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Household electricity consumption behaviour : a meta-analysis and experimental approaches

Penelope Buckley

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THÈSE

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Penelope BUCKLEY

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préparée au sein du **Laboratoire Grenoble Applied Economics Lab**
dans l'École Doctorale Sciences Economiques

**Comportement des ménages en matière de
consommation d'électricité: Une meta-
analyse et des approches expérimentales**

**Household electricity consumption
behaviour: A meta-analysis and experimental
approaches**

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École Doctorale 300 de Sciences Économiques

PhD Thesis

Présenté par

Penelope Buckley

**Household electricity consumption
behaviour: A meta-analysis and
experimental approaches**

Sous la direction de

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Introduction

0.1 Energy Transition and Residential Consumers

The transition to a green, CO₂ neutral, renewable and sustainable society is one of the key challenges of the 21st century. In 2017, the temperature of our planet increased by 1.1°C since the pre-industrial era and 2013-2017 were the five warmest years on record, so far. This warming of the planet has had far-reaching consequences across the globe; from severe storms and flooding to deadly droughts and wildfires which have had major economic impacts on human life. Human influence is the main driver behind the increasing global and regional temperatures ([World Meteorological Organization, 2018](#)).

In order to combat increasing temperatures, governments across the world have set targets to reduce our impact on the planet. The European Union has set objectives to be achieved by certain dates. The EU as a whole is on track to meet its 2020 objectives of a 20% reduction in greenhouse gas (GHG) emissions compared to 1990 levels, a 20% share of renewable energy in the production mix, and a 20% improvement in energy efficiency². By 2030, the EU will further its energy strategy by aiming to reduce GHG emissions by 40%, to have a share of at least 27% of renewable energy sources (RES) in the production mix, and to achieve energy savings of at least 25% across all sectors (industry, commercial, transport, residential)³.

Concerning GHG emissions, the EU met its 2020 target in 2014, and estimates in 2016 suggest that GHG emissions in the EU are 23% below 1990 levels. However, the EU is currently falling short of its 2030 trajectory ([European Environment Agency, 2017c](#)). Similarly, France is on target to meet its 2020 GHG emissions target, however, the rate of reduction in emissions is due to slow down, and France is unlikely to reach the 2030 target ([European Environment Agency, 2017d](#)).

Concerning renewable energy, the EU is on track to meet its 2020 objective however, growth in the share of RES is slowing, making the 2030 target difficult to reach ([European Environment Agency, 2017b](#)). In order to meet the EU's renewable energy target, France has committed to achieving a 23% share of RES by 2020. However, in 2016, France's RES share was at 15.6%, and at the current rate of progress, France will meet its 2020 objective in 2029⁴.

²See https://ec.europa.eu/clima/policies/strategies/2020_en

³See https://ec.europa.eu/clima/policies/strategies/2030_en

⁴This is calculated based on the share of renewable energy in France reported by the European Commission (see

https://ec.europa.eu/info/business-economy-euro/economic-and-fiscal-policy-coordination/eu-economic-governance-monitoring-prevention-correction/european-semester_en)

Concerning energy savings, in 2014, in the EU-28, residential energy consumption represented the third highest consuming sector with 25% of final energy consumption. Between 2005 and 2014, final energy consumption in the household sector fell by 14.8% ([European Environment Agency, 2017a](#)). However, in France, residential electricity consumption is the highest consuming sector representing 36% of final electricity consumption, and between 2001 and 2017, residential electricity consumption in France increased by 12%, remaining relatively stable from 2011 ([Réseau de Transport d'Electricité, 2018](#)). In 2014, France needed to reduce its final energy consumption (all sectors combined) by a further 7.5% in order to meet its 2020 target ([European Environment Agency, 2017a](#)).

Given that residential consumption is the highest consuming sector and that France is on track to meet only one of the EU 2020 targets within the next year ([European Environment Agency, 2017d](#)), there is clear potential for lowering consumption in the residential sector in France in order to achieve the national and European energy transition objectives.

A way of reducing GHG emissions is to move away from the use of high cost, inefficient, polluting generators. These generators are typically used during peak periods when demand is particularly high. In 2008 in France, just 6% of peak capacity was used during 1% of hours ([Faruqui *et al.*, 2010a](#)). Increasing the share of RES, which is intermittent by nature, means that there will be electricity available at certain periods of the day and of the year when the sun is shining and when the wind is blowing. Both of these imply a change in the traditional functioning of the electricity market so that demand follows supply rather than supply following demand ([Strbac, 2008](#)).

In the future, the increasing integration of electricity produced from RES will be stored for use during peak periods. Consumers will charge their electric vehicles at times when electricity is in plentiful supply and is cheaper, to then be used at times when supply is constrained, and high demand means high prices. Currently, capabilities for storing electricity are limited and expensive ([Stephens *et al.*, 2015](#)) and so other methods of encouraging demand to follow supply are needed.

In the absence of electricity storage, Demand Side Management (DSM) is a method for redistributing loads from peak to off-peak periods. In the residential sector, consumers can be encouraged to lower their consumption during peak periods to avoid connecting inefficient generators to the grid. They can also be encouraged to increase their consumption during off-peak periods when there is a supply of

renewable energy available. DSM in the residential sector requires that consumers' demand be flexible and that consumers respond to incentives used to modify their behaviour. Significant savings, both monetary and environmental, can be achieved if households are successfully incentivised to lower their peak demand.

While peak demand reduction is important for achieving the objectives of reduced emissions and for the integration of RES, it does not necessarily result in a reduction in overall demand which is necessary to meet the EU's third objective of energy savings. The effect on overall demand will depend on whether there are spillovers from the use of incentives to lower peak demand, on the demand during other periods ([Allcott, 2011a](#)), or by how much consumers increase their demand during off-peak periods after being incentivised to decrease their peak demand ([Torriti, 2012](#)).

A reduction in overall demand refers to a decrease in total energy consumption at any time of day or year. While such reductions can be made through improvements in energy efficiency (Nearly Zero Energy Building standards, retrofitting of older buildings, and use of energy efficient appliances), occupant behaviour is an important factor in reducing residential energy consumption. Building characteristics can account for 42% of a building's energy use whereas occupant characteristics and behaviour can account for 4.2% ([Santin *et al.*, 2009](#)). Though this may not seem like a large proportion, [Gram-Hanssen \(2013\)](#) find that the electricity consumption of households living in similar houses (according to building characteristics) can vary by a factor of 5 and the heating consumption can vary by a factor of 2-3. Additionally, there is an energy-efficiency gap where realised efficiency gains are less than predicted gains. This is partly due to behavioural barriers ([Hirst and Brown, 1990](#)) and partly due to rebound effects when consumption increases following an improvement in energy efficiency ([Greening *et al.*, 2000](#)). Given the variation in energy consumption and the increase in consumption after efficiency gains, there is a need to influence consumer behaviour and to encourage consumers to reduce their energy consumption. In the traditional electricity market in which consumers are passive and are unaware of their consumption, influencing behaviour is a significant challenge. However, the introduction of smart meters in the residential sector is an important technological advancement that allows for the implementation of incentives to encourage households to lower their energy consumption.

The [European Commission \(2014a, p.8\)](#) has stated that "in sectors such as housing [...] there will be a need for a significant acceleration of current efforts to tap the significant unexploited potential. This will require large investments in the building

sector (that lead to lower running costs), framework conditions and information that encourage consumers to take up innovative products and services and appropriate financial instruments to ensure that all energy consumers benefit from the resulting changes." Across the EU, Member States have invested in the installation of smart meters in residential homes. Figure 1 shows the deployment strategies of the Member States by 2020. Faruqui *et al.* (2010a) estimate that the deployment of smart meters in the EU will cost 51 billion euros and that the operational benefits⁵ will recuperate 26-41 billion euros. The missing 10-25 billion euro investment in smart metering technology can be recovered through a reduction of residential energy demand, in particular during peak periods. Smart meters are key technological advancement for an electricity market in which consumers take a more active role in energy consumption management but they alone are not sufficient to encourage consumers to lower their demand. To motivate a behavioural change, consumers need to be appropriately incentivised.

0.2 Technologies and Incentives

Through the use of smart meters, different incentives can be delivered to consumers based on accurate consumption measurements. Incentives which target overall demand reduction are traditionally information based (Darby *et al.*, 2006) - information on historic consumption or real-time feedback - or, more recently, based on insights from behavioural economics (Allcott, 2011b). Smart meters facilitate the use of financial incentives such as dynamic pricing which is used to encourage lower peak demand (Faruqui and Sergici, 2013). The following sections provide an overview of the literature on these different incentives.

0.2.1 Feedback

One of the main advantages of smart meters is the ability to communicate real-time consumption data to consumers. By providing households with information on their energy consumption, households will be made more aware of their consumption habits and will make efforts to lower their consumption. Increasing households' awareness of their energy consumption is the first step towards changing consump-

⁵Operational benefits include: remote meter reading, quicker detection of power outages, and fraud detection, among others.

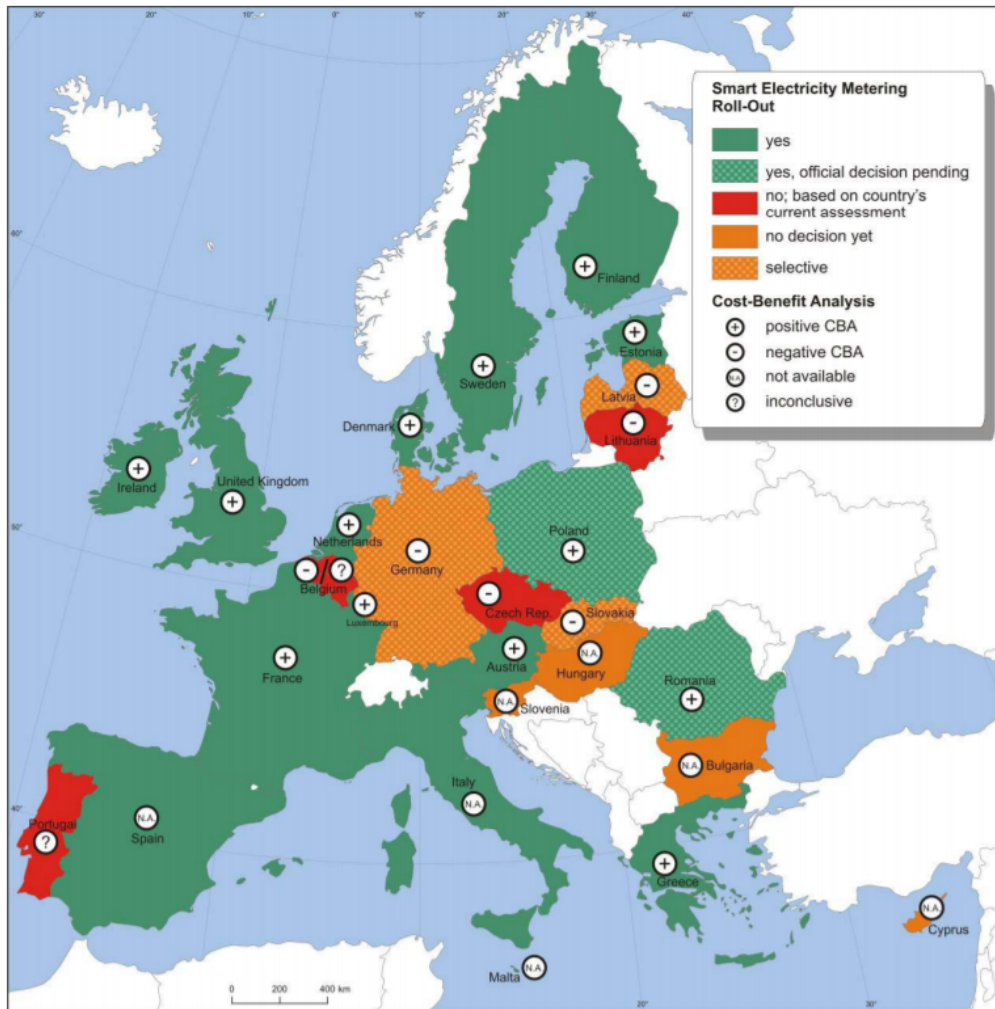


Figure 1: Smart meter deployment strategies across the EU-27 by 2020 as of July 2013, (European Commission, 2014b)⁶

tion habits (Attari *et al.*, 2010).

Paper bills are the method of feedback traditionally used to inform consumers of their energy consumption and expenditure. Darby *et al.* (2006) highlight that such feedback is useful for assessing the impact on consumption of investments in energy efficiency, as opposed to behavioural changes. Such information does not provide

⁶The map displays the results of Member States' cost-benefit analyses (CBA), either positive, negative, unavailable or inconclusive, and the state of smart meter (SM) deployment. As of 2013, countries in solid green have officially begun installation of SM, those in shaded green are planning to install SM after an official decision has been taken, those in red have decided against SM installation after a negative or inconclusive CBA, those in solid orange have not yet made a decision, and those in shaded orange have begun a selective installation. For example, in Germany SM installation is limited to new or renovated houses, to prosumers and high-consumption households (Edelmann and Kästner, 2013).

appropriate feedback on efforts to lower energy consumption as the data is received long after the behavioural change. For feedback to have an effect, the relationship between action and effect needs to be clear to households so that they can see how behavioural changes affect energy consumption (Fischer, 2008).

In order for consumers to truly benefit from the consumption information provided by the smart meter, they must be able to access the information soon after implementing a behavioural change. Data that is available online provides a greater depth of information on consumption levels and can potentially close the action and effect gap, but it requires that consumers have a computer with an internet connection, and that they log on to access the data. Studies of such feedback and its effect on energy consumption find that few people log on to the online portals and the number of connections decreases during the course of the study (Benders *et al.*, 2006, Vassileva *et al.*, 2012, Schleich *et al.*, 2013).

To further close the action-effect gap, households can use a device capable of interfacing with their smart meter which can provide them with real-time, accessible consumption information. These devices are commonly known as energy monitors, real-time monitors or in-home displays (IHD). They are dedicated platforms which provide real-time consumption data thus providing a direct link between action and effect. The use of IHDs can encourage a reduction in consumption so long as they are kept in visible locations in the home for easy and quick access to the data available, however this is not always the case and the novelty factor of consulting one's consumption in real-time tends to wear off (Hargreaves *et al.*, 2010, 2013). In order to engage households with the data provided, attention needs to be given to how data is presented, whether in monetary or energy terms (Buchanan *et al.*, 2014), whether numerical or graphical displays are used (Chiang *et al.*, 2012), or whether amount spent on consumption is displayed factually, or presented as a loss (Bager and Mundaca, 2017). Such presentations and their effect on effort are further explored in Chapter 4.

0.2.2 Dynamic Pricing

Dynamic pricing refers to the adjustment of retail electricity prices to better reflect wholesale costs of energy production. During times of peak demand, production costs are higher leading to higher retail prices which incentivise households to lower their demand during peak periods, and in some cases, to increase their demand during off-peak periods, in order to maintain supply and demand balance (Faruqui

et al., 2009). There are different tariff structures which are more or less dynamic, from time-variant, but static, time-of-use (TOU) pricing to dynamic real-time pricing (RTP). These different pricing programmes differ by degree of risk and possible reward (Faruqui and Palmer, 2011). A flat-rate tariff in which prices are fixed no matter the time of consumption is ‘risk-free’ as all kWh are consumed at the same price. A TOU tariff has a slightly greater associated risk but the risk remains much lower than that of critical peak pricing (CPP) or RTP. Figure 2 shows the risk-reward trade-off of dynamic pricing tariffs where risk refers to the exposure of consumers to volatile wholesale electricity market prices (Faruqui, 2012).

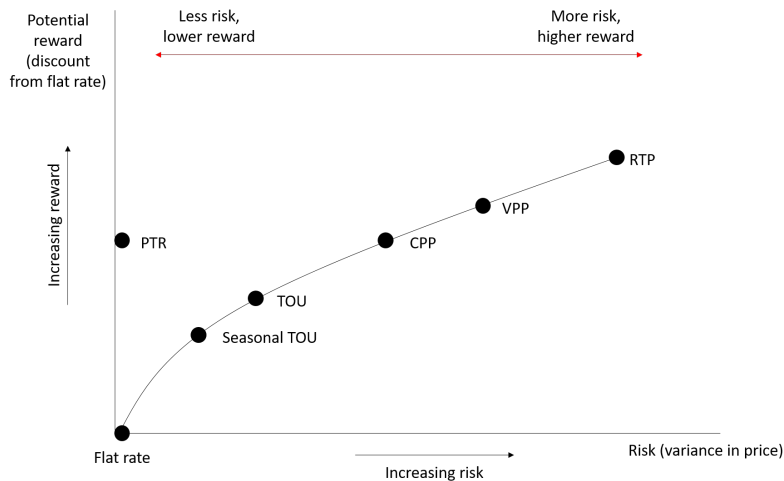


Figure 2: Risk-reward trade-off in dynamic pricing rates (adapted from Faruqui (2012, p.17))

Dynamic pricing tariffs are effective at reducing energy consumption, particularly CPP and RTP tariffs when combined with energy monitors (Faruqui and Sergici, 2013). Indeed, in order for households to successfully respond to dynamic pricing, consumers require an IHD device to inform them of the changing prices (Dütschke and Paetz, 2013), particularly in the case of RTP. However, opponents of dynamic pricing argue that residential consumers should not be asked to support the volatility of electricity prices, particularly consumers who are vulnerable to changes in electricity supply (young children, the elderly, disabled people) (Alexander, 2010), and that the peaks of demand are natural peaks due to the organisation of daily life which are difficult to shift (Naus *et al.*, 2014, Hall *et al.*, 2016).

0.2.3 Nudging

The installation of smart meters and IHDs is not sufficient to engage consumers in behavioural change. The majority of households show a lack of interest in IHDs and it is often only those who are already concerned by their energy consumption who pay attention to their IHD (Buchanan *et al.*, 2015). Increasing retail electricity prices to better match wholesale prices tends only to have an impact on those consumers who are fully informed and attentive to the price changes (Jessee *et al.*, 2016). Given this, there has been an increase in the use of tools from behavioural economics to increase consumer response to incentives. Such incentives are coined ‘nudges’ and are predominately based upon the work of Nobel prize winners Richard Thaler (2017), and Daniel Kahneman (2002).

Thaler and Sunstein (2008) define a nudge as follows:

"A nudge [...] is any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid. Nudges are not mandates."

Nudging is based on the idea of libertarian paternalism which is an approach that steers individuals towards choices which are in their best interest and will increase their welfare without limiting their freedom to choose. It recognises that individuals make choices which are not in their best interest, choices which they would not make if they had complete information and unlimited cognitive capabilities (Thaler and Sunstein, 2003).

Households have been nudged to lower their energy consumption via the use of social and injunctive norms. Social norms are a type of feedback which compares a household's energy consumption to the consumption of their neighbours' (Schultz *et al.*, 2007, Nolan *et al.*, 2008). Injunctive norms add social approval of a household's consumption in relation to that of their neighbours' (Schultz *et al.*, 2007). For example, Opower⁷ put this into practice with their Home Energy Reports (HER). These are paper bills which include a comparison of one's own consumption to the average consumption of neighbouring households along with a smiley face (injunctive norm) if you are consuming less than your neighbours (Allcott, 2011b). Figure 3 provides an example of the use of social and injunctive norms in an Opower HER.

⁷Opower was an American company which provided software for utilities to use to analyse consumption data in order to encourage demand reduction. The company was acquired by Oracle Corporation in 2016.

