?** Please select one response only. ◌ Yes - Economy 7 ◌ Yes - Economy 10 ◌ Yes - other time of use tariff ◌ No ◌ Don't know
	[INTERVENING ADDITIONAL INTERVENTIONS ADMINISTERED – THESE WERE REMOVED BECAUSE THEY ARE NOT RELEVANT TO THIS THESIS]
Q17	**We would now like to ask you some questions about your household. Before you start, a household is:** **• one person living alone; or** **• a group of people (not necessarily related) living at the same address who share cooking facilities and share a living room or sitting room or dining area** **Counting yourself, how many people, including children, usually live in your household?** Please select one response only. ◌ 1 ◌ 2 ◌ 3 ◌ 4 ◌ 5 ◌ 6 ◌ 7 ◌ 8+
Q18	**And how many of the people living in your household are aged 15 and under?** Please select one response only. ◌ 0

	○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8+
Q19	**At which of the following times is at least one household member over the age of 18 usually at home?** Please select all that apply. ☐ Mornings in the week (roughly 7am-9am) ☐ Day time in the week (roughly 9am-5pm) ☐ Evening in the week (roughly 5pm-11pm) ☐ Overnight in the week (roughly 11pm-7am) ☐ Weekends (any time)
Q20	**Is the house or flat in which you live…?** Please select one response only. ○ Owned outright ○ Owned with a mortgage or loan ○ Rented from the council ○ Rented from a housing association ○ Rented from someone else (e.g. a private landlord) ○ Rent free ○ Don’t know
Q21	**What is your main method of heating your home?** Please select one response only. ○ Gas central heating ○ Other gas heating (e.g. single point gas fire) ○ Electric night storage heaters (a heater that mainly heats up overnight and releases heat during the day) ○ Other electric heating (e.g. single point electric fires, convection heaters or electric boiler) ○ Solid fuel central heating (e.g. coal, wood) ○ Oil central heating ○ Other solid fuel heating (e.g. coal, wood) ○ Calor gas, propane or LPG ○ District heating ○ Heat pump (ground or air source) ○ Other (please specify) ○ Don't know

Q22	**Do you have any of the following appliances in your home?** Please select one response for each item.
Q23	**Do you have a 'smart thermostat'? A smart thermostat allows you to change your heating settings using a smartphone app or from a computer.** Please select one response only. ○ Yes ○ No ○ Don't know
Q24	**Does your household lease or own an electric vehicle or plug-in hybrid electric vehicle? An electric vehicle runs only on electricity which is stored in a battery in the vehicle and is plugged into the mains electricity for charging. A plug-in hybrid electric vehicle combines a petrol or diesel engine with an electric motor - it can be plugged into the mains electricity for charging.** Please select one response only. ○ Yes - own an electric vehicle ○ Yes - lease an electric vehicle ○ Yes - own a plug-in hybrid vehicle ○ Yes - lease a plug-in hybrid vehicle ○ No ○ Don't know
D4	**Please select the option that you think best describes the area you live in.** Please select one response only. ○ Urban area - cities or towns ○ Suburban area – residential areas on the outskirts of cities and towns

Q22 response grid:

	Yes - with delay timer (allows you to set your machine to run at a later time)	Yes - without delay timer	Not sure / don't know	I don't own this appliance
Washing machine	○	○	○	○
Tumble dryer	○	○	○	○
Washer-dryer	○	○	○	○
Dishwasher	○	○	○	○

	◌ Rural area - villages or hamlets
D_socialgrade	D5_socialgrade — **We would now like you to think about the main income earner in your household, that is the person with the highest income. This may be you or it might be someone else.** **<u>Which of the following groups does the main income earner in your household belong to?</u>** *[If the main income earner is retired with an occupational pension, please enter their former occupation. Please only enter 'retired' if the main income earner is only receiving the state pension. If the main income earner has been unemployed for a period of less than 6 months, please answer based on their previous occupation.]* ◌ Higher managerial/ professional/ administrative (e.g. established doctor, solicitor, board director in large organisation (200+ employees), top level civil servant/ public service employee, head teacher etc.) ◌ Intermediate managerial/ professional/ administrative (e.g. newly qualified (under 3 years) doctor, solicitor, board director of small organisation, middle manager in large organization, principal officer in civil service/ local government etc.) ◌ Supervisory or clerical/ junior managerial/ professional/ administrator (e.g. office worker, student doctor, foreman with 25+ employees, sales person, student teacher etc.) ◌ Skilled manual worker (e.g. skilled bricklayer, carpenter, plumber, painter, bus/ ambulance driver, HGV driver, unqualified teaching assistant, pub/ bar worker etc.) ◌ Semi-skilled or unskilled manual worker (e.g. manual jobs that

	require no special training or qualifications, apprentices to be skilled trades, caretaker, cleaner, nursery school assistant, park keeper, non-HGV driver, shop assistant etc.) ○ Student ○ Retired and living on state pension only ○ Unemployed for over 6 months or not working due to long term sickness
D7_employment	**Which of these applies to you?** ○ Working full time (30 or more hours per week) ○ Working part time (8 - 29 hours per week) ○ Working part time (Less than 8 hours a week) ○ Full time student ○ Retired ○ Unemployed ○ Other not working
D6	**What is your annual pre-tax household income?** **By 'household income' we mean the total income received from all sources, including wages earnt by you, your partner and/or any other earner in the household, bonuses, pension income, benefits or rents and before tax deductions.** **Your data will be kept confidential and not passed on to any third parties.** Please select one response only. ○ Up to £10,000 a year ○ £10,001 to £20,000 a year ○ £20,001 to £30,000 a year ○ £30,001 to £40,000 a year ○ £40,001 to £50,000 a year ○ £50,001 to £60,000 a year ○ £60,001 to £70,000 a year ○ £70,001 to £80,000 a year ○ £80,001 to £100,000 a year ○ £100,001 to £120,000 a year

	◌ Over £120,001 a year ◌ Prefer not to say
D8	**Do you consider yourself to have a disability or chronic illness?** Please select one response only. ◌ Yes ◌ No ◌ Don't know ◌ Prefer not to say

9 Average treatment effect of individual control group interventions on willingness to switch to the TOU tariff in the Population-Based Survey Experiment (robustness check)

Outcome=intends to switch to TOU tariff (1=yes; 0=no)	(1) OLS	(2) Logit
Bill protection	-0.011	-0.011
	(0.705)	(0.705)
EV tailored marketing	-0.154^{***}	-0.168^{***}
	(0.000)	(0.000)
Regulator approved tariff	0.001	0.001
	(0.979)	(0.979)
Disaggregated energy feedback	-0.053^{+}	-0.051^{+}
	(0.074)	(0.074)
Observations	2464	2464
R^2	0.016	0.014

Notes: Column 1 reports the results of an OLS model. Column 2 reports the results of a logit model in which the coefficients represent marginal effects estimated at the mean value of the treatment dummy variables. All models estimated using robust standard errors.
p-values in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

10 Manipulation checks: did participants pay attention and perceive the tailoring in the Population-Based Survey Experiment?

	(1) Control group (%)	(2) Tailored group (%)	(3) P-value (1)=(2)
Correctly answered the question on tariff structure	75	72	0.132
Agreed the tariff was described as being suitable for EV owners	35	80	0.000

Notes: The p-values reported in column 3 were obtained from an OLS regression of whether the individual correctly answered the question on tariff structure against the treatment dummy variable indicating whether the participant was in the tailored group (1) or the control group (0) and another regression in which a dummy variable indicating whether the individual agreed that the tariff was described as being suitable for EV owners was regressed against the tailored treatment dummy. For the tariff structure question, participants were asked to indicate whether they agreed or disagreed with the following statement "The tariff you just saw charged one price for your electricity regardless of what time of day you're using it" and for the tailored treatment question, whether they agreed or disagreed with the following statement "The tariff was described as particularly suitable for people with electric vehicles".

11 Treatment effect of tailoring on EV and non EV owners in the Population-Based Survey Experiment (logit robustness check)

Outcome=intends to switch to TOU tariff (1=yes; 0=no)	(1) Has EV	(2) No EV	(3) Don't know EV
Tailored dummy	-0.186***	0.033	-0.156***
	(0.000)	(0.681)	(0.000)
Has EV	0.394***		
	(0.000)		
Tailored * Has EV	0.180^{+}		
	(0.075)		
No EV		-0.288***	
		(0.000)	
Tailored * No EV		-0.223**	
		(0.010)	
Don't know EV			-0.003
			(0.973)
Tailored * Don't know EV			0.165
			(0.402)
Observations	2464	2464	2464
Pseudo R^2	0.055	0.048	0.013

Notes: Logit model estimated with robust standard errors in which the coefficients represent marginal effects estimated at the mean value of the treatment dummy variables.
p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

12 Emails sent to EV owners in OLEV trial

12.1 Generic email

Email subject line: Switch your energy tariff to save £300.

Email preview text (the preview text people see in their inbox): Dear [First Name],

Your current energy tariff may no longer be appropriate. Find out how to choose the right tariff to save £300.

Body text:

Office for Low Emission Vehicles | UCL ENERGY INSTITUTE | energy saving trust

You could save over £300 by switching your energy tariff

Dear **Sir/Madam**,

We recommend that you consider switching your electricity tariff.

We've partnered with the UCL Energy Institute and the Energy Saving Trust to create brand new top tips on how to choose the right tariff.

Switching tariff could save you over £300 a year.

Click here for five top tips on how to choose the right energy tariff

"I have to say that this advice is incredibly useful! I didn't know most of this stuff."

– UK energy bill payer

Visit the Energy Saving Trust's website today for five top tips on how to save money on your energy bills.

Yours sincerely,

The Office for Low Emission Vehicles, the UCL Energy Institute and the Energy Saving Trust

P.S. Wondering whether Economy 7, which gives you a cheaper rate overnight, could help lower your energy bills?

Visit our online guide today to find out how much money you could save on Economy 7 based on how you use energy at home.

Office for Low Emission Vehicles | UCL ENERGY INSTITUTE | energy saving trust

Wondering why you got this email? You're receiving this email because you received a grant from the UK Government for your electric vehicle and you agreed to be contacted as a condition of getting this grant. If you do not wish to receive emails about electricity tariffs click **here** to unsubscribe.

12.2 Tailored email

Email subject line: Cut the cost of charging your electric car by £300.

Email preview text (the preview text people see in their inbox): Dear [First Name], Now that you own an electric car, your current energy tariff may no longer be appropriate. Find out how to choose the right tariff for your EV to save £300.

Body text:

Office for Low Emission Vehicles

UCL ENERGY INSTITUTE

energy saving trust

You could save over £300 by switching your energy tariff, equivalent to 11,000 free electric miles a year

Dear **Sir/Madam**,

Now that you've bought an electric car, we recommend that you consider switching your electricity tariff. That's because, if you're charging your car at home, your electricity bill will go up.

We've partnered with the UCL Energy Institute and the Energy Saving Trust to create brand new top tips on how to choose the right tariff for your electric car.

Switching tariff could save you more than it costs you to charge your electric car for a whole year.

Click here for five top tips on how to choose the right energy tariff for your electric car

"I have to say that this advice is incredibly useful!
I didn't know most of this stuff and I've had an electric car for years."

– UK electric car owner

Visit the Energy Saving Trust's website today for five top tips on how to save money when you charge your electric car from home.

Yours sincerely,

The Office for Low Emission Vehicles, the UCL Energy Institute and the Energy Saving Trust

P.S. Wondering whether Economy 7, which gives you a cheaper rate overnight, might help you charge your car for less?

Visit our online guide today to find out how much money you could save on Economy 7 based on how much you charge your electric car from home.

Office for Low Emission Vehicles

UCL ENERGY INSTITUTE

energy saving trust

Wondering why you got this email? You're receiving this email because you received a grant from the UK Government for your electric vehicle and you agreed to be contacted as a condition of getting this grant. If you do not wish to receive emails about electricity tariffs for your electric car click **here** to unsubscribe.

13 The impact of tailored emails on open rates and click-through rates in OLEV trial (logit robustness check)

Outcome=	(1) Opened	(2) Clicked	(3) Unsubscribed
Treatment dummy	0.060***	0.094***	-0.005**
	(0.000)	(0.014)	(0.012)
Observations	7038	7038	7038
Pseudo R^2	0.003	0.009	-

Notes: All models estimated using logit with reported coefficients representing marginal effects estimated at the means with robust standard errors.
p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

14 Explaining email open rates by time since EV purchased in OLEV trial (logit robustness check)

Outcome = opened email (1=yes; 0=no)	(1) Continuous	(2) Log transformed	(3) Quartiles	(4) Dummy	(5) Dummy with controls
Time since vehicle purchased in months (p value)	-0.001* (0.027)				
Log of time since purchase in months (p value)		-0.03* (0.005)			
Quartiles of time since purchase in months (p value)			-0.012* (0.028)		
Purchased vehicle three months ago (p value)				0.344** (0.003)	0.303** (0.010)
Individual and vehicle control variables					X
Observations	7038	7038	7038	7038	2891
Pseudo R^2	0.001	0.001	0.001	0.001	0.014

Notes: All models estimated using logit with reported coefficients representing marginal effects estimated at the means with robust standard errors. The sample size in Model 5 is smaller because there are missing observations for the covariates, however a further robustness check which includes only controls for missing variables provides similar results. All regressions were estimated with robust standard errors.

p-values in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

15 Explaining email open rates by time since EV purchased with controls for missing data (robustness check)

Outcome= opened email (1=yes; 0=no)	(1) OLS	(2) Logit
Purchased vehicle three months ago	0.279**	0.30**
	(0.001)	(0.009)
Missing data on gender	-0.007	-0.01
	(0.880)	(0.882)
Missing employment status	0.172	0.25
	(0.567)	(0.529)
Missing number of cars in household	-0.017	-0.02
	(0.459)	(0.455)
Missing data on whether EV will be main household vehicle	-0.287*	-0.37
	(0.042)	(0.169)
Missing data on age group	0.016	0.02
	(0.445)	(0.441)
Missing data on estimated annual mileage	-0.212	-0.29
	(0.479)	(0.465)
Observations	7038	7038
R^2	0.007	0.005

Notes: Model 1 reports the results of an OLS regression in which the independent variable is a dummy variable which takes on the value one if the recipient received their EV three months ago and zero if the recipient received their EV four months or more ago, with the addition of dummy variables controlling for whether the recipient did not report the status of the variables included in column 5 of Table 37 in Chapter 7. Model 2 reports the results of the same variable specification as model 1 but estimated using logit with reported coefficients representing marginal effects estimated at means. All models estimated using robust standard errors.
p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Annex 1:

Policy contributions and implications

1 The Department for Business, Energy and Industrial Strategy (BEIS)

1.1 UK Smart Meter Implementation Programme Cost Benefit Analysis

BEIS could consider commissioning research to increase the precision of estimates of uptake to TOU tariffs, considering that the results of this study suggest that uptake could either be moderately higher or substantially lower than required for realising the business case for smart meters (BEIS, 2016b). This research would ideally measure uptake to TOU tariffs to which consumers can switch to rather than using surveys. For more details see Annex 2, section 1.

1.2 Power to Switch campaign

BEIS runs an annual 'Power to Switch' campaign that aims to prompt consumers to switch tariff. When encouraging EV owners to switch tariff, it will be more effective to target EV owners as a distinct group than to rely on generic mass switching campaigns, which target the 'average energy bill payer'.

Once the market for EVs is more advanced, the BEIS 'Power to Switch' campaign could include posters that are specifically tailored to EV owners to encourage them to switch to TOU tariffs. Based on the results of this trial, these messages should emphasise the cost savings for home charging their vehicle rather than the potential reduction in their household energy bill.

1.3 Gaining consent for vehicle-to-grid services

BEIS has recently invested £20 million to develop vehicles capable of returning electricity to the national grid, which could also help to balance electricity supply and demand in the future.[117] The same challenges described in this thesis for how to encourage adoption of TOU tariffs are also likely to apply to obtaining consent from EV owners to provide vehicle-to-grid services.

Whilst vehicle-to-grid is a different proposition to the TOU tariffs presented to participants in this thesis, the results suggest that future research could usefully test whether tailored marketing could be used to obtain consent from EV owners to deliver such services.

2 Office for Gas and Electricity Markets (Ofgem)

The implications of this research for the British energy regulator Ofgem were communicated to Ofgem in response to its recent public consultation "Helping consumers make informed choices – proposed changes to rules around tariff comparability and marketing" and is available online.[118] The response was co-authored by myself and a colleague at the UCL Energy Institute but the sections based on this thesis were written by me and are summarised below.

2.1 Future regulation of tariff marketing

The results suggest that tariffs which are called 'EV tariffs' are likely to be more popular amongst EV owners than generically named TOU tariffs such as 'off-peak saver' tariff. To ensure the best outcomes for consumers, a number of changes to existing regulation may be required.

[117] Department for Transport "Innovative vehicle to grid technology to receive £20 million", 8 July 2017. https://www.gov.uk/government/news/innovative-vehicle-to-grid-technology-to-receive-20-million

[118] Nicolson, M. and Fell, M. "Response to Ofgem consultation on 'Helping consumers make informed choices – proposed changes to rules around tariff comparability and marketing'", 28 November 2016. https://www.ofgem.gov.uk/system/files/docs/2017/01/ucl_energy_institute_response.pdf.

The first is that the Universal Supply Obligation which “requires suppliers to offer terms to all domestic customers that make a valid request” to protect customers against suppliers cherry-picking desirable customers may prevent suppliers from offering EV tariffs (or other group-specific tariffs). The reasons for this are outlined by Sara Bell, the CEO of the startup energy supplier Tempus Energy in its letter to Ofgem:

> *[The Universal Supply Obligation is] currently causing Tempus and other innovative suppliers significant problems in bringing their innovations to market…We consider the EU obligation of universal supply to mean that every customer is entitled to an electricity supply, not that innovative suppliers offering niche deals (for example for customers with electric vehicles or demand flexible customers) need to offer these deals to all customers. Being overly restrictive risks causing confusion for customers as suppliers are forced to offer supply to customers who are not suitable for the product…* (Bell, 2016, pp.3–5).

Second, labelling tariffs ‘EV tariff’ will only lead to better consumer decision making, if the so-called ‘EV’ tariffs really are the cheapest option for an EV owner compared to any other tariff. It is acknowledged that suppliers could take advantage of labelling effects to drive customers to more expensive tariffs and regulation may be required to prevent this.