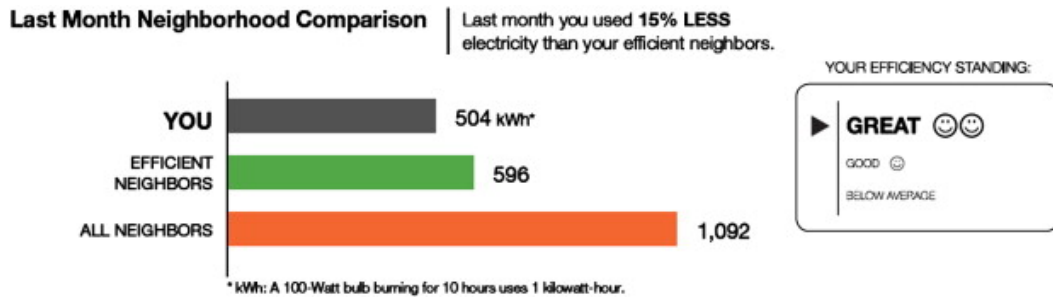


Figure 3: A Home Energy Report from Opower

In the absence of injunctive norms, i.e.: only descriptive comparisons of consumption, households who are consuming less than the average, tend to increase their consumption. [Schultz *et al.* \(2007\)](#) suggest that the use of a descriptive social norm provides a level from which it is undesirable to deviate. This level becomes the normal level of behaviour and so, being above or below is unwanted. This leads to a convergence towards the average which [Schultz *et al.*](#) call a boomerang effect. Such behaviour can also be described by a licensing effect when engagement in a good deed, lowering consumption, licenses an individual to subsequently engage in a bad deed, increasing consumption ([Khan and Dhar, 2006](#)). The inclusion of smiley faces is used to counteract these effects by providing social approval of desirable behaviour: lowering consumption.

If such relatively costless nudges are effective at reducing energy consumption, then they may be used as an alternative to costlier incentives such as dynamic pricing. Before such a step is taken, the effect of nudges and pricing should be explored in order to determine the monetary value of such nudge (see [Chapter 3](#)).

0.3 Outline of the Thesis

Smart meters are being introduced to households to embolden consumers to take active roles in their energy management, and in turn, to help meet national and European climate change objectives. Currently France is not on target to meet all of its objectives within the next year. Furthermore, there are both advantages and disadvantages to the incentives used to encourage households to lower their demand as highlighted in the previous section. The central question of this thesis is thus:

How do residential consumers respond to incentives used to encourage them to lower their consumption?

This question is addressed in four chapters, a preview of each is given below.

0.3.1 Chapter 1

The first chapter of this thesis provides a review of the existing literature which has explored how residential consumers interact with and use the incentives described in section 0.2 to lower their consumption, either peak or overall. The objective of the first chapter is to identify any issues that affect the successfulness of the different incentives at encouraging households to lower their consumption. Different barriers to the acceptance and the adoption of smart meters, IHDs and the incentives delivered by them are identified.

The objective of chapter 1 is to analyse the potential of smart meters to encourage residential consumers to lower their consumption through the use of financial and non-financial incentives.

The research question of this chapter is: **What are the main barriers to the acceptance and adoption of smart meters and the incentives they can deliver?**

The literature is organised into two main types of barriers: barriers to acceptance and to adoption, as these are two key obstacles to be overcome if households are to be incentivised to lower their consumption. Acceptance is the first obstacle as households must initially be willing to accept the installation of smart meters in their homes, and the provision of feedback on their consumption, whether it be by continued paper bills, through online portals or IHDs. The installation of smart meters paves the way for the use of dynamic pricing which is predominately implemented on an opt-in basis. After accepting smart meters and the associated incentives, the next obstacle to overcome is adoption. The installation of a smart meter, the presence of an IHD, and the changing of prices is not sufficient alone for households to lower their consumption. They must make use of and engage with these different incentives.

The extensive literature highlights that the main barrier to the acceptance of smart meters is that households do not trust energy companies, that they are unsure of what smart meters are and how they can be used to benefit consumers. Concerning dynamic pricing, households find the tariffs to be complex and so few opt-in into dynamic pricing preferring to remain on the simpler, risk-free flat-rate tariff. With regard to households' adoption of smart meters and incentives, the findings of the

literature suggest that any effects on consumption are typically short-lived. Households tend to engage with feedback initially, but their interest wanes after a few weeks or months. Furthermore, households are constrained to respond to feedback within their personal comfort levels on which they are not willing to compromise, and by the inflexibilities of daily life. In addition, the monetary savings resulting from lowering their consumption are rarely sufficiently high to encourage persistent behavioural changes.

The contribution of this chapter is a recent review of the experimental literature in order to identify the obstacles to using smart meters and associated incentives as a means to encourage households to lower their consumption.

0.3.2 Chapter 2

Given the wealth of field experiments and pilot studies exploring how consumers respond to incentives (alone or in combination, across many different countries, and under many different experimental designs) and the increasing attention given to behavioural incentives such as nudging in recent years, the second chapter uses a meta-analytic approach to analyse the results of contemporary experimental studies which have explored the effect of incentives on residential energy consumption.

The objective of chapter 2 is to quantitatively analyse the existing experimental literature to obtain precise estimates of the effect of different incentives on residential consumption.

The research questions addressed in the second chapter are: **Which incentives are most effective at encouraging households to lower their energy consumption? How does the design of the experimental study impact the effectiveness of different incentives at lowering residential energy consumption?**

Meta-analysis is the practice of combining the results of many studies which explore a same objective (the effect of incentives on residential energy consumption) in order to obtain a more precise estimate of the true effect. The idea is that the combination of many estimates of an effect size leads to a better estimate of the true effect ([Stanley and Doucouliagos, 2012](#)).

The focus for this chapter is studies conducted around the time of the "Smart Grid Era" ([McKerracher and Torriti, 2013](#)). The data collection is limited to this period in order to avoid distorting estimated effect sizes by using studies from previous decades

when greater effects of incentives on energy consumption were found (Ehrhardt-Martinez *et al.*, 2010). In the past, greater effect sizes were found due to different levels of consumer knowledge of energy consumption, and due to available technology and feedback methods. In recent years there have been more studies which have used incentives based on behavioural economic theory. In this chapter, such behavioural incentives are separated into those which provide only a social norm or descriptive comparison, and those which also include an injunctive norm. This is in order to determine whether there is a difference in effect size due to boomerang or licensing effects (Schultz *et al.*, 2007). In addition, the meta-analysis seeks to provide a better estimate of the true effect size of different incentives by including results not only from peer reviewed journals but also from government and utility reports. This is in order to avoid the "file drawer problem" (Rosenthal, 1979).

Results show that accounting for the sample size of the original study mitigates publication bias in the sample. Thus, accounting for sample size, on average, a study testing the effect of an incentive on residential energy consumption will expect to find a 2% decrease in consumption. This is a much lower effect than estimated in previous meta-analyses. Providing households with feedback on their energy consumption in real-time or in monetary terms has the greatest effect: respectively, a 2.89% and 2.86% reduction in consumption. Effect sizes are affected by study design choices such as how participants are recruited into the study. Studies in which participants choose to take part find greater reduction effects of incentives on energy consumption which suggests that a national roll-out of a particular incentive is likely to be less effective than field experiments and pilot studies have shown. This is of particular importance to policy makers.

This chapter contributes to the field of research by providing an up-to-date analysis of the effects of different incentives on residential energy consumption. In particular, this meta-analysis focuses on recent studies, and includes a greater number of experiments using behavioural incentives. It reduces the problem of publication bias, often rife in meta-analyses, and finally it takes additional study design features into consideration compared to previous meta studies.

0.3.3 Chapter 3

Highlighted in chapters 1 and 2, is the idea that dynamic pricing can be politically difficult to implement (Alexander, 2010), and that consumers find the tariffs difficult to understand (Layer *et al.*, 2017, Schlereth *et al.*, 2018). Additionally, nudges in the

form of social comparisons, both with and without injunctive norms, are effective at lowering consumption but can have the undesired licensing or boomerang effect where households who consume less than the average of their neighbours feel that they can increase their consumption (Schultz *et al.*, 2007, Allcott, 2011b). In the third chapter, each of these incentives are explored in a laboratory environment in order compare their respective advantages and disadvantages in a controlled setting. The objective of chapter 3 is to compare how individuals respond to a behavioural incentive and a financial incentive in a stylised energy consumption game.

The research questions asked in this chapter are: **Which incentives are more likely to increase socially optimal behaviour? What is the "price" of the nudge?**

Chapter 3 describes an experiment based upon a common pool resource game applied to the context of residential energy consumption. Ostrom (1990) describes a common pool resource as a resource system from which a flow of resources can be extracted. The stock of resources is renewable and can be maintained so long as the amount being extracted does not exceed the rate of renewal. Collectively, it is best if everyone does not exceed their share of the renewable amount of the resource, however, each individual would like to extract more. Previous research has discussed how this framework can be applied to energy infrastructure (Bäckman, 2011, Goldthau, 2014, Gollwitzer *et al.*, 2018). This framework is applied to residential energy consumption during a period of peak demand where maximum capacity is being used. Each household would like to consume as they see fit, however, it would be beneficial for everyone if all households made an effort to lower their consumption in order to avoid reductions in tension, brownouts and blackouts.

The results of the experiment show that both the use of a nudge and a price encourage individuals to behave in a more socially optimal manner, i.e.: reducing their consumption, than if there were no incentives. The nudge is understood quickly by individuals and has an immediate effect on consumption in the second period of the game after feedback is first received. The price takes longer to have an effect, and it is not until the fourth period of play that individuals integrate the price into their decision making. The hypothesis behind the nudge is that individuals who are not behaving optimally, i.e.: over-consuming, will be encouraged to do so after receiving the nudge, however, the results show that these individuals do not respond to the nudge and continue to over-consume. This finding is of particular importance as it highlights a potential drawback of nudge methods.

The contribution of this chapter is the application of the common pool resource framework to the electricity market within a laboratory experiment. A monetary evaluation is made for the nudge by setting a price which incentivises individuals to consume the amount observed under the nudge and seeing whether this price level successfully encourages the same level of consumption.

0.3.4 Chapter 4

Chapter 1 identifies that households do not necessarily engage with the information provided by their IHD: when the information is displayed in energy units it is incomprehensible (Raw and Ross, 2011, Buchanan *et al.*, 2014), when it is in monetary units, the potential savings are too small. Households feel that any effort they make to lower their energy consumption is not worth it as it only has a small effect of consumption and on monetary savings (Hargreaves *et al.*, 2010, 2013, Goulden *et al.*, 2014). Given the identification of these barriers, the final chapter explores how incentives can be framed to encourage greater effort when individuals are asked to make small efforts, for small rewards akin to efforts to lower consumption.

The objective of chapter 4 is to explore the framing of incentives used to encourage small efforts when the rewards are small.

The final research question is: **How can information (on IHDs) be framed to incentivise effort provision?**

Chapter 4 looks at how information can be framed to encourage individuals to make a small effort when the rewards are small. In the experiment, individuals are incentivised to make an effort to complete an artificial, real-effort task over a number of periods by different ways of framing their payoffs - gain or loss framing, and by slight changes in the payoff structure - whether payoffs are risk-free or risky. The experiment builds on findings from Prospect Theory (Kahneman and Tversky, 1979) which postulates that individuals make more effort when payoffs are framed as a loss (in particular when losses are risky), than when they are framed as a gain.

In the case of small rewards for small efforts, the present experiment finds no significant treatment effects of gain or loss framing. On average, individuals provide the same level of effort whatever the frame. However, individuals will provide more effort when payoffs are relatively higher under both framing types. This suggests that when rewards are small, as in the case of actions to lower energy consumption, individuals are equally incentivised to make an effort under both gain and loss fram-

ing. Increasing the size of the rewards associated to an action is key to encouraging individuals to make an effort.

This chapter contributes to the literature on gain and loss framing by looking at how Prospect Theory applies in a situation where individuals must make small efforts for small rewards, and by including an element of risk in the payoff structure.

Finally, the thesis concludes with an overview of the four chapters and their findings in relation to the central research question. The limitations of the research and its implications for policy makers, practitioners, and theorists are considered. The thesis ends with a discussion of avenues for further research.

Chapter 1

Barriers to Acceptance and Adoption of Smart Meters and Incentives to Lower Residential Energy Consumption

This work received funding from Innovacs⁸.

⁸See <http://innovacs.univ-grenoble-alpes.fr/>

Abstract

Qualitative studies which explore consumer acceptance and use of smart meters and incentives are reviewed in order to identify barriers to their use for encouraging consumers to lower their energy consumption and to engage in demand response. Consumers do not trust energy companies to act in their best interests and are wary of data misuse and automation of their consumption. They are uncertain of what smart meters and incentives such as dynamic pricing are and can do, and they perceive electricity contracts to be complex. While financial reasons are a significant motivating factor, the realised savings are often smaller than anticipated. Smart meters and devices encourage reductions in energy consumption in the short-run while they are a novelty, consumers use them to identify and maintain an acceptable level of consumption which trades-off energy savings for comfort, and are reluctant to lower demand further due to inflexibility in daily routines. Finally, recommendations for overcoming the identified barriers are given. Notably that a one-size-fits-all approach may not be appropriate as different segments of consumers accept and engage with smart services to different degrees.

1.1 Introduction

The average residential consumer has learnt to be a passive user of electricity. For this consumer electricity has an invisible quality; it arrives in the household through hidden wires and is consumed as part of daily life and routine which makes it difficult for consumers to connect their daily activities to specific amounts of energy consumption (Burgess and Nye, 2008, Hargreaves *et al.*, 2010). The majority of residential consumers have a limited idea of how much they are consuming for different purposes (Darby *et al.*, 2006). They tend to overestimate the energy use of lighting and other visible, low-energy uses whereas they underestimate the energy consumption of less visible, high-energy uses (Attari *et al.*, 2010).

To add to this, the majority of residential consumers pay a fixed-rate for their electricity. Under a flat-rate structure, all consumed kilowatt hours (kWh) are charged at the same fixed price; the consumer does not differentiate between a kWh that is consumed at 7pm to one that is consumed at 4am. Yet these two kWh do not have the same costs of production. The kWh that are consumed during peak hours cost significantly more to produce and to distribute (Faruqui, 2012). This lack of transparent pricing gives electricity an unlimited quality from the point of view of consumers; no matter how much they consume, no matter when they consume it, the price per kWh remains the same. Additionally, energy consumption is a relatively small part of a household's bills which further heightens the unlimited quality of electricity.

In reality, electricity is not invisible nor in unlimited supply. Electricity grids across the world are under pressure to supply enough to meet the growing demands of modern life. With the electrification of the home and the domestication of technology, energy needs have changed and energy networks cannot keep up (Verbong *et al.*, 2013). This increased demand is putting great strain on generators of electricity and certain generators are used for only a few hours a year to meet the demand on high peak days. Across the EU 5-8% of electricity network capacity is used only 1% of the time (Faruqui *et al.*, 2010a).

Across the world, countries are setting objectives to reduce humankind's impact on the climate by reducing CO₂ emissions, increasing the share of renewable energy in the production mix, and achieving greater levels of energy savings. Given these objectives, many countries are investing in the installation of smart meters in residential homes. The impetus behind the smart meter initiatives across the globe

is that residential consumers will be better informed of their energy consumption through more detailed feedback, and monetary incentives such as dynamic pricing tariffs can be more easily implemented. This use of greater information, and monetary incentives will help households to lower their consumption, and in turn environmental and supply objectives will be met.

This transition to a cleaner, sustainable energy system through the use of smart meters will require residential consumers to take on a more active role in the energy system. Households will be asked to respond to signals about the price and supply of electricity. Smart meters are the technological advancement which will help them to do so and their installation removes a technological barrier to the implementation of time-variant tariffs and to the delivery of real-time consumption information.

However, these environmental objectives can only be achieved through smart meter installation if consumers are willing to accept smart meters in their homes. Consumers are considered to be central to the success of changes taking place in the electricity grid, and as such, they are also considered to be one of the greatest barriers to smart meter implementation. Consumers' acceptance of smart meters will greatly influence the success of installation (Verbong *et al.*, 2013). Even if consumers accept the installation of smart meters and the use of different incentives, this is not sufficient alone to lower energy demand. A reduction in energy consumption will only be achieved if consumers engage with the information and incentives provided and use them to modify their daily energy consuming behaviour (Buchanan *et al.*, 2015). This first chapter discusses the different barriers to the acceptance and adoption of smart meters and incentives by residential consumers, beginning with a definition of smart meters and dynamic pricing.

1.1.1 Smart Meters

Smart meters are installed at the end-users' premises in the place of the traditional meter and allow for two-way communication between suppliers and end-users. Figure 1.1 gives an example of a smart meter in deployment in France.

On the supply side, the benefits of smart meter installation include better efficiency in electricity production, transmission and distribution, reduced fraud, greater bill accuracy, electricity outage detection, and integration of micro-generation, among others (Krishnamurti *et al.*, 2012, Darby, 2016). Faruqui *et al.* (2010a) estimate that the return on investment of these supply-side benefits are worth between 26

and 41 billion euros.



Figure 1.1: Smart meter ‘Linky’ in deployment in France

On the demand side, residential consumers will benefit from remote meter reading, real-time energy consumption information, and a greater control over one’s own consumption (Carroll *et al.*, 2014, Darby, 2016).

Smart meters correct a market failure of imperfect information as in the traditional electricity market, consumption data can be inaccurate (Carroll *et al.*, 2014). Consumers receive monthly bills based on an estimate of their consumption calculated by the energy company with meter readings taking place perhaps quarterly. Smart meters, in combination with an IHD or other enabling technology, allow the collection of real-time energy consumption data and the communication of this information to both the utility and the consumer. This gives the consumer more accurate and more frequent information about their consumption, and thus allows the consumer to take a more active role in their energy consumption. In addition to a greater depth of consumption information, different incentives can be delivered to consumers via their smart meter and IHD.

1.1.2 Dynamic Pricing

Smart meters also pave the way for the use of dynamic pricing which requires that consumers pay differing prices according to the real-time cost of electricity production. The logic behind dynamic pricing is to provide consumers with economic incentives to reduce, or to increase, their demand in order to maintain supply and demand balance in the electricity market (Borenstein *et al.*, 2002). The dynamic pricing tariffs currently used differ in degree of time-variability:

Time-of-use pricing

Under Time-of-use (TOU), as depicted in fig. 1.2, the price depends on the time at which electricity is being consumed. This could be the time of day or the time of year (Faruqui and Sergici, 2013). Typically TOU tariffs consist of two or three periods; off-peak and peak, and occasionally the shoulder or mid-peak period which transitions between the two (Faruqui *et al.*, 2009). The peak hours depend upon location and daily rhythms. For example, hotter countries have a peak during summer afternoons when the sun is at its hottest, whereas colder countries have peaks in the early morning, or later in the evening. Under seasonal TOU tariffs, there will be higher rates in summer for hotter countries when air conditioners are in greater demand and higher rates in winter for colder countries when heating is in high demand. This type of tariff is not technically a dynamic tariff as it is fixed ex-ante and does not depend on real-time electricity demand (Faruqui *et al.*, 2009).