Third, to make it easier for EV owners or other high electricity consuming groups to compare tariffs – including flat-rate and TOU tariffs – price comparison websites should be encouraged to enable EV owners to identify themselves as ‘EV owners’, to improve the accuracy of price comparison results and cheapest tariff messages. Currently, price comparison websites allow users to input their electricity consumption manually or to use an estimate (based on the median household electricity usage). However, the median (3,300 kWh) is likely to be very inaccurate for EV owners, the majority of whom are likely to be charging at home (see Chapter 7) and therefore with much higher electricity usage (depending on the efficiency of the vehicle and occupants' use patterns).

Fourth, the decision on whether to introduce a "requirement that any calculation by a supplier of the estimated annual cost figure[119] should be internally consistent (ie calculated in the same way by any given supplier for all tariffs and for all customers over time)?" (Ofgem, 2016b, p.7), should be informed by future empirical research testing methods of generating accurate price comparisons for TOU tariffs (see Section 8 of Annex 2).

2.2 Ofgem programme of trials

Given the lack of evidence on how to increase uptake to TOU tariffs without using opt-out enrolment, it is recommended that Ofgem use its recently introduced licence condition (SLC 32A) which requires suppliers to participate in customer switching trials, to test methods of increasing switching rates to TOU tariffs and not just the best available flat-rate tariffs, as was the focus of the CMA's (2016a) inquiry into the energy market. Trialling methods of increasing uptake to TOU tariffs is in alignment with all four of Ofgem's major themes: promoting value for money, promoting security of supply, promoting sustainability and delivering government programmes.

Where commercial TOU offerings are not available for testing, it would be worth exploring the option of running trials in collaboration with Ofgem's Innovation Link, which has recently established a 'regulatory sandbox' that would permit energy

[119] The estimated annual cost figure is the figure provided by suppliers and price comparison websites to consumers which presents them with the estimated annual energy bill under one or more tariffs.

suppliers and other organisations to test new offerings amongst consumers prior to full launch (Ofgem, 2017c).

Another option may be for such research to be conducted through the Virtual Energy Company, a testbed for research teams and companies to run trials of innovations in a constrained but realistic setting. The Virtual Energy Company will be funded by EPSRC through the Smart Meter Research Portal (SMRP) project (grant number: EP/P032761/1) and aims to either simulate or carry out the day-to-day operations of supplying participating customers with energy, including billing, customer support, etc. in order to achieve its objectives.

The thesis also provides some specific implications for what prompts are most likely to be effective. These are summarised below:

- Switching prompts may be more effective when tailored to specific consumer groups rather than aimed at the ‘average energy bill payer’, as current campaigns usually are. Ofgem could experiment with using prompts which are segmented by specific consumer groups.
- Although the CMA (2016a) recommends trialling tariff switching prompts delivered to consumers via their supplier, the OLEV trial suggests that switching prompts can be highly effective when sent from organisations other than energy suppliers, such as the Office for Low Emission Vehicles. Indeed, energy suppliers may not be the best organisations to deliver these prompts given that research finds that the vast majority (81%) of consumers do not pay attention to any other information in their bills except the amount they owe, suggesting that they may ignore prompts that are included on bills from their supplier (Consumer Focus, 2011). Potential organisations include councils, housing associations, schools and

people's employers. Ideally, a trial would compare the effectiveness of each of these types of messengers.

- Whilst the start of the heating season or the termination of a consumer's existing tariff may seem like an ideal time to prompt people to switch, the OLEV trial suggests that Ofgem could usefully trial the effectiveness of sending tariff switching prompts at different moments in the year or at different moments in a consumer's life. Using timely prompts to encourage consumers to switch tariff was also proposed by The Behavioural Insights Team in its consumer report for Citizens Advice (Costa et al., 2016). One potential option would be for Ofgem to partner with estate agents to provide new home buyers or new renters with information about switching tariff when they receive the keys to their new property.

3 The Office for Low Emission Vehicles (OLEV)

The results also have implications for OLEV, the partner organisation for the OLEV trial the results of which were reported in Chapter 7 of this thesis. These were communicated to OLEV in a report[120] and in further meetings with OLEV and BEIS at which the results were presented to a range of stakeholders involved in the administration of the EV plug-in grant scheme. The main points are summarised below:

- OLEV should continue to work with the Energy Saving Trust to maintain the website page of tips for EV owners and continue to send email prompts to EV owners about switching tariff. Once suppliers start offering TOU

[120] Nicolson, M., Huebner, G., Shipworth, D., Elam, S. "Do you want a time of use tariff with that? Prompting EV owners to switch tariff just after purchasing their vehicle." A report prepared by UCL for the UK Government Office for Low Emission Vehicles, November 2016.

tariffs, these emails could include links to specific tariff offerings to which EV owners could switch directly from the email.

- OLEV could run further email trials testing different ways of engaging EV owners with TOU tariffs, including emails which aim to measure the extent to which EV owners would be willing to sign up to controlled charging schemes such as the one being piloted in Electric Nation (Section 7 of Annex 2)
- If leasing continues to form a large proportion of total EV sales, then the Government could try other methods of prompting lease-holders to sign up to DSR programmes, for instance, by prompting EV owners to switch to TOU tariffs when they are carrying out mandatory or routine tasks related to having an EV, such as renewing their vehicle tax or applying for the London congestion charge exemption on the Transport for London website.
- OLEV could seek to identify whether there is a gap between the level of EV uptake required to make EV charging tariffs commercially viable and the level of uptake beyond which reinforcement of the local electricity network will be required and then how to bridge this gap (e.g. via regulation). According to My Electric Avenue (2015), 30% of the nation's low voltage feeders would require reinforcement once 40%-70% of people have an EV. However, this is a wide range and lower levels of EV uptake may still have an impact on the network without providing a business case for suppliers to offer 'smart' charging tariffs.

4 Energy suppliers

Tariffs which are called 'EV tariffs' are likely to be more popular amongst EV owners than generically named TOU tariffs such as 'off-peak saver' tariff, even if the rate and structure is identical. Suppliers should be mindful that such tariff names could lead some EV owners to sign up to tariffs that are not suitable for them, if they only pay attention to the name but little else (e.g. the tariff structure).

5 Distribution network operators

Distribution network operators (DNOs) are responsible for managing Britain's electricity distribution network. The implications of this thesis for DNOs were communicated to the Smart EV Project through my response to the Smart EV Project consultation on 16 December 2016[121], a project aiming to provide stakeholder supported recommendations to the Energy Networks Association to inform a standardised approach by which DNOs would operate controlled EV charging.

The Smart EV Project requested feedback on its proposals for "the level of choice that [EV] customers should have and the rewards that they should receive when managed charging occurs" (Cross et al., 2016, p.2): (1) a "high incentive" scenario whereby anyone purchasing an EV is forced to be subject to a controlled charging scheme, with drivers compensated through subsidies on their electricity bill; (2) a "high regulation" scenario, identical to the latter but without compensating drivers and; (3) a "market led" scenario where EV owners can voluntarily adopt managed charging, with the level of customer reward dependent on the amount of demand-response provided by the driver (Cross et al., 2016).

[121] Individual responses were not published but the summary of all responses is provided in EA Technology's "Consultation on Managed Electric Vehicle Charging: Summary of Responses Issue 1.0 Helping Electricity Networks Facilitate Electric Vehicle Uptake Delivered by EA Technology on Behalf of a Consortium of Key Government, Industry, Utility and Consumer Stakeholders", 3 March 2017. https://www.eatechnology.com/wp-content/uploads/2017/04/Smart-EV-Managed-EV-Charging-Consultation-Summary-Report-Issue-1.0.pdf.

Although controlled charging is a different DSR service from the TOU tariffs presented to participants in this thesis, the strategies which are effective for engaging consumers with TOU tariffs are unlikely to be substantially different to those which are effective for engaging them with controlled charging. Both offerings will be new to most British EV owners and, given the inertia in the energy market, the first and greatest challenge is how to engage EV owners with any type of DSR programme as opposed to how to influence them to select between different types of programmes.

The results of this thesis suggest that there are alternatives to both mandated or purely opt-in enrolment to controlled charging which are not considered by the Smart EV Project. In particular, the OLEV trial suggests that EV owners could be prompted to sign up to controlled charging schemes by emailing them within three months of purchasing their EV. The advantage of a voluntary approach over the methods proposed by the Smart EV Project (Cross et al., 2016) are that such strong limitations on consumer choice could generate negative unintended consequences, including limiting the uptake of EVs, if consumers feel it is the only way to avoid mandatory charging. Moreover, as Cross et al. (2016) notes, there is a lack of evidence on the likely level of voluntarily consumer uptake to controlled charging schemes and mandates are only a first best solution if the market-based mechanism is insufficient to prevent electricity infrastructure upgrade work.

Annex 2:

Directions for future research

1 Increase the precision of estimates of uptake to TOU tariffs

The wide range of uptake estimates described above means it is hard for the UK government to plan on certain levels of TOU penetration. For example, an enrolment rate of 1% (the lower bound estimate from the meta-analysis) could have a substantial impact on the UK Government's smart meter cost benefit analysis, which relies on uptake of 30% by 2030 (BEIS, 2016b).

How can uptake estimates be made more precise? The review in Chapter 2 highlighted a gap between the results obtained from surveys and those obtained from studies in which people were able to switch to a TOU. Given the lack of evidence of uptake based on actual switching rates, it is strongly recommended that countries obtain a measure of uptake based on recruitment rates to commercially available next-generation TOUs.