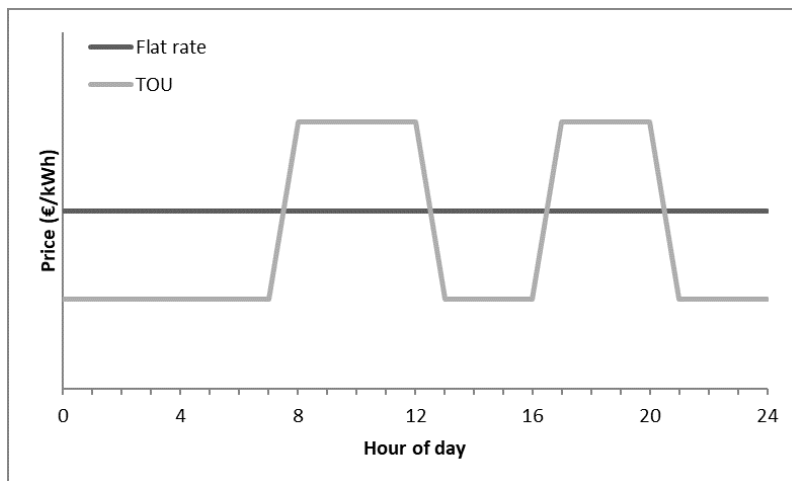


Figure 1.2: Example of a TOU tariff

Critical peak pricing

Critical peak pricing (CPP), shown in fig. 1.3, is an extension of TOU pricing: prices increase substantially on days where electricity demand soars, known as critical event days. Such days are when the temperature is particularly low (high) in cold (hot) countries. On days where there is no critical event, prices either revert to TOU prices or to flat-rate prices. This tariff is designed to communicate the true, fluctuating electricity costs to consumers during different periods (Faruqui *et al.*, 2009). Consumers receive a price signal to incentivise them to reduce their consumption during periods when electricity production is reaching maximum capacity. Customers are notified of the occurrence of critical events on a day-ahead or day-of

basis. CPP carries more risk for consumers than TOU pricing as consumers will pay a much higher price if they cannot shift their demand, however it offers a greater reward; by shifting their consumption consumers can take advantage of the much lower priced off-peak periods (Faruqui and Palmer, 2011).

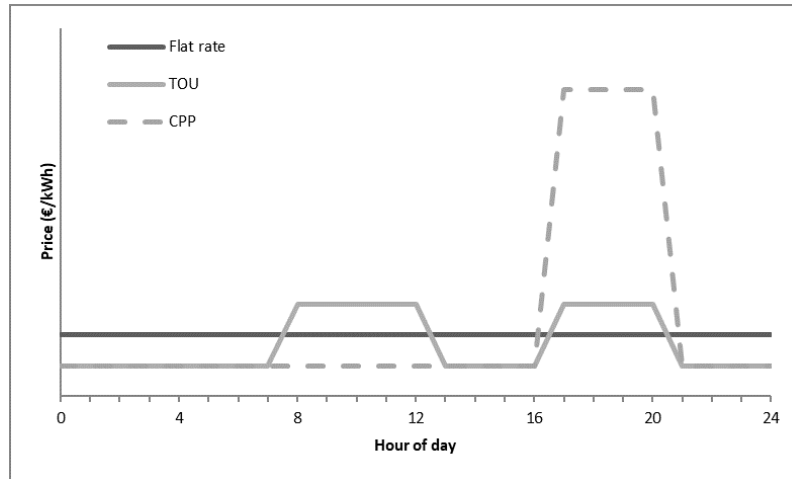


Figure 1.3: Example of a CPP tariff

Peak-time rebates

During critical events, consumers receive a rebate on their electricity bill if they reduce their demand below a certain pre-defined and individual level. During non-critical hours, the consumer faces the standard flat-rate tariff (Wolak, 2011). Faruqui and Sergici (2013) suggest that this type of tariff may be viewed more favourably from a political or regulatory point of view as a PTR tariff does not penalise consumers with a much higher price for consumption that they cannot shift. Despite the demand-side advantages to PTR, Faruqui *et al.* (2009) argue that if consumers effectively reduce their consumption as a result of PTR, then the energy companies will look to increase electricity prices in order to maintain their revenue stream. Figure 1.4 represents a PTR tariff.

Real-time pricing

Under Real-time pricing (RTP), depicted in fig. 1.5, the electricity price faced by a consumer changes on a real-time basis, typically on an hourly basis, according to current demand. The prices are communicated to consumers on a day-ahead or hour-ahead basis (Faruqui *et al.*, 2009). This pricing programme is the highest risk of the programmes described in this section, however, it has the highest potential reward compared to a standard tariff (Faruqui and Palmer, 2011); consumers have the opportunity to move their consumption to much lower off-peak prices.

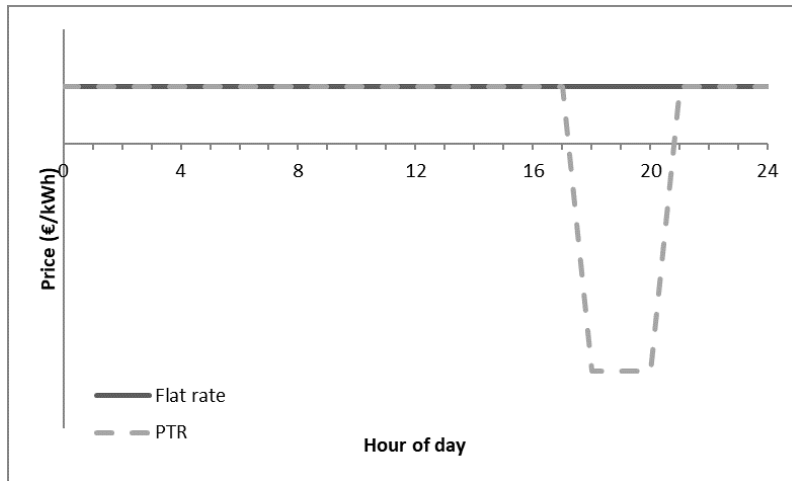


Figure 1.4: Example of a PTR tariff

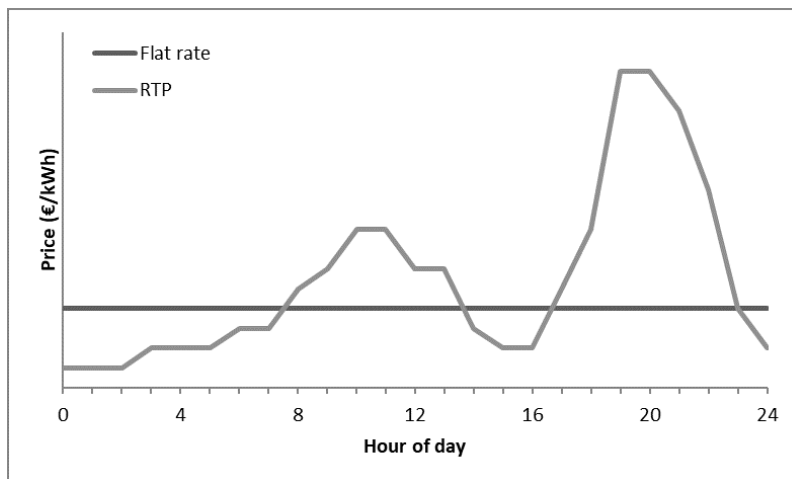


Figure 1.5: Example of a RTP tariff

1.2 Barriers to Acceptance

As highlighted above, if smart meters and their associated devices, and monetary incentives such as dynamic pricing are to result in significant and sustainable reductions in residential energy demand then the household is key; without households' implication, there will be no reduction in consumption. While neither concepts are new to the consumer, there is a certain amount of reticence and hesitation concerning their use in the home.

In today's society, much of an individual's life is tracked, monitored and analysed, via smartphones, when making credit card payments, whenever one connects to the internet. Smart meters are another example of such monitoring of daily life,

yet there is an increasing amount of opposition to their use. Nor are time-variant tariffs a new way of pricing goods and services. Consumers face dynamic pricing in numerous areas; when buying a plane or a train ticket, when reserving a hotel or a hire car, when using a toll bridge. Yet, such pricing programmes have low penetration in the electricity market (Dütschke and Paetz, 2013).

Given that consumers have some level of familiarity with the monitoring of consumption and other activities, and with dynamic pricing, this first section looks at the barriers to households' acceptance of smart meters and dynamic pricing.

1.2.1 Mistrust of Energy Companies' Intentions

With the arrival of smart meters trust issues have once again come to the forefront. Consumers are wary of energy companies' motives in offering installation of smart meters and energy monitors as previous bad experience with their energy provider leads consumers to question the energy companies' motives in providing smart metering technology (Hall *et al.*, 2016). They feel that the energy companies may not offer a smart meter package that is in the interest of the household, but one that serves the energy companies' interest (Kaufmann *et al.*, 2013). Consumers who feel that energy companies benefit most from the use of smart meters are less positive about their installation in their homes (Krishnamurti *et al.*, 2012). Furthermore, householders doubt whether the energy companies will pass on the monetary savings to customers as they feel that the energy companies will maintain their profit margins (Spence *et al.*, 2014). As participants (n=72) in Goulden *et al.* (2014) suggest, energy companies' profits increase as consumers use more energy.

In interviews with relevant Dutch stakeholders⁹ (n=37), Verbong *et al.* (2013) find that interviewees expressed ambiguity as to whether smart meters are in the interest of end-users. The stakeholders emphasised that while there are advantages for consumers, energy companies have their own motivations and it is unclear as to whose interests are better served.

Stenner *et al.* (2017) conduct a survey (n=1499) to explore the effect of trust on Australian households' willingness to participate in direct load control. The authors find that households' level of trust in their energy supplier greatly affects their willingness to participate, with those who explicitly express mistrust being much less

⁹The stakeholders interviewed represented governmental organisations, electrical and gas utility companies, researchers of energy related consumer behaviour, and residents.

likely to participate. Even when this lack of mistrust is addressed, via reassurances that their energy company is taking steps to "rebuild community support", the proportion of households willing to participate only increases by a marginal amount. These trust issues continue once the smart meter has been installed, consumers are unsure of what energy companies will do with the substantial amount of data on their energy consumption behaviour and habits (Richter and Pollitt, 2018). A small-scale study which involved interviews and workshops with five Dutch households found that participants are concerned that energy companies will use data for commercial means (Naus *et al.*, 2014). Namely, that energy companies will be able to use the real-time data to market specific services and/or products to consumers. The 228 participants in Pepermans (2014) were willing to pay a significant amount to have a smart meter which had no effect on privacy. This lack of trust increases the psychological costs that consumers face, as they must spend time monitoring energy companies' use of their data (Gerpott and Paukert, 2013).

Though trust issues are mostly viewed as a barrier to adoption of smart meters, participants (n=22) in Krishnamurti *et al.* (2012) suggest that the increased accuracy of energy bills due to real-time feedback from smart meters provides energy companies with an opportunity to build trust with consumers. However, households could face increased bills if their consumption was previously underestimated (Raimi and Carrico, 2016).

1.2.2 Uncertainty Regarding Technology

Aside from questions of trust, uncertainty is also an important issue. With new technologies of a particularly technical nature, such as smart meters, consumers are not always sure of what the technology is and what it can do. Consumers have a tendency to confuse smart meters with the devices required to obtain data concerning energy consumption (Darby, 2010). In an online survey of American consumers (n=305), Raimi and Carrico (2016) find that less than 36% participants have heard of smart meters and smart grids, and more than 64% showed no understanding of what smart meters were and could do. Other American participants (n=22) in Krishnamurti *et al.* (2012) confused the smart meter with the devices; expecting a smart meter to come with an energy monitor so that they can verify the accuracy of their energy bill and see appliance-specific feedback describing their energy consumption in detail.

In an online conjoint analysis, [Dütschke and Paetz \(2013\)](#) questioned German participants on their beliefs and expectations of dynamic pricing. They found that consumers are unsure of what dynamic electricity pricing is and what it can do. Of 160 participants, just over half (53%) believed that dynamic pricing may result in a reduction in their energy use. Added to this uncertainty are difficulties in calculating peak and off-peak consumption; consumers do not know the energy demand of the different appliances that they use ([Goulden *et al.*, 2014](#)).

This uncertainty is unsurprising given how the traditional electricity market is set up; households are accustomed to being passive users of energy. Consumers are often unaware of how much they pay for their electricity, or of the tariff they are on. This is particularly true of the older generation ([Barnicoat and Danson, 2015](#)). [Alexander \(2010\)](#) discusses the implications of dynamic pricing for residential consumers suggesting that it goes against years of policy aimed at reducing price volatility for residential consumers in the electricity market. [Alexander](#) argues that the true cost of dynamic pricing is not considered in field experiments and pilot studies. In order to implement demand response consumers require new technology which has its own cost. Furthermore, there is a cost associated with changing consumption behaviour which is not factored into savings calculations.

This uncertainty can lead to confusion of the benefits and risks of smart meter and dynamic pricing, leading to unrealistic expectations, (potentially in favour of energy companies), and disappointed consumers ([Krishnamurti *et al.*, 2012](#)).

1.2.3 Complexity of Tariffs

In a Norwegian field experiment, [Ericson \(2011\)](#) explores households' tariff choice between their standard flat-rate tariff and a CPP tariff when offered smart meter technology to automatically measure their hourly consumption. Of the 2 300 households initially approached for the study, 295 households chose the CPP rate. Similarly, both [Dütschke and Paetz \(2013\)](#) and [Schlereth *et al.* \(2018\)](#) find that when choosing a tariff, German participants (n=160, and n=779, respectively) are more likely to select a simple TOU tariff with a low variation in price, as opposed to a dynamic RTP tariff with a high price variation.

In order to determine how the complexity of tariffs affects contract choice, [Layer *et al.* \(2017\)](#) conduct an online choice experiment of German consumers (n = 664). The sample is divided into those who enjoy facing complex decisions and those

who do not. Of the four hypothetical tariffs proposed, flat-rate, TOU, CPP, and RTP, the former perceive the CPP and RTP tariffs to be complex and perceive little complexity concerning the flat-rate and TOU tariffs. The latter perceive all four tariffs to be complex. In particular, [Layer *et al.* \(2017\)](#) find that the more components a tariff contains¹⁰, if the tariff contains odd-endings to price values, and the use of percentages in tariffs leads to increased perceived complexity of tariffs.

It is perhaps the issues of uncertainty described above and tariff complexity which lead households to favour their existing, time-invariant tariffs. [Yoshida *et al.* \(2017\)](#) find that greater knowledge of energy conservation increases choice of TOU and CPP tariffs. Furthermore, after experimenting different tariffs in a smart home laboratory¹¹ for 8 weeks, three of the four participants in [Dütschke and Paetz \(2013\)](#) preferred the dynamic tariffs to the static tariffs with the exception of the most dynamic tariff which included both varying prices and load limits.

1.2.4 Reluctance Towards Automation and Third-party Control

Another issue of contention for residential consumers is the amount of control that smart meters will allow energy companies over their personal consumption. Consumers feel that the installation of smart meters means relinquishing control of their environment ([Barnicoat and Danson, 2015](#)). [Krishnamurti *et al.* \(2012\)](#) find that American consumers believe that smart meters will be used by energy companies to control household energy use. For example, to cut off the supply to households which consume too much electricity.

In a survey of 139 Dutch households, participants stated they preferred manual control to automatic control. They prefer to make their own decisions regarding when to turn-off appliances, instead of allowing a smart meter to do this for them; they are not willing to lose control for the sake of convenience ([Leijten *et al.*, 2014](#)). On the other hand, [Dütschke and Paetz \(2013\)](#) find that German participants (n=160) prefer a system in which smart appliances could react automatically to variations in prices rather than making the changes themselves.

¹⁰Price components refers to the number of differently priced periods. For example, a simple TOU tariff would have two price periods: peak and off-peak.

¹¹The smart home laboratory is a 60 metre squared house that can be lived in. It is fully equipped with functioning appliances which can be controlled for the purposes of testing new energy management technologies. See [Allerding and Schmeck \(2011\)](#) cited in [Dütschke and Paetz \(2013\)](#) for more details.

With respect to functionality Belgian participants (n=228) accept a trade-off between no automation and total automation¹², preferring to monitor and self-programme the smart meter and device to automatically turn-off appliances that have been on stand-by for too long (Pepermans, 2014).

Though some households are unlikely to allow third-party intervention to control their energy consumption, it may be unlikely that they make the necessary behavioural changes in order to reduce energy consumption (Verbong *et al.*, 2013). When comparing preferences for smart meter contracts, Pepermans (2014) conclude that as third-party intervention, and thus the effect on privacy, increases, the less the participants value the smart meter. Additionally, the extent to which consumers are willing to allow automatic control is limited by comfort; consumers do not wish to sacrifice their desired comfort level.

1.3 Barriers to Adoption

Assuming that consumers have accepted the installation of smart meters in their homes, the next issue to consider is whether consumers will use the information and incentives delivered by smart meters to reduce their energy consumption. Feedback from smart meters and dynamic pricing alone are not going to have an effect on residential energy consumption. They facilitate energy conservation by making energy visible (Darby, 2010, Hargreaves *et al.*, 2010, Gerpott and Paukert, 2013) and by reflecting the costs of production in energy prices (Faruqui, 2012). However, households need to engage with the information and respond to the incentives provided in order to lower their consumption.

1.3.1 Limited Motivation of Monetary Savings

Participants in studies across the UK and Australia state that their main motivation for accepting smart meters and dynamic pricing is financial (Hargreaves *et al.*, 2010, Buchanan *et al.*, 2014, Murtagh *et al.*, 2014, Barnicoat and Danson, 2015, Hall *et al.*, 2016). Indeed, British participants (n=1 892) expect to receive financial savings that are twice as large as the amount they are expected to pay for ‘smart services’

¹²No automation refers to a smart meter and device set-up which only allows for monitoring of energy consumption by the consumer, whereas total automation refers to ‘dynamic management of appliances’, i.e. the smart meter can send information to specific appliances to turn them off or on in response to demand or price signals (Pepermans, 2014, p.285).

(Richter and Pollitt, 2018). In Dütschke and Paetz (2013) when choosing between tariffs, German participants (n=160) were primarily motivated by monetary savings; expecting to save 50€-150€. Actual savings during the study were in the order of 20€-60€, at the lower end of these expectations.

Households participating in various UK studies were particularly interested in taking part in order to lower their energy bills. In focus groups led by Goulden *et al.* (2014), participants stated that they were motivated to shift energy consumption via dynamic pricing for monetary reasons. However, the authors suggest that the monetary saving from changing the use of isolated energy consuming appliances is likely to be too small to induce behavioural changes from financial incentives. Indeed, a single isolated behavioural change, such as turning an appliance off stand-by, is unlikely to have a large monetary impact. The behavioural changes that participants can make to lower energy consumption may have a small individual impact, but many changes can add up to a larger financial saving. For participants (n=275) in Hargreaves *et al.* (2010) the savings were not as much as they had envisioned; savings were in pennies rather than pounds. On the other hand, some participants (n=21) in Murtagh *et al.* (2014) found that each little saving adds up, yet others felt that they were comfortably well-off to not bother with trying to save energy to lower their bills.

The presentation of consumption information can have an effect on how individuals engage with it. Bager and Mundaca (2017) consider how to frame consumption information so as to encourage a greater provision of energy savings efforts on the part of consumers. They find that presenting expenditure on energy consumption as a salient loss compared to a statement of expenditure increases the percentage of energy savings that households achieve. Framing information as a loss of money invokes motivation to save energy in individuals as they do not wish to lose money that is theirs.

1.3.2 Understanding of Information on Display

In order for consumers to make the most out of the two-way communication capabilities of smart meters, they require an IHD to display their energy consumption in real-time. Indeed, German households feel that such a device is a necessity for dynamic pricing tariffs as without, they do not feel adequately informed in order to be able to make the appropriate changes to their behaviour (Dütschke and Paetz, 2013).

In an investigation of the effectiveness of energy monitor displays, [Chiang *et al.* \(2012\)](#) measured participants' (n=41) sensitivity to different presentations of consumption information (numerical, analogue or emotive) in both colour (red for high consumption, and green for low consumption) and black and white. Participants responded quickest to changes in information when presented numerically, and found the analogue information hardest to understand. Participants stated a preference for colour but this did not improve their performance.

Participants in [Hargreaves *et al.* \(2010\)](#), [Raw and Ross \(2011\)](#) and [Buchanan *et al.* \(2014\)](#) prefer consumption data to be displayed in monetary terms, rather than in energy units or CO2 emissions, as such information is more relatable and comparable. While it is understandable that monetary comparisons are more relatable for consumers, they may not be of much value if prices have changed across different time periods, in this case, energy unit comparisons would be of more use ([Darby, 2010](#)).

In hypothetical consumption scenarios, UK participants (n=170) were presented with consumption data in either monetary terms, as energy units (kWh) or as CO2 emissions and then asked to think of ways to reduce their consumption. [Spence *et al.* \(2014\)](#) find that participants who see their hypothetical consumption in monetary or energy units are more likely to state financial reasons as motivation for lowering their demand. Those who receive consumption information in terms of CO2 emissions are more likely to cite environmental reasons. While in this study, participants' motivations were clearly primed by the display treatment, the findings highlight that different displays evoke different motivations. Interestingly, [Spence *et al.*](#) find that those who were in the monetary display were most likely to say that lowering their energy consumption is not worth it.

On the other hand, after interviewing 28 Australian households, [Strengers \(2011, p.331\)](#) find that IHDs focus too much on the numbers, on quantifying what can be "saved and shaved" rather than on what households can do to change their behaviour and ultimately to lower their consumption. However, British participants (n=21), interviewed by [Murtagh *et al.* \(2014\)](#), say that they receive sufficient general energy savings advice from other outlets that the IHDs do not add anything new.

1.3.3 Inflexibility of Daily Routines

The principal objective of dynamic pricing is to lower consumption during peak periods when demand is much higher and much more costly to produce (Faruqui *et al.*, 2010a). This supposes that households are willing and able to lower their demand during such periods. However, households feel that there is little that they can do to prevent the natural peaks of energy consumption (due to non-flexible work days or ingrained energy consumption habits) without drastically changing their lifestyle (Naus *et al.*, 2014, Hall *et al.*, 2016).

Participants (n=275) in a UK study were reluctant to lower consumption below their normal level and, in fact, when prompted to do so, participants became defensive. They felt that they had no control over certain aspects of their energy consumption; certain appliances were necessities no matter how much they consumed (the definition of necessary appliances varied across households) and they were not willing to sacrifice their quality of life to save a small amount on energy (Hargreaves *et al.*, 2010).

In terms of how householders react to dynamic pricing, Dütschke and Paetz (2013) find them willing to change certain behaviours and use certain appliances at off-peak hours, such as dishwashers, washing machines and tumble driers. However, they find consumers unwilling, and potentially unable, to change the time of use of other activities related to comfort or entertainment. Goulden *et al.* (2014) describe energy consumers as willing to shift consumption of devices where energy consumption is not at the point-of-use, i.e. white goods, and unwilling to shift use of devices where consumption is at the point-of-use, i.e. showers and televisions.

Ericson (2011) hypothesises that consumers who have consumption patterns that are favourable to dynamic pricing, (i.e. their consumption is low during peak periods), are more likely to accept such tariffs. Yet, such dynamic pricing will not have the desired demand reduction effect for these consumers as they have less demand to shift to begin with. These consumers will benefit from dynamic pricing without being demand responsive. This is true of both British (n=160) and German (n=779) participants in choice experiments: those who consider that shifting consumption is an easy task, are more likely to adopt time-variant tariffs (Buryk *et al.*, 2015, Schlereth *et al.*, 2018).

1.3.4 Novelty Factor of Consumption Information

A common theme in field experiments and pilot studies using smart meters, energy monitors and dynamic pricing is that the behavioural changes made by households are short-lived. There is an initial novelty factor when households use the monitors frequently to begin with. Participants use energy monitors to identify a baseline level of consumption which a household deems to be their normal level of consumption. Any deviations from this baseline are then identified and acted upon (Hargreaves *et al.*, 2010, Strengers, 2011, Hargreaves *et al.*, 2013, Buchanan *et al.*, 2014).

In Hargreaves *et al.* (2010), this identification leads to reactive and pro-active behavioural changes. When energy consumption is unusually high, households identify and turn off appliances as necessary (reactive). In the longer term, they monitor individual appliances in order to determine which are inefficient and need replacing (pro-active). The use of the monitor affects future consumption decisions, with households taking energy-efficiency into greater consideration when purchasing new appliances. However, follow-up interviews 12 months later with 11 of the initial monitor users revealed that usage of the devices had greatly decreased, with three households having stopped using them altogether. The energy monitoring devices are rarely used by households in the longer term; they become part of the background of daily-life and are used to monitor abnormalities rather than to encourage demand reduction (Hargreaves *et al.*, 2013). This is corroborated by Schleich *et al.* (2013) who report limited use of feedback via a web portal; 70% of German participants (n=276) reported that they consulted the portal once a month, and also by Ueno *et al.* (2006) who find a decrease in the number interactions with an energy monitor a few weeks after installation.

Studies on dynamic pricing are not without questions as to the durability of demand response. Faruqui and George (2005) find that under TOU pricing, the demand response across two summers greatly decreases; 5.9% in summer 2003 to 0.6% in summer 2004. As the authors state, this result should be interpreted with caution however, as the sample size was small. Furthermore, it is not clear whether temperature variations across the two summers are accounted for. An Italian experiment finds that consumption increased under TOU pricing compared to flat-rate tariffs (Torriti, 2012). This could be considered as a type of rebound effect where households respond to the lower off-peak price by increasing their consumption by more than they lower their consumption in the peak period.

1.3.5 Effect on Household Dynamics

A final barrier of smart meters and dynamic pricing worthy of discussion is their effect on household dynamics. Household energy consumption is often discussed with the household being a single entity, however, households contain families which have varied compositions.

In [Hargreaves *et al.* \(2010\)](#) it was mostly male household members who used the monitors and who participated in the interviews, with the females of the household reported as "uninterested". In fact, the monitors were seen to cause conflict within households; as some individuals felt that their actions were being constantly monitored - how much energy was being consumed and how much money was being spent - by another member of the household. Other interviews with households revealed that although the male member may be more likely to be the bill payer, it is often the female household members who are responsible for managing the daily activities and thus the energy consumption of the household ([Murtagh *et al.*, 2014](#)).

Households with children and older people are less likely to sacrifice comfort and convenience to lower their energy demand ([Murtagh *et al.*, 2014](#)). These types of households are less flexible than others. Older generations in particular are more likely to spend more time at home, and they may have certain needs or health issues that require consuming energy ([Barnicoat and Danson, 2015](#)).

1.4 Recommendations

In order for smart meters and the incentives that they can deliver to be effective at encouraging households to lower their consumption, the barriers to acceptance and adoption discussed above will need to be overcome. Recommendations for overcoming some of the barriers identified above are discussed in this section.

Energy companies should increase their efforts to rebuild consumer trust where it has been lost. Such efforts will need to be credible given that non-verifiable attempts at "trust building" are not sufficient to increase consumers' vote of confidence in energy companies ([Stenner *et al.*, 2017](#)). Trust could be rebuilt by decreasing the uncertainty around smart meters, IHDs, dynamic pricing and other incentives. As consumers are typically unsure of how smart meters and IHDs or other monitors differ in their capabilities, being more transparent in explaining this new technology to consumers could be one avenue for trust rebuilding. In particular, as the

introduction of smart meters results in more reliable billing, some consumers whose consumption was previously undermeasured and underbilled will see an increase in their bill despite not changing their behaviour. To build trust with these consumers, energy companies could pledge to not increase consumer bills for a certain transition period after the installation of a smart meter due to more accurate measurement in order to allow households to familiarise themselves with the technology. This would be a similar practice to that of designing dynamic pricing tariffs to be revenue neutral (Faruqui *et al.*, 2009).

Given the increased complexity of dynamic pricing tariffs relative to flat-rate tariffs, consumers need to be carefully informed of the detail and educated as to how such tariffs can be profitable to them. In particular, energy companies should take care to limit the complexity of tariffs by reducing the number of different components, using even-numbered prices for different periods, and where possible providing consumers with savings in absolute amounts rather than in percentage form (Layer *et al.*, 2017). Furthermore, previous research has shown that consumers who are more familiar with dynamic pricing tariffs through educational campaigns or direct experimentation are more likely to be willing to accept such tariffs (Dütschke and Paetz, 2013, Yoshida *et al.*, 2017). Consumer participation in dynamic pricing contracts could therefore be increased through improved knowledge of these tariffs. Engaging consumers with the information provided by smart meters and the incentives used to encourage them to lower their consumption is paramount to them being effective. Rather than encouraging energy savings efforts, simply stating how much money households are saving highlights that small monetary amounts are saved with each energy saving action and may serve to discourage energy saving efforts (Hargreaves *et al.*, 2010, Murtagh *et al.*, 2014). Different presentations of consumption information invoke different motivations to save energy and different individuals respond differently to these presentations (Spence *et al.*, 2014). Given this, it is unlikely that a one-size-fits-all approach would be as successful at encouraging reductions in consumption, a more individual approach may be appropriate. Various research has identified different consumer segments. With regard to smart service preferences, Kaufmann *et al.* (2013) identify four different segments of Swiss consumers: ‘technology minded’, ‘safety minded’, ‘risk-averse’ and ‘price sensitive’. Murtagh *et al.* (2014) categorise British participants into one of three groups: ‘monitor enthusiasts’, ‘aspiring energy savers’ and ‘energy non-active’. Richter and Politt (2018) find three specific clusters of British consumer types: ‘private data’, ‘risk

averse', and 'open data'. Concerning choice of dynamic tariffs, [Schlereth et al. \(2018\)](#) separate German consumers into three different groups: 'price sensitive', 'flexible' and 'risk averse'.

Across these different categorisations of consumers, four clear segments can be identified. There are the technophiles who are enthusiastic about receiving data on their consumption and managing it, and who are open to sharing their data in order for energy companies to provide automated control of appliances. Secondly, there are those who are conscious of how their data can be exploited, and who prefer to retain control of their own energy consumption. The third segmentation concerns those consumers who are risk averse. These consumers have strong preferences for a tariff with a low peak/off-peak price ratio or a flat-rate tariff. They do not value potential monetary savings as highly, and are more technology-averse. The final segment are those who are price-sensitive. This group prefer a tariff with a high peak/off-peak price ratio and are more likely to switch to dynamic pricing contracts.

An additional segment to be considered is that of pro-environmental consumers. Such consumers gain additional utility from using a smart meter and device due to the pro-environmental benefits of reducing energy consumption and making an effort to slow global warming. [Gerpott and Paukert \(2013, p.486\)](#) suggest that certain consumers derive this additional utility due to a 'warm glow' effect of giving. That is to say, consumers receive utility from the act of helping others, in this instance, from helping the environment.

If these different segments of consumers can be identified, then appropriate technology and incentives can be offered to them such that these consumers will have the tools which are relevant to their characteristics, motivations and situation, which they can successfully engage with and use to lower their consumption. Therefore, rather than a one-size-fits-all approach to energy saving, a consumer segment specific approach is recommended.

That being said, a consumer segment that may not necessarily benefit from the use of a smart meter and device to reduce energy use is the segment of consumers for whom energy consumption is already low, as they will have little scope to further reduce their demand [Darby \(2010\)](#). Hence, these consumers may not accept smart meter installation. Such consumers may be pro-environmental consumers who have already reduced their consumption through other mechanisms, or low-income consumers who may not have the means to consume large quantities of energy, nor the scope to further reduce their consumption without becoming fuel-poor. Consideration should

be taken when targeting this segment of consumers.

Finally, automation and third-party control was found to be a significant barrier to acceptance. However, this may help to overcome the barrier to adoption concerning the inflexibility of daily life. Given that households may find it difficult to shift some consumption, the recommendation here is to focus on the demand that can be shifted, and to provide households with the technology that will allow for automatic peak demand shifting. Introducing automation and third-party control may also help to increase consumer trust in energy companies if the latter helps consumers to achieve energy savings with minimal effort. Such technology will not be readily accepted by all consumers and so the focus here should be on the technophiles and price-sensitive consumers.

1.5 Conclusion

Smart meters and dynamic pricing correct two market failures in the residential electricity market; smart meters make energy visible by providing consumption information, and dynamic pricing limits how much energy can be consumed by charging residential consumers prices which reflect actual costs at a given time. This first chapter has provided a qualitative review of predominately qualitative literature on how households and consumers perceive, interact with and use smart meters, energy monitors and dynamic pricing as tools and incentives to lower their energy consumption. Recommendations were also made to overcome some of these barriers.

Given that households have long been passive users of electricity, smart meters and energy monitors are the tools that households can use to become more aware of their energy consumption and are the technology via which different incentives can be communicated to households in order to encourage them to lower their demand for energy. Signals regarding the real-time price of electricity can be sent to households which will allow for electricity pricing which is reflective of the real cost of electricity production at different times of the day and the year, thus diminishing the unlimited quality of electricity from the point of view of households.

The review of the literature has highlighted four key barriers to acceptance and five key barriers to adoption of both smart meters and dynamic pricing.

First and foremost, households show low levels of trust in their energy provider. Households mistrust energy companies' intentions concerning the installation of

smart metering technology and their use of the data collected. Should significant energy, and monetary savings, be made, households do not trust energy companies to pass on these savings to the final consumer. Given that [Stenner *et al.* \(2017\)](#) find a simple two-line sentence alleviates a small amount of misgivings that consumers have regarding their energy company, utilities should consider credible methods in which trust can be rebuilt between themselves and residential consumers.

Whether households trust their energy company or not, many remain uncertain of what smart meters do and how dynamic pricing of electricity works. Tied in with uncertainty is the issue of the complexity of dynamic pricing tariffs. Consumers who perceive tariffs to be complex are more likely to opt for a simple flat-rate, or perhaps a two-period TOU tariff. However, when the benefits of such tariffs are explained to consumers, they are more willing to accept the tariffs which suggests that there is a problem of information. Through experience with the dynamic tariffs, consumers have a better understanding of how they can use them to save both energy and money, and are more likely to select such tariffs ([Dütschke and Paetz, 2013](#)). Energy companies should work on effective communication strategies to better inform households about both technology and incentives as doing so can be used to build trust, and has been shown to increase consumers' willingness to accept smart meters and smart services, and dynamic pricing.

A consumer's household is their domain, it is where they make decisions regarding their consumption. Households perceive smart meters as a way for third-parties to gain control of their daily life. Some consumers are concerned that energy companies will foist external control and automation on them against their will. Other consumers prefer a degree of external control, within their personal comfort parameters, as making behavioural changes is seen to be an inconvenience. A segmented approach to the implementation of different technologies (from monitoring to automation and control) and of different incentives is recommended to increase consumer participation and engagement.

The section on barriers to adoption explored how households interact with and use smart meters and dynamic pricing to lower their energy demand. Regarding the display of consumption information on energy monitors, households have a preference for simple, monetary metrics. They are less interested in the amount of energy consumed in kWh, nor in the emissions created by their consumption. Though such information awakens consumers' environmental motivations for lowering their energy consumption ([Spence *et al.*, 2014](#)). Some consumers would prefer less focus on

the data and more on actions that can be taken to lower their consumption ([Layer et al., 2017](#)).

Although households may prefer monetary information, and are mostly motivated to lower their energy consumption for financial reasons, some households are quickly discouraged to make further efforts to lower their consumption when they realise that energy saving actions do not necessarily result in sizeable monetary savings. This should be taken into consideration when designing how monetary information is displayed on IHDs, and when communicating to households the benefits of dynamic pricing programmes as with the latter, greater monetary savings are possible.

A significant barrier to households adoption of dynamic pricing is the lack of flexibility in their daily lives. Daily life is shaped in such a way that there are natural peaks in demand which are difficult for households to shift. Households who are perhaps most likely to choose dynamic pricing tariffs are those who have favourable consumption patterns and so are those who have less possibility to shift their demand ([Ericson, 2011](#)). Households which have less favourable consumption patterns could benefit from the introduction of automated responses to price signals in order to make saving energy simpler.

Finally, many studies have shown that there is a novelty factor at play in households which use energy monitors. Initially, households interact a great deal with their monitors in order to identify their normal level of consumption and any anomalous levels of consumption. However, this initial interest tends to disappear as households use their monitors less and less often. Keeping households engaged in their energy consumption management is key to achieving energy savings.

Chapter 2

Incentivising Households to Reduce Energy Consumption: A Meta-analysis

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¹³See <https://ecosesa.univ-grenoble-alpes.fr/>

Abstract

A meta-analysis approach is used to analyse the results of recent field experiments and pilot studies which explore the effects of different methods of incentivising residential consumers to lower their energy consumption. The strategies currently used fall into one of two categories: financial incentives (pricing strategies, monetary information), and non-financial incentives: informational incentives (historic feedback, real-time information, tailored advice, generic savings tips) and ‘nudges’ (social norms, social approval). Heterogeneity in studies is limited by focusing only on recent studies (2005 onwards) when there has been a greater understanding of the risks of climate change. Both peer-reviewed and grey literature (utility and government reports) are included to limit publication bias. The sample includes 105 observations from 39 papers. Results show that, on average, across studies, real-time feedback and monetary information have the greatest effect at reducing energy consumption. Compared to previous meta-analysis, the results show that recent studies use larger samples and are more robust (include a control group, subjects are assigned randomly to treatments, demographics and weather are controlled for). As a result, the effect sizes observed are generally smaller than those reported in previous meta-analyses and more indicative of the results of a national roll-out.

2.1 Introduction

Across the globe, countries are committing to increasing the share of production from renewable energy sources (RES) (United Nations, 2017). This transition is facilitated by the upgrading of the grid to a smarter, more efficient, more reliable network in which RES can be more easily integrated (Gungor *et al.*, 2011). The movement from a fossil fuel dependent energy system to one based on production from RES requires a re-imagining of the way in which residential consumers interact with the electricity grid. Rather than supply following demand, as is the traditional operation of electricity markets, the intermittent nature of production from RES calls for a greater level of flexibility in demand in order for demand to follow supply. Previous demand reduction strategies have focused on increasing energy efficiency¹⁴ as a way to lower consumption. However, despite a 33% increase in energy efficiency (European Environment Agency, 2016), residential energy consumption in the EU has increased by 9% between 1990 and 2013¹⁵. The increase in consumption can be associated to the rebound effect and the focus on energy efficiency as end rather than a means to achieving energy demand reduction (Maréchal and Holzemer, 2015).

Another strategy for reducing electricity demand focuses on ways to incentivise residential consumers to modify their electricity consuming behaviour. The installation of smart meters as part of the wider smart grid infrastructure, provides two-way communication between the household and the energy company, via the use of an energy monitor, and allows residential consumers to take an active role in the management of their electricity consumption. In the traditional electricity market, the residential consumer is a passive user for whom electricity is invisible and readily available (Darby *et al.*, 2006, Burgess and Nye, 2008, Hargreaves *et al.*, 2010). In the new market, the residential electricity consumer is better informed and more conscious of how much they consume.

Consumers have long been aware of the need to turn off unused lights, to not leave appliances on standby, to unplug chargers, to name a few, however due to a lack of information on the impact of such actions on consumption, consumers have not necessarily had the impetus to act. With the technological improvements being made to the grid, consumers can receive appropriate incentives to lower their electricity

¹⁴Such energy efficiency measures include the installation of home insulation, and the upgrading of old appliances to more energy efficient appliances, among others.