There are three mechanisms by which this research could be conducted depending on the commercial availability of TOU products: (1) Ofgem's programme of consumer trials; (2) the regulatory sandbox that is part of Ofgem's Innovation Link; (3) the Virtual Energy Company[122], funded through Smart Meter Research Portal, a five year project funded by EPSRC to provide smart energy data to the research community (grant number: EP/P032761/1).

The Virtual Energy Company intends to be a testbed for research teams and companies to run trials of innovations in a constrained but realistic setting. It aims to either simulate or carry out the day-to-day operations of supplying participating customers with energy, including billing, customer support, etc. in order to achieve its objectives.

[122] This idea is being developed by Michael Fell at the UCL Energy Institute.

2 Test whether tailored marketing effects generalise to electric heating owners in a trial on recipients of the Government's Renewable Heat Incentive

Tests of the efficacy of tailored marketing could also be carried out on how high power users such as those with electric heating, for instance, by partnering with BEIS who administer the Renewable Heat Incentive, a subsidy scheme for renewable heating technologies including heat pumps. The administrative database associated with these subsidies will contain the names and contact details of all heat pump owners in the country. This could be used to run a similar trial to the one presented in Chapter 7, in which email prompts were delivered to recipients of the UK Government's EV grant.

3 Test why whether tailored marketing is effective

The studies presented in this thesis were not designed to test why tailoring worked. The tailoring intervention as implemented in the OLEV trial may be exploiting mental accounting (Thaler, 1980, 1985, 1999) and de-shrouding (Gabaix and Laibson, 2006) whilst in the Flex Trial it is may be due to de-shrouding or the theory that personalisation leads to greater likelihood of information processing (Rimer and Kreuter, 2006).

A future study could disentangle the effect in the OLEV trial by testing the impact of a tailored message emphasising the way in which home charging increases one's electricity bills (de-shrouding) relative to another message which frames the savings to be made on household energy bills from switching to a TOU tariff as savings to be made on the cost of charging the EV (to exploit mental accounting). Disentangling these mechanisms from increased information processing is likely to be best achieved through investigation at the neural level as in neuroscientific studies on loss-aversion (Tom et al., 2007; Canessa et al., 2013). Alternatively, time taken to act on the information could be used as a proxy for speed of processing. Understanding why tailoring is effective could also help us to narrow down the other likely applications of tailoring.

4 Test methods of identifying consumers with 'flexibility capital'

> *…flexibility will not be sold or bought in a one-time transaction, but must be re-purchased and re-performed again and again in response to each instance of over voltage, under voltage, generation – supply imbalance and so on…[and therefore] rather than a commodity [a good that can be exchanged for financial reward], demand flexibility might be usefully thought of as a form of socio-technical capital held by end users of energy* (Powells and Bulkeley, 2013, p.1).

Although heat pump and EV owners may have higher flexible electricity consumption than the average energy consumer, flexibility may be determined by a number of overlapping characteristics such as the presence of particular electrical appliances, automation technologies, work schedules and so on. It could be imagined that each of these characteristics can make an individual more or less able to shift their consumption away from peak times or in line with the price on a real-time TOU tariff as well as make an individual have more or less flexible electricity use available for automated DSR. It could be imagined that each of these characteristics could be scored for every individual, to provide an overall index of an individual's total 'flexibility capital', to adapt a term coined by Powells and Bulkeley (2013).

By identifying the characteristics that drive a persons' flexibility through empirical investigation, such a flexibility capital index could be created. This may therefore enable energy suppliers or other third parties to match consumers to DSR tariffs and services on the basis of their flexibility capital index, targeting them using tailored marketing. This research should not stop at identifying clusters of users who have the potential to use electricity flexibly[123]; to be most useful, it needs to identify easily observable characteristics that are proxies for having flexibility capital for targeted marketing purposes.

5 Test the impact of non-punitive TOU tariff structures

An alternative way of minimising the risk that consumers could be made financially worse off from switching to a TOU tariff is to create tariffs which aim to stimulate demand-response in ways that present consumers with the option to reduce their energy bills if they do participate but which will never increase them if they fail to participate.

Such ‘non-punitive’ tariffs could take two main forms. One design would reduce the price of electricity at off-peak times without also increasing it at peak times. Another option would be to pay consumers a fixed fee for reducing their electricity at peaks, known as a critical peak rebate. Critical peak rebates can also be paired with direct load control, where a third party automatically reduces consumption at peak times, a practice which has been found to increase the demand-responsiveness of customers (Frontier Economics and Sustainability First, 2012).

The key aim is to identify whether such tariffs are more or less attractive to consumers than punitive tariffs and, most importantly, whether non punitive tariffs are less effective at reducing peak energy demand than punitive tariffs. This may happen if, rather than delaying electricity consumption until the cheaper hours, consumers simply increase their overall electricity demand by increasing their off-peak electricity use.

[123] An EPSRC funded project at the University of Reading – Red Peak – has “identifying clusters of users who might provide flexibility for peak shifting intervention” as one of its aims.

Critical peak rebates have never been tested in the UK – aside from one trial in London which is ongoing[124] – but evidence from the US suggests that critical peak rebates are effective although less effective than the punitive alternatives (Hledik et al., 2017). However, if uptake to critical peak rebates is substantially higher, this lower level of demand-responsiveness may be compensated by the higher levels of customer enrolment. Only empirical research can determine whether or not this is likely to be the case.

6 Test whether disaggregated energy billing for EV owners can maximise the consumer savings from TOU tariffs

Although not an original aim of the thesis, a side-product of generating the tariff advice for EV owners on the Energy Saving Trust website for the OLEV trial is that, unless EV owners can use some of their other household appliances at off-peak times in addition to charging their vehicles at off-peak times, not all EV owners will be financially better off on a two-rate TOU tariff.

In theory, the proportion of EV owners who could save money from switching to a TOU tariff could be substantially increased if the electricity used to charge an EV was billed independently from the electricity an EV owner used for their other household electrical appliances. In this way, an EV owner could have a TOU rate applied to the electricity used to charge their vehicle but still remain on a flat-rate for the remainder of their household electricity demand. Since it is a household's high consuming electricity loads that will place the greatest strain on the electricity network it arguably makes more sense to distinguish between the high consuming flexible loads like EV charging from low consuming and less flexible

[124] Energywise is a project led by UK Power Networks in collaboration with UCL and local charities to assess the impact of critical peak rebates on the electricity consumption patterns of British Gas customers of a housing development in Tower Hamlets, London. http://innovation.ukpowernetworks.co.uk/innovation/en/Projects/tier-2-projects/Energywise/.

loads like cooking than to charge all electricity in the same way depending on time of day.

A number of energy suppliers in the US already offer this service to EV owners using sub-metering[125] but such an approach could be implemented at lower cost using smart meters, which are capable of metering up to two different sources of electricity at a time. Alternatively, it may be possible to implement a disaggregated billing service using non-intrusive load monitoring (NILM) whereby “computational techniques are used to estimate the power demand of individual appliances from a single meter which measures the combined demand of multiple appliances” (Kelly, 2016, p.1). In 2016 it was reported that over 30 companies are offering disaggregation services to consumers (Kelly, 2016), implying that disaggregation technology is indeed working and making it a potential option for delivering disaggregated billing for EV owners. Indeed, Kelly (2016) notes that this type of appliance-targeted DSR is one potential use case for NILM.

However, since there is insufficient empirical research to suggest how much other electricity an EV owner can shift into the off-peak times, research is required to test whether disaggregated energy billing for EV owners could reduce overall DSR from EV owners by removing any incentive to adjust the timing of electricity use apart from the electricity used to charge their EV. This research could also usefully test whether disaggregated billing could increase overall switching rates to TOU tariffs amongst EV owners, for example, if it increased the perception amongst EV owners that such a method would be more likely to save them money than if their whole household electricity use was charged on TOU scheme. If

[125] For examples, see Portland Gas and Electric that offer a two-rate TOU tariff for EV owners which records the electricity used to charge the vehicle separately using a second meter: https://www.pge.com/en_US/residential/rate-plans/rate-plan-options/electric-vehicle-base-plan/electric-vehicle-base-plan.page.

disaggregated billing was substantially more popular, then any decrease in demand-response could be compensated for or exceeded by the increased enrolment numbers.

7 Test the consumer acceptability of EV controlled charging schemes with/out vehicle-to-grid services

The key potential advantage of automated/controlled charging[126] over TOU tariffs is that it will allow suppliers or DNOs to respond to immediate events on the network and to help avoid herding effects that could create new peaks. Despite its advantages, there is still a lack of knowledge over the extent to which the average EV owner would consent to having their charging remotely controlled and how to obtain this consent, from a sufficiently large number of EV owners, to increase participation in controlled charging.

For example, although My Electric Avenue found that the majority of its trial participants were “comfortable or very comfortable with Esprit being able to curtail their charging”(My Electric Avenue, 2015, p.10), this information cannot be generalised to the wider population of current and future EV owners. This is because the finding is based on surveys conducted with fewer than 100 people who had already agreed to participate in a 12 month research trial involving controlled charging of their EVs and were willing to complete the survey.

Since no research has been conducted which aims to establish what proportion of EV owners would voluntarily sign up to controlled charging, it is not known whether adoption rates would be higher, lower or equal to what is required to defer or avoid reinforcement of the electricity network. If voluntary uptake is likely

[126] Controlled charging is the process by which a third party remotely controls the current delivered to an EV when plugged in.

to be equal to what is required, then mandated charging is not required; however, if uptake is likely to be lower, then research is required for how to increase adoption without using mandates, given that mandates could be unpopular and less effective overall.

Research is therefore required to meet three objectives:

- Obtain a measure of likely voluntary adoption of controlled charging schemes amongst EV owners. There are two main ways this could be tested: (1) introduce a question into the EV PICG survey which asks people how willing they would be for a third party to control their charging (question wording would need to be developed carefully) and how likely they would be to choose controlled charging over some of the alternatives such as ‘smart’ static TOU tariffs; (2) put this question to a nationally representative sample of EV owners in an online market research panel, which also requires EV owners to select what option they would choose if they could sign up to controlled charging, a ‘smart’ TOU tariff or a number of other options that are likely to be available to them – most market research companies run weekly panels and results can be obtained relatively quickly and at relatively low cost.
- Test methods of obtaining active consent from EV owners to participate in controlled charging. To be effective, this method must be able to reach a sufficiently large proportion of EV owners in the UK, for example by encouraging tariff switching through an email from OLEV delivered to EV grant recipients or in the dealership when EV owners purchase their EV as part of their completion of the survey they complete when accepting the grant.

- Test the extent to which EV owners will override automated charging. Even if EV owners sign up initially to controlled charging schemes, it still seems likely that EV owners would be permitted to override the automated control should they need to. More research would be required to establish whether EV owners would override automated control and, if so, how often and with what impact for the distribution network.

8 Develop an accurate method for comparing TOU tariffs

Price comparison websites are now a key part of the landscape for switching tariffs, with about a third of tariff switches occurring through price comparison websites (Ofgem, 2015). However, as discussed in Chapters 4 and 5, estimating a customers' annual bill on a TOU tariff is not straightforward because TOU tariffs are expected to generate, but do not guarantee, alterations in household electricity consumption patterns.

There is therefore a need for research into how to create accurate energy bill projections on TOU tariffs that are understood by energy consumers. One potential method for allowing consumers to compare TOU tariffs is to provide consumers with a projection based on three possible scenarios – a scenario in which their total energy consumption and energy consumption patterns stay the same; a scenario in which they shift their electricity use away from the peak times moderately and; a scenario in which they shift their electricity use substantially away from peak times. This projection could be given as a vignette in which consumers are asked to identify with some fictional energy bill payer (are you more like John, Jack or Amy?) or explicitly based on their own potential usage (decide whether you will continue as you are, change a little or change a lot?). This should be tested in empirical trials to monitor its impact on the quality of the individuals' decision (i.e. whether they sign up to a tariff that saves them money in reality) as well as on their likelihood of switching to a TOU tariff (i.e. whether they switch from a flat-rate tariff to a TOU tariff).

This research is required to ensure that price comparisons involving TOU tariffs provide consumers with as realistic an approximation as is possible about their likely energy costs. Further, if Ofgem follows the CMA suggestion to "require suppliers to have regard in the design of their tariffs to the ease with which customers can compare 'value for money' with other tariffs they offer" (CMA, 2016d, p.23), this could have the unintended consequence of dis-incentivizing suppliers from offering more complex tariffs like TOU tariffs which are naturally much harder to compare (or will at least require more development effort to provide an easy method of comparison) than flat-rate tariffs. The comparability of TOU tariffs is therefore potentially very important for the success of DSR in the domestic sector in the UK.

9 Test tailored marketing in other consumer good markets for which opt-out enrolment is unethical

As noted in Chapter 3, there are many contexts in which there is a need to influence consumer decisions without manipulating default options, either because the choice architects lack the information required to identify a suitable default (e.g. in the case of credit cards, mortgages or health insurance schemes) or in cases which require on-going engagement rather than just a one-time decision such as enrolment in a course of antibiotics or a weight loss programme (Keller et al., 2011). In these cases it is necessary to prompt consumers to make an active choice. There are also some decisions for which the public or policymakers feel that automatic enrolment would unethical even in cases where it has been shown to save lives; many countries have rejected calls to make registration to their national organ donor register an opt-out rather than opt-in choice (A Spital, 1995; Spital, 1996) despite the evidence that opt-out enrolment results in much higher registrations and organ donations (E. Johnson and Goldstein, 2003). This suggests the value of research testing whether tailoring interventions at particular consumer groups could be effective at improving decision making in these contexts too.

As pointed out by Ofgem and the CMA (2016), the energy context is relatively unique in the sense that there is no trigger point for making a decision; if you want to buy a home or get credit you have to choose a mortgage or credit card. However, energy tariffs share many similarities with these other consumer groups: like energy tariffs, mortgages and credit cards are relatively homogenous by comparison to other consumer goods such as supermarket food or of what gym to become a member. Choosing an energy tariff is similar to a health insurance programme in the sense that, at least if health insurance is not mandatory, there is no trigger point in the way that there is when an individual runs out of milk or bread (or at least not until it may be too late).

Annex 3:

Using survey weights

1 Survey weights – when they will be used, and when they will not

1.1 Using weights to correct for selection error

The Tariff Decision Making Experiment recruited amongst a nationally representative sample of the urban population of Britain whilst the Population-Based Survey Experiment used quota sampling to recruit a nationally representative sample of the British population. Nevertheless, as a result of unequal probabilities of selection due to sampling design in the Population-Based Survey Experiment as well as participant non-response across both surveys, the final samples may not be representative of the urban or whole British population respectively. In addition, since the target population for these two studies is British energy bill payers, a variable against which participants were screened during the survey, there is no guarantee that the sample is perfectly representative of British energy bill payers.

Survey weights can be used to account for unequal probabilities of selection due to the survey sampling design; unequal response rates across groups in the sample and; differences between the characteristics of people in the sample and the population of interest, for example in this thesis between the participants who are sampled in the Tariff Decision Making Study and the Population-Based Survey Experiment and the average energy bill payer in Britain (so called post-stratification sampling weights (Debell and Krosnick, 2009)). If the survey uses a quota sampling design, as was used in the Population-Based Survey Experiment although not in the Tariff Decision Making Study, then weighting to account for unequal probabilities of selection and non-response will usually achieve the third aim of making the sample more like the population. However, whether or not sample weights should be used in the analysis of survey data depends on whether the data is being used to provide descriptive statistics for a given population or to estimate causal effects (Solon et al., 2013: 22-23):

> *In our detailed discussion…we have noted instances in which weighting is not as good an idea as empirical researchers sometimes think. Our overarching recommendation therefore is to take seriously the question in our title: What are we weighting for? Be clear about the reason that you are considering weighted estimation, think carefully about whether the reason really applies.*

1.2 Weights are used for descriptive statistics

Following the recommendation in Solon et al. (2013), this thesis will present descriptive statistics in both unweighted and weighted forms. Characteristics will be discussed in terms of in-sample estimates rather than weighted estimates if the two are substantively similar. Deciding what constitutes a notable demographic discrepancy is a matter of judgement however according to Debell and Krosnick (2009) "demographic discrepancies exceeding 5 percentage points are "notable"", "discrepancies [of] less than 2 percentage points are not" and those "in the 2 to 5 point range may be notable if the characteristic is of special interest for the study or is strongly associated with key outcome variables" (Debell and Krosnick, 2009). I will therefore interpret in-sample estimates in both the Tariff Decision Making Study and the Population-Based Survey Experiment if they are similar but discuss any significant discrepancies and their possible impact on the interpretation of the results.

1.3 Weights are not used in causal analysis

Weights will not be used to estimate the causal effect of tailoring on intention to switch to the time-varying tariff in the Population-Based Survey Experiment. This is for two reasons. First, any sampling error introduced through non-response will be the same on average across treatment and control groups and therefore does not pose a threat to the estimate of causal effects. As noted in Wooldridge (2009) who discusses the use of weights in non-experimental analyses, weighting has no impact on the consistency of standard error estimates and can reduce precision when sampling is exogenous.

Second, weighting the observations to help make the participants in the sample more like the target population, namely the average British energy bill payer, requires a reference dataset that disaggregates the characteristics of British energy bill payers by demographic variables that can be used to construct weights. However, such a reference dataset does not exist and Census data is not sufficiently granular to be used for creating bespoke weights. Moreover, even if better data were available, since weights can only eliminate sources of sample selection error that are correlated with the variables from which the weights are constructed (Imai et al., 2008), weighting on its own cannot guarantee that the sample population is the same as the population of interest.

A more transparent option which this thesis adopts is to present the descriptive statistics of the sample compared to the characteristics of the average British member of the population. The thesis draws on a dataset obtained by the author from a survey run with a professional market research company with a nationally representative sample of British adults who identified as energy bill payers. When the necessary comparison data is not available in this latter dataset, the thesis draws on Census data. This means that the results can be interpreted in this light whilst acknowledging the fact that there may be differences between the average energy bill payer and the average member of the public.

Annex 4:

Ethics, internal and external validity of RCTs

1 Internal and external validity

1.2 Threats to internal validity

According to Shadish et al. (2002), a study which is interested in answering a causal research question has internal validity “if the observed covariance between a treatment and an outcome” (Athey and Imbens, 2016, p.5) represents a causal effect. This thesis will discusses the results of the studies using a RCT design in terms of this definition of internal validity.