¹⁵In 2014, the European Environment Agency (2017a) report the first decrease in total household energy consumption since 1990 of 4%. In all previous years, household energy consumption has increased compared to 1990 levels, peaking in 2010.

consumption.

The incentives that are tested in pilot studies and field experiments fall under two categories: monetary incentives, and non-monetary incentives. Monetary incentives include information on monetary expenditure on energy, and pricing strategies. Such incentives allow households to better connect their consumption with its costs and encourage them to modify their behaviour to lower their costs. In the case of pricing strategies such as dynamic pricing, increasing the cost of electricity should, according to standard economic theory, incentivise households to consume less.

Non-monetary incentives can be further categorised into personal feedback on consumption, and social feedback. Personal feedback refers to information on a household's own consumption, which can be delivered in real-time via an energy monitor, made accessible on an online portal, or delivered as a monthly bill. Personal feedback also includes advice on how to reduce energy consumption, whether this is general advice or advice tailored to a particular household. By providing consumers with electricity consumption information and informing them of the consequences of increased consumption, rational consumers will make the decision to lower their electricity demand (Frederiks *et al.*, 2015). In reality, individuals do not behave rationally and so providing a greater level of information and monetary incentives may not be sufficient to encourage all consumers to modify their behaviour.

The sub-category of social feedback refers to comparisons of a household's consumption with that of other households. Such incentives are based on theories in behavioural economics and psychology which suggest that individuals use heuristics, or rules-of-thumb, to simplify complex decision making (Samson *et al.*, 2018). In the current context, households are informed of their consumption compared to the average consumption of their neighbours and receive social approval of their behaviour when they consume less than their neighbours via the use of positive reinforcement (Schultz *et al.*, 2007).

This chapter uses a meta-analysis approach to explore the strategies and public policies which employ such incentives in field experiments and pilot studies in order to evaluate the effect of the different incentives on households' energy consumption behaviour. The objective is to combine the results of many studies to provide a better estimate of the true effect of the different incentive types on residential energy consumption.

The current meta-analysis adds to literature on meta-analyses which explore incentives for reducing household electricity consumption by including solely recent

studies, those published from 2005 up to 2016, the time of data collection. By focusing on this time period, named the "Smart Grid Era" ([McKerracher and Torriti, 2013](#)), a more accurate estimate of the effect of an incentive on current electricity consumption is calculated. Additionally, the present analysis includes studies from both peer reviewed literature and utility and government reports in order to have as varied a database of studies as possible as the objectives of those carrying out the experiments are not the same. Academic researchers have a final objective to publish their research, whereas those working for utilities and governments seek to determine the return on investment in incentives. It can be argued that experiments with larger sample sizes provide more robust results, often the utilities have the means to run large trials of different incentives. Finally, if only peer reviewed articles are taken into consideration, there may be an issue of bias in the selection of studies used for the meta-analysis. The issue of publication bias is assessed in this chapter.

Compared to previous meta-analyses, a finer level of detail regarding the different incentives is used. In particular, the incentives regarding social feedback are separated into those which provide comparative feedback alone and those which also include approval or disapproval of behaviour as the former has been shown to result in a boomerang effect where households who consume less than their neighbours increase their consumption ([Schultz *et al.*, 2007](#)). The final added-value of the present meta-analysis is the inclusion of a greater level of study design variables, such as how households are recruited into the study, and how they are assigned to the treatment groups. Studies which recruit participants on an opt-in basis and do not randomise assignment to treatment groups may be subject to selection bias as those households who have favourable consumption patterns or are predisposed to lower energy consumption are more likely to take part ([Alexander, 2010](#), [Ericson, 2011](#), [Buchanan *et al.*, 2015](#)).

The following section describes the different incentives used in the experimental literature and sets out the hypotheses which will be tested. This is followed by a discussion of previous meta-analyses and reviews in [Section 2.3](#). [Section 2.4](#) describes the data collection method, the model used and the variables of interest. [Section 2.5](#) presents the results, [Section 2.6](#) discusses the results and finally, [Section 2.7](#) concludes.

2.2 Incentives for Lowering Electricity Consumption

The principal strategies employed to incentivise households to reduce their consumption can be separated into monetary and non-monetary incentives. In this section, the different strategies used in the literature are described and the hypotheses that will be tested are stated.

2.2.1 Monetary Incentives

Monetary incentives can be separated into one of two categories: electricity cost information and pricing strategies. Monetary information is included here as although it is not a direct monetary incentive, such incentives display information in monetary terms thus informing households of how much they are spending on electricity or how much they are saving. By providing households with information as to how much their electricity consumption costs (as opposed to information on the amount of electricity consumed) households can see the monetary benefits of reducing their electricity consumption. In interviews with households participating in electricity conservation field experiments, residents preferred to receive feedback in monetary terms as this is considered to be more relatable and more comparable than energy units (Hargreaves *et al.*, 2010, Raw and Ross, 2011).

Further, with the installation of smart meters in residential homes, a major technological barrier to the implementation of pricing strategies such as dynamic pricing has been lifted. Dynamic pricing provides consumers with economic incentives to reduce (increase) their electricity consumption during peak (off-peak) periods by better aligning the retail price of electricity with the wholesale price in order to maintain supply and demand balance in the electricity market (Borenstein *et al.*, 2002). Such pricing tariffs are effective at reducing demand during periods of high demand but are not necessarily effective at reducing overall demand (Torriti, 2012). However, such strategies can have spillover effects when behaviour to reduce consumption during a peak period carries on into off-peak periods (Allcott, 2011a). Such pricing strategies are therefore included in the present meta-analysis.

Hypothesis 1a: *Pricing strategies reduce electricity demand.*

Hypothesis 1b: Monetary information reduces electricity demand.

2.2.2 Non-monetary Incentives

Non-monetary strategies refer to those which provide households with more detailed information on their electricity consumption. In the experimental literature, this type of incentive can be categorised into personal feedback and social feedback.

2.2.2.1 Personal Feedback

Personal feedback provides households with data on their own electricity consumption with comparisons to consumption during a different period, such as the previous day, month, or year. Such feedback is received in a number of ways: through detailed electricity bills (see Carroll *et al.*, 2014, Schleich *et al.*, 2013), online via a website or email (see Benders *et al.*, 2006, Ueno *et al.*, 2006, Glerup *et al.*, 2010, Vassileva *et al.*, 2012, Mizobuchi and Takeuchi, 2013, Schleich *et al.*, 2013, Harries *et al.*, 2013, Houde *et al.*, 2013), in real-time via a monitor in the home (see Van Dam *et al.*, 2010, Grønhoj and Thøgersen, 2011, Alahmad *et al.*, 2012, Carroll *et al.*, 2014, Schultz *et al.*, 2015).

The provision of information on individual electricity consumption allows households to develop a greater awareness of their electricity consumption. By comparing their consumption from one period to another, such information allows households to see which behaviours result in increased consumption, so that they can follow their electricity consuming activities and determine when and how they consume the most electricity, and thus when and how to reduce their consumption.

Hypothesis 2a: Individual feedback on electricity consumption reduces electricity demand.

Hypothesis 2b: Real-time feedback on electricity consumption reduces electricity demand.

A further type of personal feedback that households may receive is advice on how to lower their consumption tailored to their particular situation (both building and household characteristics) (see Allcott, 2011b, Ayres *et al.*, 2012, Costa and Kahn, 2013) or more general electricity savings tips (see Ueno *et al.*, 2006, Mountain, 2008,

Van Dam *et al.*, 2010, Raw and Ross, 2011).

For example, Allcott (2011b) provides households with "action steps" based on their actual energy use and household characteristics, on how they can lower their energy consumption. In Mountain (2008, p.31), participating households are provided with a list of 10 generic energy savings tips including, "Run your dishwasher during off-peak hours", and "Turn monitor off instead of using a screen saver while you are not using a computer".

Hypothesis 3a: Personalised advice on how to save electricity reduces electricity demand.

Hypothesis 3b: Electricity savings tips reduce electricity demand.

2.2.2.2 Social Feedback

Social feedback refers to information on others' electricity consumption, such as neighbours or similar households. It is an intervention which has been increasingly explored in recent experimental studies and uses the notions of social and injunctive norms. A social norm refers to descriptive consumption feedback of personal consumption compared to that of other households. An injunctive norm reinforces whether a particular behaviour is socially approved or disapproved of. In the case of electricity consumption, an injunctive norm confirms whether a household's consumption is pro-social, i.e. whether the household is a low-consuming household (Schultz *et al.*, 2007).

These two types of social feedback have been separated in the present analysis as there is evidence that solely descriptive comparative feedback leads to a boomerang effect where low-consuming households increase their consumption, converging towards the average (Schultz *et al.*, 2007, Allcott, 2011b, Ayres *et al.*, 2012). The inclusion of injunctive norms reinforces the idea that households who consume less than average are engaged in pro-social behaviour and so they do not increase their consumption (Cialdini *et al.*, 1990).

Such methods of feedback may be successful via two mechanisms: by creating competition within a neighbourhood, or by highlighting the social cost of energy consumption. Regarding the latter, such social feedback may create a situation of conditional cooperation where households consume more (less) after learning that

others are consuming more (less) (Allcott, 2011b). Such behaviour is observed in public goods (Fischbacher *et al.*, 2001, Frey and Meier, 2004) and common pool resource games (Ostrom, 1990, Velez *et al.*, 2009).

Hypothesis 4a: *Social norms do not have an effect on electricity demand.*

Hypothesis 4b: *Injunctive norms reduce electricity demand.*

2.3 Previous Meta-Analyses

The effect of different feedback types and monetary incentives on electricity consumption has been studied by researchers and utilities alike since the 1970s, and as such, several reviews and meta-analyses have been undertaken (see Darby *et al.*, 2006, Ehrhardt-Martinez *et al.*, 2010, Faruqui *et al.*, 2010b, Delmas *et al.*, 2013, Faruqui and Sergici, 2013, McKerracher and Torriti, 2013). Table 2.1 summarises the results of the previous reviews and meta-analyses discussed in this section.

Authors	Objective	Time frame	Studies	Effect
Darby (2006)	Effect of direct and indirect feedback on energy (gas and electricity) consumption	1979-2006	38	Direct: -15% to -5% Indirect: -10% to 0%
Ehrhardt-Martinez et al. (2010)	Effect of different feedback treatments on energy consumption	1974-2010	57	-12% to -4%
Faruqui et al. (2010b)	Effect on IHDs on energy consumption	1989-2010	12	-13% to -3%
Delmas et al. (2013)	Reduction in energy consumption via different treatments	1975-2012	59	-55% to +18% Weighted ATE ¹⁶ : -7.4%
Faruqui and Sergici (2013)	Peak demand reduction of time-varying prices.		34	-58% to 0%
McKerracher and Torriti (2013)	Effect of IHDs on energy consumption	1979-2015	27	-5% to -3% ATE: -6.4%

Table 2.1: Summary of results of previous reviews and meta-analyses

Darby *et al.* (2006) reviews 38 feedback studies from 1979 to 2006 and concludes that, on average, direct feedback which is received immediately after the energy consuming behaviour is more effective than indirect feedback such as an energy bill. Both Faruqui *et al.* (2010b) and McKerracher and Torriti (2013) analyse the effect of real-time feedback, via an in-home display (IHD), on energy consumption. In a

review of 12 pilot studies (1989-2010), [Faruqui *et al.* \(2010b\)](#) find an energy reduction of 7% on average. [McKerracher and Torriti \(2013\)](#) perform a wider analysis of 27 peer and non peer reviewed studies between 1979-2011. The authors find that as sample size increases, the reported treatment effect decreases. Additionally, they classify studies via sampling selection and recruitment method and find that studies with more representative samples report lower percentages of energy reduction.

***Hypothesis 5:** With larger samples, the reduction in energy consumption due to an incentive is smaller*

[Ehrhardt-Martinez *et al.* \(2010\)](#) review 57 studies from 1974-2010 covering both feedback and dynamic pricing studies using advanced metering infrastructure. The authors conclude that feedback interventions result in a greater overall reduction in energy consumption than dynamic pricing which is more effective at decreasing demand at peak times.

Focusing on the effect of pricing strategies, [Faruqui and Sergici \(2013\)](#) find that the more dynamic the pricing strategies¹⁷, the greater the amount of peak energy conserved, all the more so when enabling technology is used.

[Delmas *et al.* \(2013\)](#) provide the most recent analysis of studies from 1975 to 2012 finding that tailored advice and energy conservation tips are most effective at reducing energy consumption. The authors compare the average treatment effects of more robust studies (those which include a control group, demographic information and control for weather changes) to studies with fewer controls. They find that more robust studies report a lower reduction in energy consumption ([Delmas *et al.*, 2013](#)).

[McKerracher and Torriti \(2013\)](#) also look at how study design affects results by considering how participants are recruited to participate in studies and how this affects their effort to reduce their consumption. They group studies into three categories by sample size, use of representative sampling, and whether participants opt-in or opt-out. They find that studies which use larger samples, representative sampling and opt-out participation show a smaller reduction in energy consumption. The present analysis goes further in exploring the effect of different levels of controls by comparing studies which use all controls to those which use fewer, and also by

¹⁷Real-time pricing strategies are considered to be more dynamic as the price faced by final consumers fluctuates in line with wholesale prices. Time-of-use tariffs are less dynamic as the prices are fixed for certain hours. Critical peak pricing and peak-time rebates fall in-between the two.

estimating the effect of each individual control on energy consumption.

***Hypothesis 6:** More robust studies (inclusion of control group, weather controls, demographic controls, opt-out recruitment, random assignment to treatment group) show a smaller reduction in electricity demand.*

Each of these reviews and analyses have covered studies across a long time period, from the 70s and 80s to the present. [Ehrhardt-Martinez et al. \(2010\)](#) find trends in energy savings across two distinct periods; the Energy Crisis Era from the seventies to 1995, and the Climate Change Era from 1995 to 2010. [McKerracher and Torriti \(2013\)](#) identify an additional era, from 2005 onwards which they name the Smart Grid Era. The current paper seeks to better understand the effect of different interventions on energy consumption by considering solely studies from 2005 onwards so as to focus on the Smart Grid era. Studies conducted since 2005 are different to those conducted in the 70s and 80s. The more recent studies benefit from technological advances in terms of the provision of treatments and the measurement of treatment effects. It would be erroneous to include results from such varied time periods. As [Ehrhardt-Martinez et al. \(2010, p.74\)](#) note, "studies that compare feedback-related savings across all four decades may result in inflated expectations regarding potential energy savings today".

***Hypothesis 7:** Average effect of incentives on electricity consumption is lower in Smart Grid Era compared to previous eras.*

2.4 Method

2.4.1 Data Collection

In order to find appropriate articles for this analysis, the following databases were searched: ScienceDirect, EconLit, Web of Science, SpringerLink, Econpapers, SSRN, NBER, for the following sets of keywords using Boolean logic:

- Keywords concerning type of consumption: electricity consumption, electricity demand, electricity usage, energy consumption, energy demand, energy usage,

and;

- Keywords concerning the type of incentive:
 - Incentive, behaviour
 - Informational feedback: smart meter, advanced metering, feedback, nudge, norm,
 - Financial feedback: dynamic pricing, tariff, time of use, critical peak pricing, real time pricing, peak time rebate, and;
- Keywords concerning the level of consumption: residential, household, consumer, and;
- Keywords concerning the study type: pilot, trial, experiment, field.

Across all databases, after eliminating doubles, the search terms resulted in a list of 1,490 studies. The titles and abstracts of these studies were reviewed. In addition to the database search, the reference lists and the lists of citing articles for each selected article, as well as previous meta-analyses, were scanned for further relevant studies. This procedure resulted in a selection of 84 articles and 27 reports on the topic of using incentives to reduce residential electricity consumption. Each article and report was read and a final selection of 24 articles and 15 reports were kept for the analysis.

The final list of articles, those in which the treatment effect is reported as the change in electricity consumption of treated households compared to either a baseline or control group and details on why 72 papers were excluded can be found in Appendix A¹⁸. A coding protocol was implemented for the final selection of 39 studies which involved an experimentation of the above incentives. The majority of articles came from economics, business, and energy journals. The reports are from utility and government websites as well as from consulting companies.

Figure 2.1 displays the geographical distribution of included studies. The majority of studies come from the United Kingdom and North America as these regions have been at the forefront of field experiments and pilot studies on incentives to reduce electricity consumption. In addition, this could also be explained by the fact that one of the inclusion criteria is that the paper be written in English and that

¹⁸The main reasons for excluding papers are: a different treatment effect measure was used (peak demand reduction, appliance level data), sample is non-residential, or studies were based on simulations or laboratory experiments.

experiments carried out by national utilities and governments are likely to be written in the native language. This restriction could result in publication bias which will be assessed below.



Figure 2.1: Geographical distribution of included studies

2.4.2 Model and Estimation Method

Meta-regression analysis is a quantitative method of systematically analysing the results of empirical studies with a common objective. It goes beyond a literature review in that it allows the analyst to calculate a mean treatment effect across studies by discovering which variables lead to differences in experiments which study the same treatment effect (Stanley and Jarrell, 1989, Nelson and Kennedy, 2009). Meta-analyses are used to estimate a more precise estimate of the true effect of a treatment than any single study can do alone (Borenstein *et al.*, 2009).

Using notation from Nelson and Kennedy (2009, p.8), the following meta-regression model is estimated:

$$\tilde{\beta}_i = \alpha_0 + \alpha_1 x_{i1} + \dots + \alpha_K x_{iK} + e_i \quad (2.1)$$

where (x_{i1}, \dots, x_{iK}) is a vector of study characteristics, $(\alpha_1, \dots, \alpha_K)$ are unknown parameters to be estimated, and e_i is the normally distributed sampling-estimation error with zero mean and variance σ_i^2 , $\forall i = 1, \dots, N$.

This model can be estimated by ordinary least squares (OLS). However, given that in the sample of primary studies, there are treatment effects from studies of varied sample sizes, the method of estimation by OLS may lead to inefficient and biased estimates. This bias can be mitigated by using White or Huber-White robust standard errors (Sebri, 2014).

Furthermore, the standard OLS approach may not be appropriate due to issues highlighted by [Nelson and Kennedy \(2009\)](#) and [Stanley and Doucouliagos \(2012\)](#) which are prevalent in meta regression analysis such as publication bias, heterogeneity, heteroscedasticity and non-independence. Publication bias is an issue across much social science research when results that show a significant effect are favoured for publication over those which do not. Heterogeneity is present due to either differences in the experimental design and methods used in the primary studies, or to differences such as geographical location and historical context. The issue of heteroscedasticity arises from the inclusion of primary studies with different sample sizes, and finally, non-independence occurs when more than one observation is used from a single primary study. Each of these issues are a concern in the present meta-analysis and steps are taken to reduce their impact on the results as discussed below.

Other approaches used in meta-regression analysis to estimate the model in eq. (2.1) include using fixed- or random-effects estimation (FEE and REE respectively)¹⁹. FEE weights each treatment effect estimate by its precision squared, or the inverse of its variance. Furthermore, FEE assumes that all primary observations of treatment effects are drawn from the same population ([Stanley and Doucouliagos, 2012](#)). In the present sample, treatment effects are taken from primary studies from different countries which thus have different samples. Given such heterogeneity in the sample, [Stanley and Doucouliagos \(2012\)](#) suggest that the REE is a technically more appropriate estimator as the weight used accounts for this heterogeneity.