Section 3.1 of Chapter 4 highlighted the three key assumptions that must be met for the difference in average outcomes across control and treatment groups in a RCT to represent a causal effect: (1) random assignment; (2) excludability and; (3) non-interference, also known as the stable unit treatment value assumption (SUTVA). The key threats to the internal validity of RCTs are therefore: violations or interference in the randomisation mechanism (Gerber and Green, 2012) and anything which could lead to violations of the excludability and non-interference assumptions as discussed in both Gerber and Green (2012) and Glennerster and Takavarasha (2013), including partial compliance and evaluation-driven effects (Glennerster and Takavarasha, 2013).

Spillovers and attrition can also affect the internal validity of a randomised trial by lowering statistical power and by introducing bias if it is correlated with participant factors that are also correlated with response to the treatment (Glennerster and Takavarasha, 2013). These threats are relevant to RCTs conducted in survey contexts (and therefore the population-based survey experiment) as well as those conducted in the field. Details of how each of the studies in this thesis were designed to mitigate these threats are described in the following sections.

1.2.1 Violations or interference in the randomisation mechanism

This assumption will be satisfied as long as all subjects are allocated to treatment and control groups by the same procedure. To avoid violations of this assumption, randomisation in all the randomised control trials was performed by a machine. This means there was no researcher discretion in the mechanism.

To ensure that the assignment mechanism was truly random – for example, that subjects were randomly sorted and then treatment randomly assigned to half of the subjects rather than by some haphazard mechanism – I made sure that I understood what mechanism was being used by the email tool for the OLEV trial, by the developer who designed the website for the Flex Trial and by the survey company who implemented the randomisation in the survey software (the exact mechanisms are reported in the relevant sections above). In all cases, randomisation balance checks will be conducted and results presented in each of the results chapters to provide evidence that randomisation was performed successfully. For the Flex Trial, for which there is no baseline data, the results of balance tests on the group sizes across treatment and control conditions will be presented.

1.2.2 Excludability

The excludability assumption is that observed outcomes “respond solely to the receipt of treatment, not to the random assignment of the treatment or any indirect by-products of random assignment” (Gerber and Green, 2012, p.45). The assumption would be violated if different procedures are used to measure outcomes across treatment and control groups or if other actors intervene in either just the treatment or control group because the experiment is taking place. Plausible scenarios for the latter example are when the random assignment of an intervention, for example bed nets to reduce malaria transmission in developing countries, triggered local organisations to increase their provision of bed nets in control regions by highlighting the potential importance of bed nets. In other cases, such behaviour could introduce bias, for example if the people implementing the trial deliberately deviate from the protocol by extending the treatment to people based on perceived need (Glennerster and Takavarasha, 2013), for example, school teachers who were responsible for administering free milk to some students and not others in a large but non-cluster randomised control trial in the 1970s UK (Baker et al., 1980) may have deviated from the protocol by giving free milk to the students they felt were in greater nutritional need, which would result in the trial underestimating the impact of free school milk. The latter scenarios are examples of what is called one-sided non-compliance (Gerber and Green, 2012), whereby the control group is treated when it should not be, and the second also involves interference in the randomisation mechanism.

The excludability assumption is highly unlikely to be violated for the trials presented in this thesis for three reasons. First, across all trials, the same methods are used to measure outcomes in treatment and control groups.

Second, because random assignment is being performed by a machine and both I and any partners (such as OLEV) are blinded to the assignment until outcome measures are observed, it would be impossible for us to know who was in which group in order to intentionally treat the control group differently from the treatment group. It is potentially plausible that, by engaging OLEV in a trial of this type and suggested that tailored messages would be more effective, I may affect how OLEV deals with its grant recipients. However, prior to the trial and throughout the trial, OLEV had never before contacted its grant recipients. There is therefore minimal risk that they would have sent them tailored correspondence in the time prior or during the trial. OLEV also reviewed the trial protocol and was aware that nothing should be sent to participants prior or during the trial to avoid influencing results.

Third, emails prompting electric vehicle owners to switch tariff are arguably less emotive than free milk for hungry children or bed nets for people in regions with high malaria incidence; the common motivations behind external bodies interfering with treatment assignment are therefore less likely to play a role here. The nature of the interventions tested in this thesis also makes interference between groups less likely too, as the next section will outline.

1.2.3 Non-interference (the stable unit treatment value assumption)

This assumption states that potential outcomes in the control group reflect only the treatment status of the individual in the control group and not the treatment status of individuals in the treatment group, or vice versa. According to Gerber and Green (2012), this assumption would be threatened as a result of three main occurrences: (1) partial compliance whereby participants in the treatment group come into contact with participants in the control group and pass on the benefits or dis-benefits of the intervention, for example if the families of children being treated with deworming medicine move to a region assigned to the control group; (2) subjects are aware of the treatment that they and other subjects receive, leading the treatment group to “work harder” than they would normally (Hawthorne effect), the control group to compete with the treatment group (John Henry effect) or the control group to resent not having the treatment and thus work less hard than they would normally (Resentment/demoralisation effects); (3) resources that are used to treat participants in the treatment group diminish resources that would otherwise be available to participants in the control group.

The risk of any of these scenarios occurring is minimal to non-existent in the case of the studies in this thesis because of the nature of the intervention and the way in which the studies have been designed. Consider the first issue – interference due to contact between participants in the control and treatment groups. In all trials, the pool of participants will be so geographically dispersed that the likelihood of participants coming into physical contact with one another and discussing a website they visited, a survey they completed or an email they received about energy tariffs is minimal. A more plausible scenario is that, if the prospect of electric vehicle or heat pump tariffs is popular amongst electric vehicle and/or heat pump owners that participants of the Flex Trial[127] or OLEV trial[128] could post about it online. However, even in the unlikely event that someone was interested in energy tariffs enough to post something online about it, it is unlikely that such a post would receive sufficient attention (e.g. go viral) to have a substantial impact on participants. If such a post did go viral, I would find out about it and could consider its impact on the results.

Participants in the Flex Trial and OLEV trial are not made aware that they are being observed for research purposes at all, which eliminates the threat of Hawthorne or John Henry effects. Although participants in the population-based survey experiment are aware that they are participating in research, they are not made aware that the tariff descriptions vary randomly and, since participants can only complete the survey once, there is no plausible mechanism by which panellists could discuss what they saw with one another and then go back and change their response.

The prospect of an intervention resulting in the loss of resources to others who form the control group may be feasible in the context of some trials. For example, where an intervention, such as bed nets, is already being administered in some form and providing more bed nets to the treatment group could reduce the ability of a partner organisation to provide the baseline level of bed nets it was already providing (Glennerster and Takavarasha, 2013). However, the interventions delivered in this trial are very low cost – they involve amending the wording of text on a website, an email and in a survey describing tariffs – and were not being administered in any form prior to these studies. For instance, OLEV was not sending any email correspondence to its grant recipients prior to the trial.

1.2.4 Partial compliance as a result of compliers and defiers

Partial compliance can also have effects on the internal validity of trials beyond just violating the excludability and non-interference assumptions. Broadly speaking, partial compliance occurs when participants do not receive the treatment that was assigned to them (Glennerster and Takavarasha, 2013). This happens when some of the participants in the control group end up being treated and/or when some of the participants assigned to the treatment group do not get treated at all or do not get treated fully.[129] Although this can happen as a result of the deviations from the trial protocol, it can also happen purely as a result of participants undertaking their normal everyday behaviour. For example, in a clinical trial designed to assess the impact of mammograms on breast cancer mortality rates (Freedman et al., 2004), whilst many participants in the treatment group may indeed go get a mammogram and most in the control group will not (compliers), some participants assigned to the treatment group will not attend whilst some in the control group may go and get a mammogram (defiers).

In the presence of compliers and/or defiers, the ability to estimate the impact of the treatment on the outcome of interest is threatened because doing so requires the treatment group to be significantly more likely to receive the treatment than participants assigned to the control group. In the case of the Population-Based Survey Experiment, the existence of compliers and defiers is unlikely because, conditional on completing the survey, participants will be treated and the analysis is only performed on those who complete the survey. In the case of the OLEV trial, all participants with a valid email address will receive the treatment and treatment effects are only estimated amongst the group who receive the email, and this should be the same across both treatment and control groups (this will be tested). Although some participants will not open the email and therefore be exposed to the treatment in the body copy of the email (as opposed to just the copy in the subject line), all analyses are performed as intent-to-treat to avoid introducing bias.

In the case of the Flex Trial, there is a small probability that individual people could be treated with more than one treatment if they visit the website from multiple browsers, given that the study randomises at the cookie level, which identifies a combination of a user account, browser and device not a person. This is how all online field experiments (Lambrecht and Tucker, 2011; Edelman and Duncan S. Gilchrist, 2012; Blake et al., 2017) and commercial organisations run randomised control trials online. However, whilst this remains a possibility, the probability that any such incidents will have a substantive effect on results is low. First, given that the supplier is not well known, it is assumed that the overwhelming majority of participants will not visit the website more than once, meaning that the outcome recorded for most people will be based on a single visit. This data will be collected so it will be possible to identify what proportion of participants are new rather than returning users.

Second, interference amongst the minority of participants who may return to the site on multiple occasions is unlikely because the cookie is registered on devices and on the users' browser profile making it unlikely that a unique person would 'mistakenly' be treated as two separate individuals in the experiment. This is because, the first time that a unique user account/browser clicks on an advert, a cookie is dropped to mark the treatment to which the individual is assigned so that if they ever visit the website again from that browser or from that device, the original treatment assignment is honoured to prevent interference across groups. This means that a unique individual who visits the website on Internet Explorer from their laptop and then visits the website from their mobile phone but using the same browser will still be presented with the website variation to which they were originally assigned. The only time there would be a violation of this rule would be if an individual visited the site from a different browser and a different device. Researchers who use online data that rely on unique identification of individual people generally consider that the Internet does, in practice, identify unique individuals with good accuracy (Rutz and Bucklin, 2008; Lambrecht and Tucker, 2011).

1.2.5 Attrition

By reducing the total sample size or lowering variation in outcome measures, attrition can reduce statistical power and therefore the ability to detect whether any difference in average outcomes across treatment and control groups occurred by chance or due to the treatment itself, which is the aim of an experiment. In general, attrition is less likely to be a problem in the studies in this thesis because, compared to other trials where an intervention is delivered and outcomes measured months or sometimes year later, there is very little time between intervention exposure and outcome data collection. Nevertheless, the risk of attrition is not zero and attrition can be more problematic if it differs across treatment and control groups since this could bias treatment effect estimates (Glennerster and Takavarasha, 2013).

To minimise the risk that attrition would adversely affect my ability to measure treatment effects, the following steps and/or design choices were made:

- For both surveys, the market research company and advertising agency oversampled participants based on an expected non-response rate;
- For the Flex Trial, the primary outcome measure was the proportion who get a quote for the tariff, an outcome which is collected on the homepage and which participants can complete by entering just their postcode on the basis that making it easy for participants to provide this outcome measure increases the likelihood that they will. The 'get a quote' textbox was placed at several locations throughout the website to maximise the likelihood that participants would complete it before leaving the website. However, whilst the success of these efforts were important for generating sufficient variation in the outcome measures for statistical power, they are not required to minimise missing data since the outcome of interest is whether or not people do provide a quote or do switch to the tariff. To minimise the proportion of people leaving the website before indicating whether they own an electric vehicle or a heat pump, the survey that participants were presented with if they entered their postcode consisted of just three questions, to minimise fatigue and therefore attrition.

- For the OLEV trial, power calculations for detecting differences in click-through rates to the email accounted for the fact that a large proportion of recipients were unlikely to open the email

1.2.6 Spillovers

Spillovers are positive or negative externalities arising from implementing the intervention of interest (Glennerster and Takavarasha, 2013). Glennerster and Takavarasha (2013) give the example of a vaccination programme which could lower disease incidence in the community as a whole, an informational programme in which non-participants also learn of the benefits of using bed nets, marketwide effects whereby firms fire older workers because the intervention gives them incentives to hire young workers and behavioural effects whereby individuals in the control group imitate the behaviour of those in the treatment group.

If spillovers occur but are not measured, then I could underestimate the impact of the interventions tested (Glennerster and Takavarasha, 2013). If spillovers affect participants in my control groups, then the control group would no longer represent a good counterfactual of what would happen in the absence of the intervention (Glennerster and Takavarasha, 2013).

Since the studies in this thesis are conducted online and over a relatively short period of time, spillover effects are unlikely. The likelihood of control-group participants imitating the behaviour of participants in the treatment group in any studies is very low given that participants are most likely to be undertaking the study in privacy of their own home.

The interventions in the Flex Trial and the Population-Based Survey Experiment also do not lend themselves to positive or negative externalities; unlike an immunisation program, it is hard to see how tailored messaging on a website or as part of an intervention delivered in a survey experiment could convey meaningful effects beyond the group of participants exposed in the study. Although it is possible that non-participants of the email trial could find out about the webpage on the Energy Saving Trust website if trial participants post about it online, since the outcome measures of interest are open rates and click-through rates from the email, there is almost no chance that such spillovers could affect the outcomes in the control group and therefore undermine the quality of the control group as a valid counterfactual.

If non-participants of the trial access the webpage and download the PDF information, my trial will not be able to directly attribute this effect to the emails since there is no identifier that can link email recipients to the downloads; however, since the Energy Saving Trust is providing data on the number of downloads of the PDFs, I will be able to capture the total downloads of the information on the website.

The probability that the trials could increase switching rates and therefore competition in the retail electricity market in Great Britain is very low because, although the trials are relatively large compared to many trials in the social sciences, the sample size is not large enough in the context of 25 million household electricity consumers to have an impact on the market as a whole.

The most likely positive spillovers that would not be captured by the studies in this thesis is the impact of the tailored prompt on actual tariff switching rates in the OLEV trial. This is unavoidable given that I cannot link my data to energy supplier customer data; the only way of doing so would have been to have entered a data sharing agreement with every energy supplier in Great Britain and this was not deemed feasible given the timescales of the project or worthwhile given that I did not know how effective, if at all, the email prompts would be. However, when presenting the results I will attempt to estimate the potential size of these potential positive spillover effects based on assumptions about the proportion of recipients who would switch, and how this would affect the total number of switchers in the treatment and control condition in the event that the tailored email results in higher open and click-through rates.

1.2.7 Measurement error

Aside from the OLEV trial, all of the studies in this thesis use self-reported data collected through surveys. A survey instrument is valid if it measures what it intends to measure however self-reported data can introduce error and steps should be taken to minimise this. For instance, the Population-Based Experiment relies on people accurately reporting whether they own an electric vehicle since this variable will be used to test for treatment effect heterogeneity in the impact of tailoring. The wording of the question used to identify electric vehicle ownership was piloted in cognitive based interviews for a prior survey that I conducted on a different nationally representative sample of electric vehicle owners (M Nicolson et al., 2017) to check that people correctly understood the question. The question briefly explains what an electric vehicle is as it is not assumed that it will be common knowledge: “An electric vehicle runs only on electricity which is stored in a battery in the vehicle and is plugged into the mains electricity for charging. A plug-in hybrid electric vehicle combines a petrol or diesel engine with an electric motor - it can be plugged into the mains electricity for charging”. Although some people may inaccurately report their electric vehicle ownership status, randomisation ensures that the same number of people will give an inaccurate report in both the treatment and control groups so measurement error is not expected to affect the validity of the treatment effect estimate.

The same goes for measuring intention to switch to the tariff in the Population Based Survey Experiment, which requires people to say whether they would or would not switch to the tariff presented. Although some people may be undecided and so select a response at random, the measurement error will be the same on average across the groups.

Measurement of electric vehicle and heat pump ownership is also self-reported in the Flex Trial however since it is not required for assessing the treatment effect this is not a major threat to the internal validity of the trial.

Although the OLEV trial uses behavioural outcome data, self-reported data will be included as covariates in the regression equation to test for the habit discontinuity effect including details such as expected annual mileage and whether the owner intends to use the electric vehicle as their main vehicle. These questions are answered by the person making the purchase in the dealership on the day they purchase their vehicle with the assistance of the dealer. OLEV explained that they are conducting periodic checks to ensure that the details are being completed by the purchaser rather than the dealer and these checks have not revealed any problems with data collection. Some data may be missing but this will be handled by controlling for missingness, for example, if gender or age is missing, a dummy variable will be included for gender or age being missing.

Behavioural outcome data is used in both the Flex Trial and the OLEV trial and although it is less problematic than self-reported data care has also been taken to avoid errors introduced by myself as the researcher. For instance, in the Flex Trial, the behavioural outcome measures (get a quote rates, clicks on the Switch to Us icon, page views, switching) are collected by Google Analytics tracking installed on the website by the professional website developer. The only potential source of measurement error that could be introduced in the behavioural data is through inaccurate coding during dataset cleaning, for example, if I were to mistakenly identify an action as ‘get a quote’ when it was some other action taken by the user on the website as a result of mistranslating the web language. To minimise this risk, the developer provided me with a code book that associated all the labels that they gave in the web language to a description that I understood. Using pilot data, we coded up the data and verified that we each produced the same results; for instance, that the counts for each of the outcome variables were identical for us both.

As in prior research (Lambrecht and Tucker, 2011; Edelman and Duncan S. Gilchrist, 2012; Blake et al., 2017) I do not have data to address measurement error introduced in the data collected by the Flex Trial resulting from inaccurate identification of unique individuals who visit the website from multiple devices and browsers. However, the risk of this is relatively low in principle because it is expected that most participants will only visit the website on one occasion.

The OLEV trial uses behavioural data collected through the email campaign tool and administrative data collected at the point of purchase. The data on the date of purchase is recorded on the system automatically when a purchase is made so is unlikely to be subject to error; it is this data that will be used to test the habit discontinuity effect.

1.2.8 Multiple hypothesis corrections

Since each of the studies will involve testing multiple hypotheses, this increases the risk of erroneously accepting a hypothesis that is actually false unless measures are taken to correct for this. Following the recommendations of Fink et al. (2012) and Almeida et al. (2012), the Benjamini and Hochberg (1995) correction will be employed to minimise the false discovery rate (FDR). The FDR "correction allows for an appropriate level of caution in interpreting the results of testing many hypotheses, without becoming so conservative that we can no longer draw important conclusions about heterogeneity in responses to treatment" (Fink et al, 2012: 18).

The correction will be applied to groups of hypotheses tested. For instance, it will be applied to correct all p-values used to test the average treatment effect of tailoring in the Flex Trial across each of the four outcome measures. A separate correction will then be applied to correct for multiple hypothesis testing owing to running treatment effect heterogeneity analyses.