In further research, [Stanley and Doucouliagos \(2015\)](#) find that the weighted least squares (WLS) estimator is preferable to both FEE and REE. The authors find that under heterogeneity, WLS outperforms FEE, and in the case of publication or small sample bias, WLS does better than REE. Given the characteristics of the data used in the present meta-analysis, several approaches are taken to overcome the potential issues of publication bias, heterogeneity, heteroscedasticity, and non-independence.

Firstly, to limit issues of publication bias, both peer reviewed articles and reports from the grey literature are included in this analysis. In addition, after a description of the dataset and before any models are estimated, the selection of primary studies used in the meta-analysis is assessed for publication bias. This analysis leads to the conclusion that publication bias is present up to a factor of 2 and that using the

¹⁹These terms refer to estimators used in meta-analysis and not to those used in panel data econometrics ([Stanley and Doucouliagos, 2012](#)).

sample size as a weight mitigates this problem.

Second, to tackle the sources of heterogeneity, a set of binary variables describing the study characteristics which are potential sources of heterogeneity are included in the regression (section 2.4.3 describes the variables used in the analysis), and the temporal context has been limited to primary studies published since 2005 representing the *Smart-Grid Era* (McKerracher and Torriti, 2013).

Next, to account for heteroscedasticity, the model in eq. (2.1) is estimated by WLS. The preferred weight is the inverse standard error of the treatment effect, however, given that these are not always reported in the primary studies, a common approach is to proxy the standard error using the sample size (Nelson and Kennedy, 2009, Stanley and Doucouliagos, 2012). As such, the square root of the sample size is used as weights for the estimation following Delmas *et al.* (2013), Seabri (2014) and Van Houtven *et al.* (2017) such that experiments with a larger sample are given more weight. Experiments with larger samples are considered to be more representative of the population and so the estimated effect is a better estimate of the true effect. Finally, to address the non-independence of several treatment effects coming from the same primary study, the estimated standard errors are clustered by primary study.

2.4.3 Variables

Dependent Variable

The variable of interest is the treatment effect reported in primary studies as the percentage change in electricity consumption as a result of the implementation of an incentive. When a control group is present in an experiment, the percentage change relative to the control group is used. If no control group is present, the percentage change relative to the baseline is used²⁰. In the following analysis the dependent variable is referred to as the Average Treatment Effect (ATE).

Independent Variables

The independent variables refer to the type of intervention tested in the primary study and the controls used. As discussed above, there are *pricing strategies*: households receive a financial reward which is directly linked to their electricity conservation effort. For example, changing prices are used to influence consumers electricity

²⁰Presence of a control group is controlled for in the analysis to come.

consumption by aligning the retail price of electricity with the wholesale price. Or participating households are given feedback on how much their electricity consumption costs (*monetary information*).

Non-monetary strategies are separated into those which provide personal feedback, and those which provide social feedback of others' electricity consumption. *Individual feedback* refers to interventions where participants receive information on their current and previous consumption in energy units. This refers to consumption information that is in addition to the standard electricity bill, be it a more detailed bill, or consumption information on a website. *Real-time feedback* refers to the same type of information which is delivered in real-time via an energy monitor²¹. Households can also receive *personalised advice* specific to their living situation on how to lower their electricity consumption, or generic electricity *savings tips*.

Studies which provide social feedback are separated into those which provide *social norms* feedback: descriptive feedback of personal consumption compared to that of other households, and *injunctive norms* feedback which also provides social approval or disapproval of a household's consumption behaviour.

Finally, a set of control variables are included in the analysis: *control group*: presence of a control group; *weather controls*: whether weather is controlled for; *demographic controls*: the collection of demographic information; *random*: households are assigned randomly to control and treatment groups as opposed to choosing an intervention; *opt-in recruitment*: households choose to participate in the study; and *duration*: duration of study. These control variables are included in order to capture the heterogeneity between the different experiments. Furthermore, studies which include such variables control for changes in behaviour which cannot be explained by the use of an incentive alone.

²¹Only data that are received via an IHD or monitor are considered to be *real-time feedback* in the present analysis. Real-time data are made available to households via websites (see [Houde et al., 2013](#)), however, the data are not accessible to consumers in real-time. They must log-on to the site in order to access the information. The incentives used in such experiments are included in *individual feedback*.

2.5 Results

2.5.1 Descriptive Statistics

The analysis covers 105 observations from 39 unique papers giving, on average, 2.7 observations per paper. In meta-analysis it is preferable to limit the analysis to one observation per study in order to reduce correlation between studies (Nelson and Kennedy, 2009). However, given that some reports describe the results of more than one experiment, and also, due to the design of the sample experiments, doing so would greatly limit the number of observable treatment effects. To account for potential heterogeneity due to several observations being taken from one study, in the following analysis, standard errors are clustered by study.

Table 2.2 provides descriptive statistics of the independent and dependent variables for the full sample. Within the sample of studies selected for this analysis, *individual feedback* is the most experimented treatment representing 70% of the observations and 77% of the studies. Compared with previous meta-analysis, the share of studies involving a form of social feedback (*social norms* or *injunctive norms*) has increased. The *injunctive norms* treatment represents 27% and 26% of the observations and studies, respectively.

Concerning the design of the primary studies, the majority use a control group for comparison and control for demographic differences in the sample population, 90% and 85% respectively. Fewer studies (59%) control for variations in the weather. 68% of observations randomly assign subjects to a treatment but this is not a practice adopted in all studies, 49%. Opt-in recruitment is the more common method of recruitment, 67% of observations and 69% of studies.

2.5.2 Average Treatment Effects

Table 2.2 also provides both a non-weighted and weighted ATE by incentive. The ATE are weighted using study sample size as frequency weights following Schmidt and Hunter (2014) which gives more weight to studies with larger samples. The ATE across all incentives is 3.37% reduction in consumption. The weighted ATE takes into consideration the differing sample sizes in each study and equates to a 1.85% reduction in electricity consumption. This means that, on average, an incentive in a typical electricity conservation study will result in electricity savings of slightly less than 2%. In the sample of studies selected, the effect of incentives on electricity

consumption ranges from an 22.2% reduction (Kendel and Lazaric, 2015) to a 13.69% increase (Torriti, 2012).

From table 2.2, it can be seen that *real-time feedback* and *monetary information* have the greatest effects on electricity consumption with a weighted ATE of 2.89% and 2.86%, respectively, indicating a reduction in consumption. *Pricing strategies* have the smallest effect on overall electricity consumption with a weighted ATE showing a reduction in consumption of 0.99%.

Study characteristic	Mean	Std. dev.	Primary obs.	Primary studies	Average sample size	Min (%)	Max (%)	ATE (%)	Weighted ATE (%)
Average treatment effect									
Pricing strategies	0.34	0.48	34%	28%	6685	-22.20	13.69	-3.37	-1.85
Monetary information	0.31	0.47	31%	46%	1986	-7.60	13.69	-2.57	-0.99
Individual feedback	0.70	0.46	70%	77%	716	-18.06	5.30	-4.18	-2.86
Real-time feedback	0.37	0.49	37%	38%	9429	-22.20	5.30	-3.56	-1.88
Personalised feedback	0.18	0.39	18%	13%	566	-18.06	5.30	-4.69	-2.89
Savings tips	0.52	0.50	52%	46%	19504	-5.80	-1.20	-2.22	-2.01
Social norms	0.10	0.29	10%	21%	4706	-16.71	5.30	-3.30	-1.78
Injunctive norms	0.27	0.44	27%	26%	530	-18.00	-0.35	-4.66	-1.74
					21720	-7.02	-1.00	-2.26	-1.95
Control group	0.90	0.31	90%	85%	7445				
Weather controls	0.73	0.44	73%	59%	6128				
Demographic controls	0.85	0.36	85%	79%	6511				
Random assignment	0.68	0.47	68%	49%	9218				
Opt-in recruitment	0.67	0.47	67%	69%	540				
Duration (months)	13.60	8.81	100%	100%	6685				
Sample size	6685	14863	100%	100%	6685				
Number of observations			105	39					

A negative percentage indicates a reduction in electricity consumption, whereas a positive percentage change indicates an increase in electricity consumption.

Table 2.2: Descriptive statistics and average treatment effects

Incentive	Weighted ATE	
	Peer reviewed (%)	Grey literature (%)
Overall	-1.96	-1.71
Pricing strategies	2.31	-1.25
Monetary information	-3.63	-2.77
Individual feedback	-2.02	-1.72
Real-time feedback	-2.83	-2.89
Personalised advice	-2.01	
Savings tips	-3.01	-1.76
Social norms	-2.36	-1.12
Injunctive norms	-2.01	-1.85
Number of observations	57	48

Table 2.3: Comparison of weighted average treatment effects by literature type

For comparison between the literature types, table 2.3 provides the weighted average treatment effects by study type, i.e.: whether the study is from a peer-reviewed journal or from the grey literature. In the sample of studies collected, there are no reports which use personalised feedback as an incentive. Across all incentive types, on average, a peer-reviewed study shows a weighted ATE of a 1.96% reduction, and a study from the grey literature shows a weighted ATE of a 1.71% reduction in consumption. Studies from the grey literature tend to show a smaller effect of an incentive on electricity consumption. Among the peer reviewed studies, the weighted ATE of the use of *pricing strategies* is an increase in electricity consumption of 2.31%, indicating that such strategies are more appropriate for reducing peak demand rather than overall demand.

The primary studies are separated into those which use a higher number of controls; a control group, weather and demographic controls, randomly assign households to treatments, and use an opt-out method of recruitment, as such studies are assumed to show a more representative estimate of the true treatment effect. Studies which compare the treatment effect to a control group rather than the baseline of the same group of households, provide a more robust estimate of the treatment effect. The same applies to studies which use weather controls and collect demographic information. Studies which adopt a random treatment assignment method and an opt-out method of recruitment are more representative as they use samples in which households have not chosen their treatment method nor are subject to selection bias. Table 2.4 gives the average treatment effects by robustness. More robust studies

	Primary obs.	Min (%)	Max (%)	ATE (%)	Weighted ATE (%)
All studies	105	-22.20	13.69	-3.37	-1.85
More robust studies	23	-5.40	-1.17	-2.17	-1.98
Less robust studies	82	-22.20	13.69	-3.71	-1.67

Table 2.4: Average treatment effects by study robustness

are considered to be those which include all the above controls, less robust studies are those which include less. Of all the studies, 22% can be considered to be more robust. These studies have an ATE of a 2.17% reduction whereas the less robust studies have an ATE of a 3.71% reduction. These ATE are significantly different (p -value < 0.001 , Wilcoxon signed rank test). The more robust studies show a greater reduction when sample size is taken into consideration.

Table 2.5 provides the correlations between variables. There are no strong correlations between *treatment effect* and the treatment variables as treatment choice is typically random. Strong positive correlations can be seen between both the *personalised feedback* and the *social norm* and *injunctive norm* treatments, and strong negative correlation with *opt-in recruitment* as for these treatments, participating households took part in the study by default and opted-out if they did not want to take part. These studies are typically large-scale experiments led by utilities which have the means to carry out such studies (Allcott, 2011b, Ayres *et al.*, 2012).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Average treatment effect	1.00																
(2) Pricing strategies	0.13 (0.17)	1.00															
(3) Monetary information	-0.13 (0.20)	0.07 (0.46)	1.00														
(4) Individual feedback	-0.07 (0.50)	-0.31* (0.00)	0.27* (0.01)	1.00													
(5) Real-time feedback	-0.23* (0.02)	0.03 (0.79)	0.63* (0.00)	-0.09 (0.36)	1.00												
(6) Personalised advice	0.13 (0.20)	-0.34* (0.00)	-0.32* (0.00)	0.26* (0.01)	-0.36* (0.00)	1.00											
(7) Savings tips	0.02 (0.87)	0.09 (0.38)	0.07 (0.48)	-0.09 (0.35)	0.26* (0.01)	-0.49* (0.00)	1.00										
(8) Social norms	-0.10 (0.32)	0.04 (0.69)	0.06 (0.54)	0.00 (0.97)	-0.12 (0.24)	-0.15 (0.12)	0.11 (0.24)	1.00									
(9) Injunctive norms	0.15 (0.11)	-0.44* (0.00)	-0.41* (0.00)	0.35* (0.00)	-0.42* (0.00)	0.67* (0.00)	-0.20* (0.04)	-0.20* (0.05)	1.00								
(10) Control group	0.27* (0.01)	0.18 (0.06)	0.10 (0.32)	0.25* (0.01)	-0.12 (0.21)	0.16 (0.10)	-0.14 (0.16)	-0.10 (0.31)	0.21* (0.03)	1.00							
(11) Weather controls	0.17 (0.09)	0.16 (0.10)	0.08 (0.40)	-0.02 (0.80)	-0.07 (0.47)	0.17 (0.08)	-0.19 (0.06)	-0.32* (0.00)	0.22* (0.03)	0.36* (0.00)	1.00						
(12) Demographic controls	-0.13 (0.20)	-0.25* (0.01)	0.06 (0.55)	0.18 (0.07)	-0.00 (0.97)	0.20* (0.04)	0.02 (0.84)	0.14 (0.16)	0.14 (0.17)	-0.06 (0.55)	0.10 (0.29)	1.00					
(13) Random assignment	0.17 (0.09)	-0.01 (0.88)	-0.10 (0.30)	0.29* (0.00)	-0.27* (0.01)	0.27* (0.00)	-0.05 (0.62)	-0.26* (0.01)	0.37* (0.00)	0.49* (0.00)	0.41* (0.00)	0.39* (0.00)	1.00				
(14) Opt-in recruitment	-0.22* (0.02)	0.30* (0.00)	0.39* (0.00)	-0.29* (0.00)	0.38* (0.00)	-0.56* (0.00)	0.13 (0.17)	0.09 (0.35)	-0.81* (0.00)	-0.18 (0.07)	0.15 (0.13)	0.15 (0.28)	-0.19 (0.06)	1.00			
(15) Duration	0.19 (0.05)	-0.18 (0.06)	0.04 (0.70)	0.22* (0.02)	-0.07 (0.47)	0.31* (0.00)	-0.08 (0.41)	-0.05 (0.63)	0.24* (0.01)	0.11 (0.27)	0.31* (0.00)	0.28* (0.00)	0.43* (0.00)	-0.13 (0.19)	1.00		
(16) Sample size	0.16 (0.10)	-0.23* (0.02)	-0.27* (0.00)	0.28* (0.00)	-0.32* (0.00)	0.41* (0.00)	-0.14 (0.15)	-0.14 (0.17)	0.61* (0.00)	0.15 (0.13)	-0.06 (0.53)	-0.03 (0.78)	0.25* (0.01)	-0.59* (0.00)	0.20* (0.04)	1.00	
(17) Peer reviewed	0.02 (0.87)	-0.30* (0.00)	-0.33* (0.00)	-0.07 (0.49)	-0.28* (0.00)	0.43* (0.00)	-0.26* (0.01)	0.10 (0.30)	0.25* (0.01)	-0.31* (0.00)	-0.16 (0.09)	0.14 (0.15)	-0.14 (0.14)	-0.08 (0.41)	-0.26* (0.01)	-0.00 (0.97)	1.00

Standard errors in brackets. * $p < 0.05$

Table 2.5: Pearson cross-correlation table

Figure 2.2 shows the distribution of treatment effects by publication year. The majority of studies were published from 2010 onwards. Almost half of the observations in the sample were published in 2011. There does not appear to be a trend in the effects of incentives on electricity consumption over this time period.

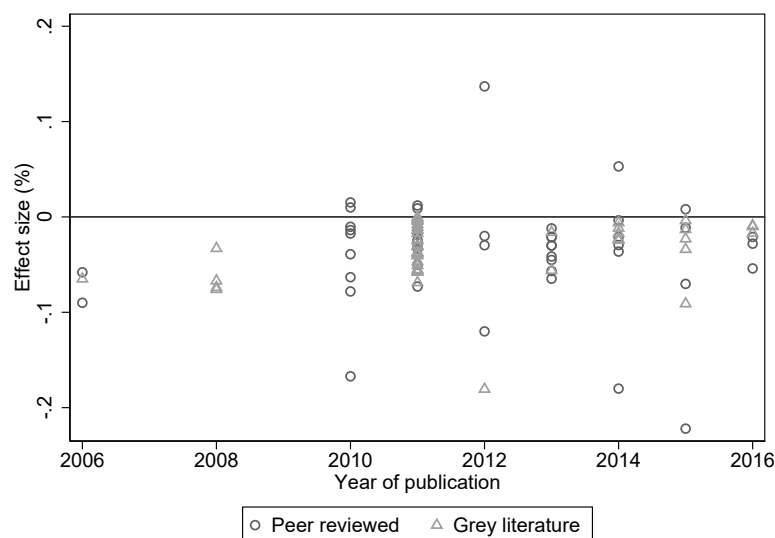


Figure 2.2: Treatment effects by year of publication

Figures 2.3 to 2.5 are box plots of the spread of treatment effects by the presence of a control group, the use of weather controls, or the collection of socio-demographic data. Figure 2.3 shows that the median treatment effect is slightly smaller when a control group is present, and that the spread is greater in the absence of a control group. Whether weather effects are controlled for or not, the median treatment effect is similar. The spread is slightly tighter around the median when weather is controlled for. Concerning the collection, or not, of socio-demographic data, the median and the spread of the treatment effects are similar. From these box plots, there is evidence of certain outlying values of the treatment effects.

Figures 2.6 and 2.7 are box plots showing the spread of the data by treatment assignment method and by sample selection method. Approximately two-thirds of the sample studies use random assignment and/or opt-in methods. In both cases, the median values are similar, however, the spread is more closely concentrated around the median values when treatment assignment is random and when participants must opt-out of the study. Households can achieve greater levels of electricity consumption reduction when they are not randomly assigned to a treatment and when they choose to participate in a study.