I do not apply the correction across all the hypotheses tested in this thesis or on a chapter-by-chapter basis because the purpose of multiple hypothesis corrections is not to penalise each additional p-value computed by a researcher in their lifetime (Perneger, 1998) but to control the error rate for the specific judgement that is being made by the researcher in their research (Cyrus, 2017).

1.2.9 Arbitrary statistical significance thresholds

Another consideration when assessing the internal validity of a trial is its dependence on conventional standards for statistical significance for assessing whether there is evidence against the null hypothesis. Although it is conventional to treat p-values which fall below the threshold of $p=0.05$ as statistically significant and those which exceed $p=0.05$ as not statistically significant, the p-value is a continuous variable which, if interpreted as such, can provide a more informative or nuanced account of the likelihood that any given result casts doubt on the null hypothesis (Halsey et al., 2015; Wasserstein and Lazar, 2016).

This is because, “In the same way that a small P value does not guarantee that there is a real effect, a P value just above 0.05 does not mean no effect” (Hackshaw and Kirkwood, 2011, p.1), particularly if the independent variable of interest has a small effect on the dependent variable of interest or the outcome measure has a low baseline prevalence in the population. For instance, since very few people switch tariff, field experiments which test methods of increasing switching rates are likely to have very low variation in many outcome variables of interest.

Although researchers should ensure they recruit enough subjects to run a sufficiently powered study – given the pre-study odds of the hypothesis being true at a certain statistical significance level (Ioannidis, 2005) – Glennerster and Takavarasha (2013) argue that researchers should also be cautious about ignoring promising results of early studies which may find evidence of a possible relationship which could be tested again in future research. This is a sensible approach given that the results of one isolated study can never, on its own, provide sufficient evidence to reject a given null hypothesis (Ioannidis, 2005).

Following the recommendations of the statement on p-values published by *The American Statistician*, I will interpret my results using the p-value and other contextual factors including the study design, the way the interventions were implemented, the quality of the outcome data collection and the external evidence for the phenomenon under study (Wasserstein and Lazar, 2016, p.9).

Following the approach adopted in the *American Economic Review*, as well as a number of other top economics journals, results tables will highlight results which are statistically significant at the 10% confidence level using a + sign. The convention of only highlighting results which are significant at the 99.9%, 99% or 95% confidence level is influenced by medical research where the risk of a false positive could be life-threatening. For the purposes of this thesis, being able to have 90% confidence, or even 80% confidence, that one type of marketing intervention would increase uptake to a TOU tariff may provide sufficient grounds for marketing the tariff in that way rather than the alternative against which the intervention was being evaluated, particularly if the results are consistent across each of the studies in the thesis and the effect sizes are large. In any case, the reader can draw their own judgement on these effects.

Note also that adopting this approach to evaluating statistical significance can work both in favour or against the researchers' pre-existing assumptions about whether an intervention will be effective or not. For instance, although it is hypothesised that tailored marketing will increase uptake amongst EV and heat pump owners it also hypothesised that uptake will either be lower or no different amongst participants who do not belong to this group.

2 Evaluating external validity

Another type of validity considered by Shadish et al. (2002) is external validity, which they define as "the extent to which a causal relationship holds over variation in persons, settings, treatments, and outcomes" (p.83). This is echoed in Gerber and Green (2012) who put forward a four-part typology for evaluating the 'fieldiness' of field experiments but which is arguably applicable more broadly, including to population-based survey experiments and non-experimental surveys, both of which are employed as methods in this thesis.

According to Gerber and Green's (2012) typology, external validity should be assessed on the basis of the extent to which: (1) the context in which the study is conducted is the same as or similar to the real-world context in which the behaviour of interest would be observed; (2) the interventions tested in the study are similar to or the same as the intervention as it would be implemented in real life; (3) the participants recruited into the study are the same as or like the population who are likely to be subject to the intervention and; (4) the outcomes measured in the study are the same as or similar to the outcomes that matter in real life.

There are many other typologies used to assess external validity and I am not suggesting this is the only one; only that it is a suitable typology for the research methods used in this thesis.

Nevertheless, two relevant aspects that this typology does not capture is that knowing that one is in a study can affect peoples' behaviour (see the discussion of evaluation-driven effects in Glennerster and Takavarasha [2013]) and the fact that, whilst studies can be designed to generate generalisable results as best as possible (in the manner described above), proof of generalisability can never come from considering the design or results of a single study or from a number of studies from a single research group or team but only from repeated experimentation and replication (McDemott, 2011). In this sense, the important factor is whether the multiple studies in this thesis produce results that are consistent with each other, a factor that will be discussed in the global discussion of this thesis (Gerber and Green, 2012).

When discussing the results of the studies, I will refer to the criteria laid out by Gerber and Green (2012) as well as in relation to evaluation-effects in terms of the expectations I have of the studies in terms of their generalisability.

3 Ethical considerations

It is not possible to obtain informed consent from participants in natural field experiments. Informed consent is one of the first standards laid out in The Nuremberg Code of 1947 by which all medical research must abide when conducted on human participants. The Code was created to prevent the types of immoral experiments conducted on Nazi prisoners of war ('The Nuremberg Code (1947)', 1996).

However, as stated by List (2011), whilst voluntary consent remains essential for "experiments that can affect the physical health of the participants…the case for voluntary consent in [social science] experiments is less clear-cut." (p.8). Framing studies are particularly suitable candidates for natural field experiments since manipulating the way in which information is presented poses no physical risk to participants so arguably falls outside of the scope of experiments for which informed consent is explicitly required. For instance, consider a field experiment run by Bertrand and Mullainathan (2004) which aimed to test the impact of race on employment outcomes by sending identical CVs to prospective employers with names that signal different races. The employer suffers no physical harm from this experiment and perhaps suffers only a minimal harm from having their time taken up considering CVs for fictional individuals; on the other hand, revealing the true purpose of the experiment may have changed the way the employers had responded. As argued by List (2011), with "the benefit of…oversight [from ethical review boards], there are valid arguments for not making informed consent an ironclad rule in natural field experiments” (p.8).

Annex 5:

Choosing regression estimators – OLS versus random effects and logit

1 Random effects versus OLS for the meta-analysis

The meta-analysis reported in Chapter 2 used OLS with Fixed Effects rather than a Random Effects model. This was done for three reasons. First, study effects are unlikely to be random because studies were not randomly sampled from a larger population of studies. On the contrary, the systematised review design used means that studies were purposively sampled on the basis that they met specific inclusion criteria.

Second, the key difference between random and fixed effects models is that random effects models partition the unexplained variation in the outcome measure into two components: between-study variation and also within-study variation. In clinical trials, where outcomes are monitored for multiple patients over time, there is likely to be considerable within-study variation. However, in this study, within-study variation is likely to be minimal because the outcomes were not recorded over time; substantively, it is more likely that differences in tariff design will account for differences in uptake within studies since the only reason there are multiple measures of uptake from the same study is if the same study tested different tariff types, and this is included as a fixed effect in the model.

Third, random effects models for meta-regression in clinical trials are motivated on the basis that the true treatment effects obtained across multiple studies are unlikely to be the same across studies and the random effects model, unlike the fixed effects model, accounts for this. However, the meta-regression in this research is not being used to aggregate treatment effects obtained from multiple independent randomised control trials or even to obtain an estimate of the average uptake; rather it is being used to estimate the impact of different features of TOU tariffs, such as the presence or absence of automation or upfront cash incentives, on uptake, whilst controlling for observed differences in study design such as whether it was a survey experiment or TOU tariff trial. Unlike in clinical trials, which treat these moderators are treated as nuisance variables to be controlled for using random effects, this study is interested in the size and statistical significance of these moderators, which motivates inputting these variables as fixed effects. By including a fixed effect for each study, I also control for other unobserved differences across studies that may affect the outcome. Moreover, I do not assume that estimates of uptake are constant across studies, which is why the average uptake is presented as a range based on the two most important determinants of uptake identified in the meta-analysis, namely the method by which uptake was measured and whether recruitment was opt-in or opt-out.

2 Choice of statistical model – OLS vs logit

The outcomes variables in this thesis are all binary. Following Angrist and Pischke (2008), this thesis will report treatment effects estimated using OLS regression rather than logit. This is because, the conventional wisdom in the econometrics literature is that "while a nonlinear [probit, logit] model may fit the CEF [conditional expectation function] for [binary dependent variables] more closely than a linear model" (Angrist and Pischke, 2008, p.103), logit and OLS regression generally produce very similar results, both in practice and in Monte Carlo simulations in which the data generating process is known (Beck, 2011).[130] Most applied economists therefore use OLS regression on binary dependent

[130] The exceptions in the simulated models are when there is extreme kurtosis or skewness in the dependent variable since then OLS can produce coefficients which are greater than 1, which is nonsensical when the dependent variable is binary.

variables (Beck, 2011). In addition, it is well accepted that logit should not be paired with fixed effects (Neyman and Scott, 1948; Katz, 2001), which are used in a number of analyses throughout this thesis.

Nevertheless, it is also acknowledged that methodological conventions vary across disciplines. Some researchers argue that, since the only advantage of OLS over logit is that OLS coefficients are easier to interpret than marginal effects, logit may be safer than OLS regression because the data generating procedure is more likely to resemble a logit than a linear model (Beck, 2011). Therefore, robustness checks in which the equations are run using logit with marginal effects estimated at the mean value of the independent variables will also be run. Since the OLS and logit results are substantively identical, the logit results are reported in the appendices for brevity.