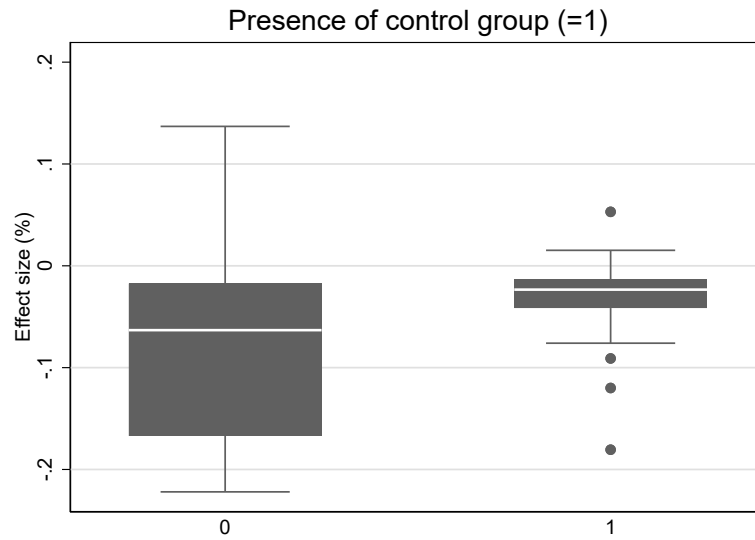


Figure 2.3: Treatment effects by presence of control group

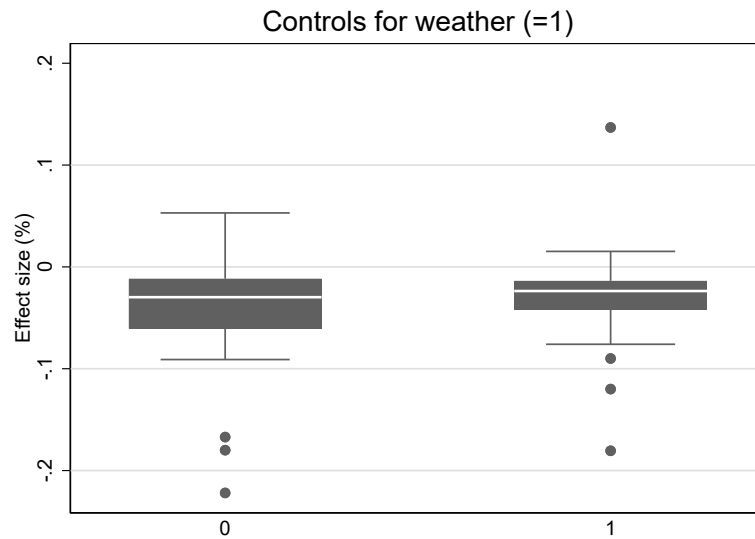


Figure 2.4: Treatment effects by use of weather controls

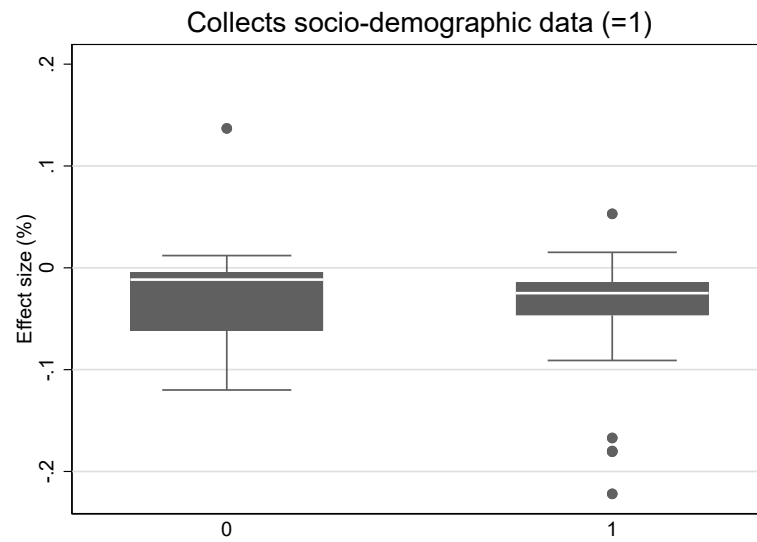


Figure 2.5: Treatment effects by collection of socio-demographic data

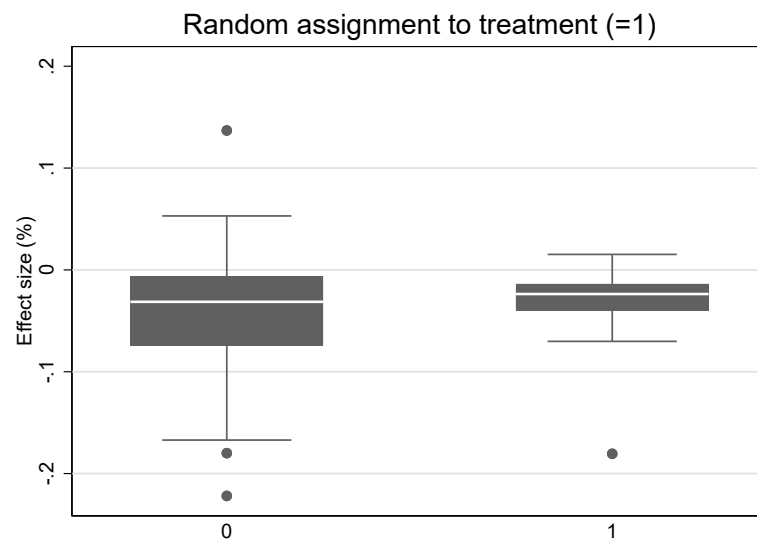


Figure 2.6: Treatment effects by treatment assignment

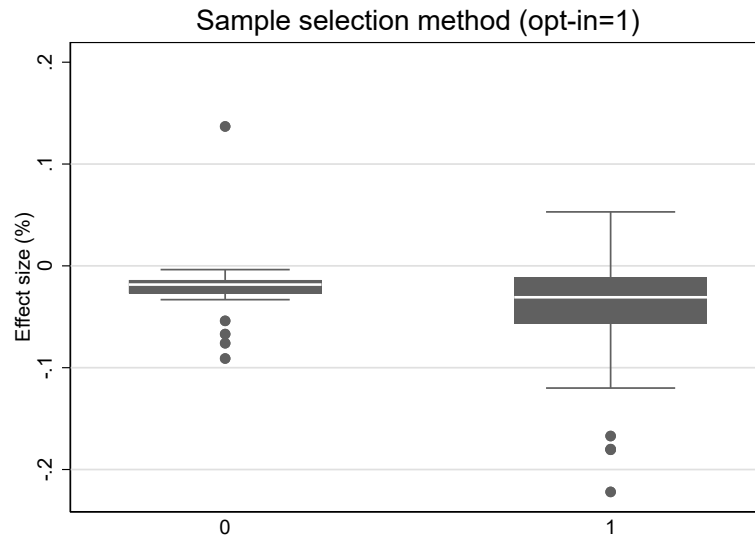


Figure 2.7: Treatment effects by sample selection method

Figure 2.8 shows the distribution of treatment effect by duration of the study. The majority of studies are short in duration (shorter than 12 months). There are a cluster of studies lasting one or two years. The majority of the longer studies are those that are led by utilities. Finally, there are a few utility led studies which last for almost three years. From the figure, it appears that longer studies show a smaller effect of incentives on electricity savings.

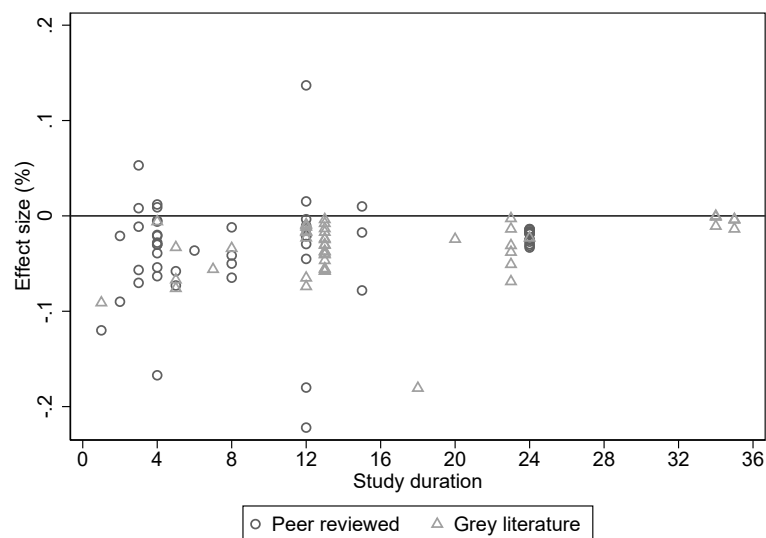


Figure 2.8: Treatment effects by study duration

The above graphical analysis indicates that the treatment effects reported in primary

studies may be particularly affected by the presence of a control group, treatment assignment and sample selection methods.

In studies without a control group, the change in electricity consumption is compared within the same group of households between the treatment period and a baseline period. Whereas in studies with a control group, the change in consumption is compared both within the same group of households and between groups of households whose consumption is measured during the treatment and baseline periods; a difference-in-difference method. The latter studies allow researchers to account for additional factors which affect electricity consumption during the course of the study and appear to show a lesser treatment effect to the former.

Households who choose to participate in a study on electricity consumption may be particularly motivated to reduce their consumption. Those who participate in studies on an opt-out basis (which is arguably more representative of a national roll-out of such interventions) achieve much smaller levels of electricity reduction.

When households are randomly assigned to treatment groups, they achieve smaller electricity savings than when they are not. This would suggest that a tailored approach to treatment design corresponding to households existing motivations to change their electricity consumption is pertinent. Such motivations maybe monetary, environmental, or other.

The inclusion of weather controls and the collection of socio-demographic data does not appear to have a strong impact on the reported treatment effects.

The impact of these study design choices on the treatment effects will be further analysed in section [2.5.4](#).

2.5.3 Publication Bias Analysis

According to [Card and Krueger \(1995\)](#) there are three potential sources of publication bias in economic research: (1) a predisposition to accept studies which are consistent with the conventional view; (2) an inclination to report models based on the presence of a conventionally expected results; (3) a tendency to publish only statistically significant results.

Potential publication bias in the sample of primary studies used in this meta-analysis can be analysed graphically using a funnel plot, as shown in [fig. 2.9](#). These graphs plot treatment effects against a measure of precision, such as the inverse standard error of the treatment effect or the square root of the sample size of the treatment

group. The intuition is that the accuracy of the treatment effect increases with the level of precision. Studies with larger standard errors and smaller sample sizes are dispersed at the bottom of the graph, with the spread of treatment effects decreasing as standard errors decrease and sample sizes increase. In the absence of publication bias, the result is a symmetrical, inverted funnel shaped graph. On the other hand, if there is a publication bias, an asymmetrical funnel can result due to an absence of publications of non statistically significant results (Egger *et al.*, 1997, Sterne *et al.*, 2004).

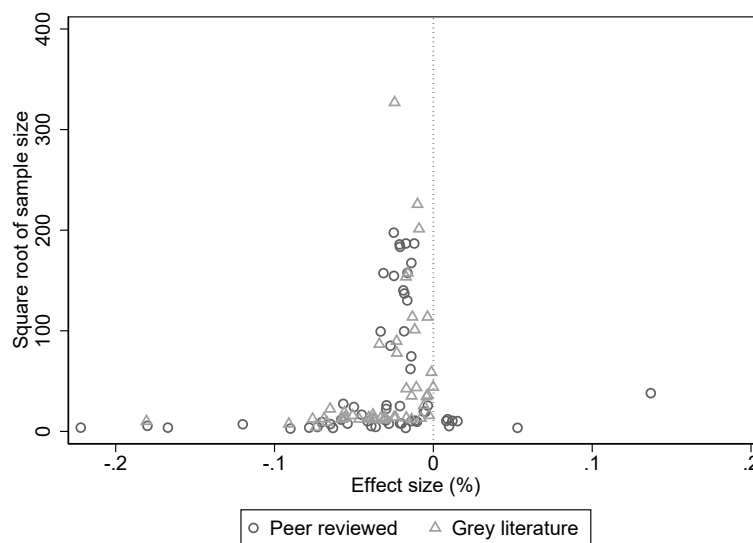


Figure 2.9: Funnel plot of treatment effects versus sample size

The funnel plot in fig. 2.9 plots treatment effect against the square root of sample size. The plot shows that the majority of treatments result in a reduction of electricity consumption. No studies from the grey literature report an increase in electricity consumption and there are more observations from peer-reviewed articles dispersed at the bottom of the funnel. The somewhat asymmetrical nature of the funnel plot suggests that there may be an issue of publication bias in the present sample due to results not being included in the analysis.

Stanley *et al.* (2010) suggest that publication bias may be reduced and scientific inference improved by averaging the treatment effects of the top 10% of the funnel as these are the most precise estimates. Table 2.6 shows the non-weighted and weighted ATE for the full sample and the top decile according to the weight used²².

²²Where the inverse standard error is used as a weight, there are only 42 observations in the sample as the standard error is not available for all studies. This sub-sample is used as a robustness check for issues of publication bias as the standard error is the preferred weight.

Comparing the ATE for the top 10% of the funnel and the full sample suggests that, on average, the effect of incentives on electricity consumption is overestimated by a factor of 2. When sample size is accounted for, as the weighted ATE shows, the distortion due to publication bias is greatly reduced and the difference is not significant ($p = 0.8641$).

As the inverse standard error is the preferred measure of precision, the non-weighted and weighted ATE of the 42 observations for which standard errors are reported or can be constructed are also given. The distortion due to publication bias is smaller for this subset of the sample when comparing ATE between the top 10% and the full sample (a factor of 1.8), and the difference in values is not significant ($p > 0.1$) once sample size is accounted for.

	ATE (%)		Weighted ATE (%)	
	Sample size	1/SE	Sample size	1/SE
Top 10% of funnel plot	-1.69	-1.69	-1.79	-1.62
Full sample	-3.37	-3.06	-1.85	-1.75

Table 2.6: ATE correcting for publication bias

The above correction for publication bias suggests that if present, any bias is small and not statistically significant once sample sizes have been accounted for in calculating weighted average treatment effects. Nevertheless, it is prudent to test for the existence of such bias.

In the presence of publication bias, treatment effects are positively correlated with their standard errors (Stanley and Doucouliagos, 2012). This suggests that the size of an effect will depend on its standard error:

$$treatment_effect_i = \beta_0 + \beta_1 SE_i + \epsilon_i \quad (2.2)$$

To account for differences in the primary studies, the equation is weighted by a measure of precision, ideally the inverse of its standard error (Stanley *et al.*, 2010):

$$t_i = \beta_0(1/SE_i) + \beta_1 + v_i \quad (2.3)$$

where t_i is the t-statistic of the treatment effect. As standard errors are not available for all observations, this equation is also constructed using the square root of sample size as the measure of precision:

$$treatment_effect_i/sample_size_i^{0.5} = \beta_0(1/sample_size_i)^{0.5} + \beta_1 + v_i. \quad (2.4)$$

In the presence of publication bias, treatment effects are positively correlated with their standard errors, and negatively correlated with sample sizes, as standard errors are inverse functions of sample size (Stanley and Doucouliagos, 2012, Schmidt and Hunter, 2014). Estimates of β_0 from eqs. (2.3) and (2.4) are an alternative correction of publication bias (Stanley and Doucouliagos, 2012). Table 2.7 shows the results of the estimations of the models in eqs. (2.3) and (2.4) for the sub sample of 42 studies for which the standard error is present and for the full sample using the square root of sample size as a proxy measure of precision.

Testing $H_0 : \beta_1 = 0$ is a test of whether publication bias is present, the funnel asymmetry test. If the coefficient is significantly different from zero then there is publication bias. In the first specification (eq. (2.3)), the null hypothesis cannot be rejected. In the second and third specifications when the sample size is used as a weight for both the sub sample and the full sample, the null hypothesis is rejected (p -values = 0.076 and 0.096, respectively). There is thus marginal evidence of publication bias in the full sample using the sample size as a proxy for provision.

A second test, the precision effect test, of whether there is a genuine empirical effect can be tested: $H_0 : \beta_0 = 0$. In both models, the null hypothesis is rejected, implying that there is a genuine empirical effect which merits further analysis.

Graphically, the funnel plot suggests that there is a potential issue of publication bias. When comparing the ATE of the full sample to the top 10% of the funnel, this bias is of a factor 2. Testing for publication bias suggests that publication bias is present in the full sample. However, accounting for sample sizes reduces the bias to a small and statistically insignificant amount. Therefore, a WLS estimation will be used to mitigate publication bias and to account for heteroscedasticity in the sample of primary observations, as discussed in Section 2.4.2.

2.5.4 Effects of Individual Incentives

The analysis of publication bias has shown such bias to be mitigated by taking sample sizes into consideration. The square root of sample size is therefore used as a weight in the following section in which the effects of the different incentives on

	(1) Standard error <i>Equation (2.3)</i>	(2) Sample size <i>Equation (2.4)</i>	(3) Sample size <i>Equation (2.4)</i>
β_0	-1.578*** (0.305)	-7.040*** (0.204)	-7.752*** (1.909)
β_1	-32.499 (40.713)	0.015* (0.008)	0.015* (0.009)
Observations	42	42	105
R^2	0.777	0.577	0.501

Standard errors in parentheses

Standard errors are clustered by primary study.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: Estimation of publication bias

electricity consumption are analysed²³.

Table 2.8 shows the results of the WLS meta-regression analysis across the different incentive types. Specifications 1-3 focus on a particular incentive strategy (monetary, personal feedback or social feedback). The fourth considers the study design features and the final specification includes all variables. Each specification includes a variable accounting for the duration of the study and the type of literature it is from. Finally, standard errors for each estimation are clustered by study to account for any dependence between studies. Coefficients on the different incentives are interpreted as a change in electricity consumption relative to the consumption of the control group, when present in the study which is the case for 90% of the observations, or the baseline level of consumption. A negative coefficient signifies a reduction in electricity consumption.

Pricing strategies have a significant positive effect: electricity consumption is increased by 2.8 percentage points. When all incentives are controlled for, this significant effect falls out. The effect of *monetary information* becomes significant, showing an increase in electricity consumption of 2.5 percentage points. These results are opposite to those predicted by the theory. It may be that as *pricing strategies* such as dynamic pricing provide households with the possibility of consuming at a lower price during off-peak periods²⁴, the rebound effect of consumption outweighs the

²³The results of a cluster-robust OLS estimation are provided in Appendix A as a benchmark for the following WLS estimation.

²⁴Studies which used such incentives were included in the present meta-analysis as the primary authors also considered the effect of the incentive on overall household electricity demand.

	(1) Monetary	(2) Personal feedback	(3) Social feedback	(4) Study design	(5) All incentives
Pricing strategies	2.790* (1.462)				1.318 (1.571)
Monetary information	0.662 (1.384)				2.492* (1.414)
Individual feedback		-3.115** (1.358)			-3.919** (1.675)
Real-time feedback		-0.651 (1.415)			-2.138 (1.584)
Savings tips		4.385** (2.104)			4.069** (1.967)
Personalised advice		0.562 (2.021)			-0.746 (2.425)
Social norms			-4.316* (2.387)		-4.518** (2.174)
Injunctive norms			-5.000** (1.998)		-3.238 (3.281)
Control group	7.278** (3.307)	10.790*** (3.259)	8.483** (3.414)	7.642** (3.489)	11.161*** (2.840)
Weather controls	-0.095 (1.436)	0.804 (1.449)	0.856 (1.385)	0.671 (1.311)	-0.671 (1.985)
Demographic controls	1.295 (2.631)	1.314 (2.857)	2.524 (3.118)	1.104 (2.962)	2.455 (2.776)
Random assignment	-1.704 (2.216)	-2.727 (2.446)	-1.642 (2.777)	-1.490 (2.419)	-2.783 (2.457)
Opt-in recruitment	-1.604 (1.554)	0.546 (1.710)	-3.795* (2.179)	-0.466 (1.336)	-3.262 (2.840)
Duration	0.198* (0.102)	0.265** (0.119)	0.205* (0.105)	0.170 (0.103)	0.325*** (0.111)
Peer reviewed	4.638*** (1.698)	4.208** (1.840)	4.831*** (1.635)	3.503** (1.549)	5.801*** (1.883)
Constant	-15.394*** (4.160)	-19.722*** (5.760)	-14.319*** (4.352)	-14.936*** (4.201)	-17.496*** (5.348)
Observations	105	105	105	105	105
Adjusted R^2	0.195	0.342	0.218	0.181	0.381

Standard errors in parentheses

Inverse square roots of sample size are used as analytical weights.

Standard errors are clustered by primary study.

A negative coefficient reads as a reduction in energy consumption.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: WLS estimation of treatment effects

savings encouraged by the higher peak price (Geelen *et al.*, 2013, Khan *et al.*, 2016). An explanation as to why *monetary information* does not have the predicted effect is that the possible savings are too small to be motivating (Hargreaves *et al.*, 2010, Goulden *et al.*, 2014), or that households expenditure on electricity is small relative to their income (Faruqui *et al.*, 2010b, Schleich *et al.*, 2013).

In both the personal feedback and the full specification *individual feedback* has a significant negative effect indicating a reduction in electricity consumption of 3-4 percentage points. When such feedback is delivered in real-time no additional significant effects on electricity consumption are found. This could indicate that the effectiveness of feedback is captured in the individual feedback variable, or that real-time feedback reinforces the fact that individual actions to save energy do not amount to large savings (Hargreaves *et al.*, 2010, Goulden *et al.*, 2014). The use of *savings tips* indicates an increase in consumption of 4 percentage points. Generic advice on how to save electricity appears to not be effective at reducing consumption. One reason for this is that householders generally know what they should do to reduce their consumption and that reminding them of such behaviours serves to crowd out any intrinsic motivation they had to do so.

In this meta-analysis, social feedback is separated into social norms and injunctive norms. Specification 3 shows that both types of social feedback result in a reduction in consumption of 4-5 percentage points. This provides new evidence of the effectiveness of such feedback compared to findings in Delmas *et al.* (2013) who found no significant effect of such feedback. Since their meta-analysis, there has been an increase in large-scale studies of such incentives.

Across the five specifications, the 10% of studies which do not use a control group show a greater increase in electricity reduction of between 7.3 and 11.2 percentage points compared to those that do use a control group. This suggests that when electricity savings are calculated compared to a baseline of the same group, they may be overestimated. *Duration* of the study has a small significant positive effect on electricity consumption in specifications 1-3, and 5. This adds to the previous evidence that electricity conservation experiments are subject to attrition of the effects of incentives over time (Delmas *et al.*, 2013). The positive coefficient on *peer reviewed* suggests that peer reviewed experiments are more conservative in their estimations of the effects of an incentive on electricity consumption than those from the grey literature.

2.6 Discussion

The meta-analysis presented in this paper provides a comparison of different incentives used in the experimental literature to incentivise residential consumers to lower their electricity demand. Contrary to previous analyses, it provides a comparison of contemporary experimental studies by focusing on studies from 2005 onwards, the "Smart Grid Era". Previous analyses risk overstating the potential of different incentives by including older studies (McKerracher and Torriti, 2013). By restricting the time frame, the intention is to limit the analysis to studies with similar available energy monitoring technology, in order to avoid exacerbating issues of heterogeneity due to differing temporal contexts.

In order to avoid issues of publication bias, the present meta-analysis adopted a wide search method to collect data from both peer-reviewed and grey literature studies. To verify the extent of the publication bias issue in the sample of studies used, a detailed analysis of the potential bias was carried out as a graphical examination of the potential publication bias suggested that this may be an issue. However, estimations of the amount of bias and tests of its presence have shown it to not be a significant issue for the present sample of studies once sample size is accounted for. Furthermore, the precision effect test shows that there is a genuine underlying effect of interest.

In addition, the experimentation of new methods of encouraging households to lower their electricity demand are included in the present meta-analysis, namely the use of injunctive norms in addition to social norms. Furthermore, a greater level of study design controls are included to control for heterogeneity between studies. This provides an opportunity to disentangle the effects of such incentives and to carry out a more extensive comparison of the effects of different study methods on residential electricity demand.

The analysis has shown that on average and before taking into consideration primary study sample size, the different incentives result in a reduction in electricity consumption ranging from 2.22 to 4.69%. Across all incentives, a study on the effect of an incentive on electricity consumption can be expected to show a 3.37% reduction in electricity consumption. This effect is lower than reported in previous meta-analyses, however it is in line with the conclusion of McKerracher and Torriti (2013) that there is a downward trend in the size of conservation effects. Accounting for sample sizes, as the publication bias analysis suggests, a study will show on

average a reduction in consumption of 1.85%.

In terms of the level of controls used in the studies, compared to previous meta-analyses, there has been an increase in the number of studies using control groups, and controlling for demographic variables and weather variations which leads to lower, but arguably more reliable, estimates of the effect of incentives on electricity consumption. The two differing levels of study controls show a difference in estimated electricity savings of 1.54 percentage points: more robust studies with more controls result in a lower average reduction in consumption of 2.17% compared to 3.71% for less robust studies. If such incentives are to be implemented at a national level, these more robust studies may be a better reflection of the level of electricity savings that may be achieved. A graphical analysis showed that in studies in which households are randomly assigned to a treatment there is a smaller spread in treatment effects.

In studies in which households choose to participate, there is a greater spread of treatment effects. These households may have motivations to take part in electricity consumption field experiments and pilot studies that are not necessarily accounted for in the experiment. These participants may be predisposed to make a greater effort than if the incentive were to be implemented at a national level (Alexander, 2010, Ericson, 2011). This implies that caution should be exercised when viewing the results of experiments in which participants self-select into a treatment.

While at the descriptive level, all incentives result in a reduction of residential electricity consumption on average, the econometric analysis shows that only certain incentives have a significant effect once other variables are controlled for. *Monetary*-based incentives (*pricing strategies* and *monetary information*) tend to result in an increase in residential electricity consumption. Hypotheses 1a and 1b can be rejected for the present sample.

Individual feedback has a significant effect at reducing electricity consumption, however, there is no significant effect of *real-time feedback*. *Real-time feedback* is effective at reducing consumption, as shown in the descriptive analysis, however when other informational feedback and study design variables are controlled for, the effect is not significant. Given that *real-time feedback* is often proposed in combination with other incentives, it may be difficult to isolate the effect of *real-time feedback* alone. Concerning the two types of guidance that can be given to households, *personalised advice* does not have a significant effect on electricity consumption. However, *savings tips* are shown to increase electricity consumption. There is evidence to support

hypothesis 2a, and to reject hypothesis 3b. There is inconclusive evidence to neither support nor reject hypotheses 2b and 3a.

Next, it was hypothesised that the use of *social norms* would have a significant reduction effect on residential electricity consumption only in the presence of *injunctive norms*. Both the use of descriptive *social norms* and *injunctive norms* have a significant negative effect on electricity consumption when other incentives are controlled for. There is evidence to refute hypothesis 4a, *social norms* alone do have the desired effect of reducing electricity demand. There is also evidence to support hypothesis 4b.

Hypothesis 5 refers to the effect of incentives with respect to sample size: as sample size increases, the effect of an incentive on electricity consumption falls. As fig. 2.9 shows, there is greater variation in ATE when sample sizes are smaller, whereas with larger samples, the treatment effect is smaller. This provides some evidence to support hypothesis 5.

Similarly to previous meta-analyses, the sample set is separated by number of controls used. More robust studies are those which are deemed to be more representative of the population (use random treatment assignment and an opt-out method of recruitment) and which include greater controls of potential heterogeneity (use a control group, account for weather variation and collect socio-demographic data). The more robust studies show a statistically significant smaller ATE than the other studies. This provides evidence to support hypothesis 6.

Finally, hypothesis 7 refers to the downward trend in ATE over time. Previous meta-analyses found that incentives reduced electricity consumption by upwards of 6.4%. The present analysis found an overall ATE of 3.37%, or a weighted ATE of 1.85%. This lends support to the hypothesis that the incentives used have a smaller effect on electricity consumption in the Smart Grid Era compared to the eras identified in previous meta-analyses.

2.7 Conclusion

This paper has provided an analysis of the effects of different incentives used in recent residential electricity consumption studies across the fields of economics, psychology, marketing and building research. This meta-analysis provides the most up to date assessment of recent experimental literature including newer methods of

incentivising consumers to lower their energy consumption.

On average, an incentive designed to reduce household electricity consumption will result in a reduction in consumption of 3.37%. Accounting for the different sized samples used in the individual studies, an incentive can be expected to reduce electricity consumption by 1.85%. This result indicates that electricity consumption reductions can be attained by incentivising households to make behavioural changes to reduce their electricity consumption.

In particular, less costly incentives such as informing households of their individual consumption²⁵, or of the average consumption in their neighbourhood shows a greater level of reduction on electricity consumption compared to more costly incentives such as pricing strategies. This has important policy implications given that the latter incentive is often not readily accepted by consumers (Alexander, 2010). This indicates that lower-cost incentives may be sufficient and that there is not necessarily a need to use costly pricing strategies when the objective is to reduce overall electricity consumption. Much focus in recent years has been on injunctive norm based incentives. One conclusion of this analysis is that descriptive social norms may be sufficient on their own.

The present meta-analysis faces certain limits. To begin with, the meta-analysis is as reliable as the primary studies included in the dataset. Certain primary studies found treatment effects which were much larger, in both the direction of reducing and of consuming more electricity. Such results should not necessarily be excluded from the dataset as they meet the criteria set out in section 2.4.1, however, they may influence the findings and conclusions of the analysis. Secondly, few experiments test the effect of a single incentive on electricity consumption as they often combine several incentive types. This makes it difficult to separate the effects of individual incentives on electricity consumption due to confounding effects. A third limit concerns the differences in the design of the various studies that are not accounted for in the present study. For example, the composition of the samples in the primary studies is not necessarily identical: participants may have previously participated in similar studies, or the study may focus on a particular type of household.

For future research, this analysis highlights that it is important to undertake field studies which are methodologically rigorous; studies which include control groups, control for demographic information and variations in weather. Including a control group and controlling for the weather provides a better estimate of the effect of an

²⁵Predominately via paper bills or on a website in the current sample of studies

incentive as there may other factors which affect electricity consumption in addition to the incentive used. Furthermore, when individuals self-select into studies, and/or treatments, the reported effects of incentives are of a greater reduction in electricity consumption than when an opt-out or random treatment assignment approach is used. This provides support for the idea that a national roll-out of a particular incentive may not be the best approach as greater electricity savings can be attained if households are able to pick an incentive which is appropriate to them. A one-size-fits-all may not be the most effective. However, a tailored approach may not be feasible. More research needs to be done in this area to determine whether households are able to pick appropriate incentives, and on the effect of tailored incentives on electricity consumption.

Chapter 3

Demand Response as a Common Pool Resource Game: Responses to Incentives to Lower Consumption

Joint with Daniel Llerena²⁶.

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²⁷See <https://ecosesa.univ-grenoble-alpes.fr/>

²⁸See <https://www.faae.fr/fr/51-prix-de-l-ae.html>.

Abstract

The aim of demand response is to encourage consumers to be more flexible with their energy consumption during peak periods. Using a contextualised common pool resource (CPR) framework, energy consumption choices are studied. Subjects choose how much to consume by deciding whether to use five different appliances during 10 periods. The total consumption of these activities is the CPR contribution, and payoffs depend on personal consumption and the amount consumed by the group. In the nudge treatment, subjects are nudged towards the socially optimal level of consumption by the use of a happy or sad face if they are under-consuming or overconsuming. In the price treatment, a price is set to incentivise subjects to choose the level of consumption observed in the nudge treatment. The objective is to quantify the nudge via an equivalent price. Across all 10 periods, consumption is significantly lower in treatment groups compared to control groups. There are implications for policy makers as the nudge treatment performs as well as an equivalent price without the implied loss of welfare, and is understood and integrated into subjects' decision making quicker than an equivalent price. However, the nudge reinforces existing consumption behaviour as those who over consume continue to over consume.

3.1 Introduction

After a discussion of households experiences with smart meters and dynamic pricing for both energy flexibility and overall demand reduction, and an analysis of incentives used to encourage households to lower their electricity consumption, this chapter focuses on two particular incentives and their effectiveness for lowering peak energy demand. The meta-analysis has shown that monetary incentives are perhaps not best used to incentivise overall demand reduction; they are more effective at encouraging flexibility (Faruqui and Sergici, 2013) and that non-monetary incentives, such as social feedback, were shown to have a significant effect at reducing overall electricity consumption. In this chapter, these two types of incentive are put to the test in a laboratory-based, stylised energy consumption game.

The main research hypothesis is that the management of end-use electricity consumption during peak periods is similar to the management of agents who use a common pool resource (CPR). Here, the CPR is the limited renewable energy sources which are sustained so long as electricity consumption does not exceed power capacities. Such an approach provides the possibility of exploring, in an experimental setting, the impacts of demand response tools on consumers' behaviour when they are placed in the social dilemma resulting from the need to balance supply and demand, while maintaining their desired level of consumption and comfort. Following Ostrom (1990), and more recently Melville *et al.* (2017) in the energy field, this dilemma is the conflict between the personal interest of consuming electricity without constraint, and the collective interest of maintaining power supply reliability.

This introduction provides the background on the impacts of increasing the share of renewable energy on power supply reliability, and consequently on the need for demand response programmes based on monetary, and non-monetary incentives or nudges. The principal objective of the experiment is to use a contextualised CPR game to explore the effect of nudges and peak prices on subjects' consumption choices compared to when no policies are used, and to give a monetary value to the nudge. The secondary objective is to compare subjects' choice of which appliances to use and which electricity-consuming activities to take part in when faced with a need to reduce their demand. This section sets out the theory behind the CPR game used in the experiment, and Section 3.2 describes the experimental design. Section 3.3 presents and discusses the results, and Section 3.4 concludes and provides policy recommendations.

3.1.1 Renewable Energy and Demand Response Programmes

In the last two decades, there has been an increase in the share of renewable energy and in the number of distributed power generators ([Renewable Energy Policy Network for the 21st Century, 2016](#)). This calls for new strategies in the management of the electricity grid in order to maintain power supply reliability and quality, particularly at times when intermittent energy sources constitute a significant part of total system capacity. This need is all the more important given that the European Union has set ambitious targets to reduce greenhouse emissions and to increase the share of renewable energy sources in the production mix by 2030 ([European Commission, 2014a](#)).

Reliable management of the electricity system requires a perfect balance between supply and demand in real time. Given the increase in renewable energy sources, this balance is harder to achieve as supply and demand levels can change rapidly and unexpectedly, in particular on high demand days and when natural conditions are unfavourable for the use of renewable energy sources. Moreover, the power generation infrastructure is highly capital intensive, such that demand side management may be one of the cheaper tools available for balancing supply and demand. Given the greater difficulty of producing peak electricity, there is a need to have a more flexible residential energy demand, particularly during peak periods. Demand response programmes, defined as the changes in electricity usage by end-use consumers from their normal consumption patterns in response to signals, are the main tool used or experimented in the management of the electricity grid ([Balijepalli *et al.*, 2011](#)).

Current methods used to incentivise households to lower their energy demand include dynamic tariff structures, informational incentives, or nudge-based incentives. Under certain tariff structures consumers face financial incentives to reduce their energy demand as during certain hours or on days when demand is particularly high, the price of electricity is greater than at off-peak times. This increased price is designed to induce lower electricity use at times with high wholesale market prices or when system reliability is jeopardised ([Borenstein *et al.*, 2002](#), [Faruqui *et al.*, 2010b,a](#), [Hargreaves *et al.*, 2010](#), [Raw and Ross, 2011](#)). Informational incentives involve providing the household with increased information on their consumption to allow them to make a more informed decision. Such incentives include information on how personal consumption compares from one day to another, or on a weekly or a monthly basis ([Benders *et al.*, 2006](#), [Houde *et al.*, 2013](#), [Mizobuchi and Takeuchi,](#)

2013, Schleich *et al.*, 2013, Carroll *et al.*, 2014, Schultz *et al.*, 2015). Nudge based incentives go beyond simple information by changing the way the information is presented in order to exploit behavioural biases (Schultz *et al.*, 2007, Thaler and Sunstein, 2008, Allcott, 2011b, Ayres *et al.*, 2012).

This experiment is particularly related to laboratory experiments which study the effect of monetary and non-monetary incentives, or nudges, on behaviour. These areas of literature are discussed below.

3.1.2 Monetary Incentives and Nudges in the Laboratory

In CPR laboratory experiments, monetary incentives are often modelled as taxes. These are a first best policy for managing behaviours which result in negative externalities (Ballard and Medema, 1993). In experimental games with negative externalities, studies have shown that taxes result in subjects performing at near optimal levels (Plott, 1983, Cochard *et al.*, 2005). Yet, taxes are seldom accepted by the public. This can be explained by a preference for the status quo (Cherry *et al.*, 2014), by tax aversion: individuals feel that negative incentives, such as taxes, impede their free-will and are controlling, and by framing: acceptance for taxes increases when the mechanism behind them is explained (Kallbekken *et al.*, 2011, Heres *et al.*, 2013).

Given that monetary interventions such as taxes, and dynamic pricing in the context of electricity consumption, can be politically difficult to implement (Alexander, 2010) as well as costly, policy makers have also used non-price interventions to influence households to reduce their energy consumption, such as nudges.

A nudge is defined as a change to a choice setting which alters individuals' behaviour without removing any of the choices available to them nor affecting their economic incentives. Nudges are designed to incentivise individuals to pick an option that is in their best interest, an option which they would not necessarily choose for themselves (Thaler and Sunstein, 2008). While the idea of nudges is not recent, the term has certainly seen an increased level of interest in recent years. The nudge intervention used in this experiment relates to both information on suggested play as the feedback is based upon the optimal level of consumption, and on social approval as an element of whether an individual's consumption behaviour is approved of or not is included in the nudge.

Experiments using suggested play recommend a course of action to subjects con-

cerning their contribution to a public good or their extractions from a common pool resource. In a threshold public good game, Marks *et al.* (1999) and Croson and Marks (2001) find that suggesting a fair contribution to subjects before they decide on their contribution only results in the provision of the public good when preferences are heterogeneous. Dal Bó and Dal Bó (2014) find that suggested play works only under the addition of an element of moral suasion; the idea that in a public good game, increasing your contribution to the maximum amount benefits everyone. In a CPR game, Delaney and Jacobson (2015) suggest to groups what they should do to increase their payoffs using both informative and normative messaging and compare this to a subsidy. They find that the subsidy is the most effective, followed by normative then informative messaging. The authors note that it is unusual that the normative messaging treatment results in only a slight greater reduction in extraction level when compared to information alone given that previous research has found significant effects on energy and water consumption reduction through the use of normative messages (Schultz *et al.*, 2007, Allcott, 2011b, Ayres *et al.*, 2012, Ferraro and Price, 2013). They suggest that the non-significant difference in the results may be due to small sample sizes ($n=15$). However, it may also be due to a certain level of overlap between the two treatments, as the information treatment also contains normative language. The two treatments, information and normative messaging should perhaps instead be viewed as a weak normative message and as a strong normative message, respectively.

Boun My and Ouvrard (2018) explore the impact of recommended play, or a nudge, and taxes on contributions to a public good for reducing pollution. They hypothesise that reaction to a nudge is greater when subjects are more sensitive to environmental issues. After measuring environmental sensitivity, subjects are split into groups according to whether they are more or less environmentally sensitive than average and are then faced with either a nudge; a statement of the socially optimal contribution to the public good, or a tax; a linear tax based upon the optimal contribution.

The tax treatment shows the greatest increase in contributions for both high and low environmentally sensitive groups, a 45% and 34% increase in contributions, respectively. They find that the nudge divides subjects according to their environmental sensitivity, with the least sensitive reducing their contribution by 29% compared to the baseline, and the most sensitive increasing their contribution by 14%. In their set-up, Boun My and Ouvrard (2018) create groups of either all highly environmentally sensitive subjects, or of less environmentally sensitive subjects. This

is perhaps not entirely reflective of the situations where individuals interact with people of differing levels of environmental sensitivity.

In addition to suggested play, the nature of the nudge used in this experiment provides social approval or disapproval of an individual's behaviour in the game. The rationale is that social approval increases optimal behaviour in CPR games as subjects perceive utility (disutility) from social approval (disapproval) (Rege and Telle, 2004). There is mixed evidence as to whether social information and approval increases or decreases optimal behaviour in collective action games. It has been shown both theoretically (Holländer, 1990, Fehr and Schmidt, 1999) and experimentally (Cialdini, 2003, Rege and Telle, 2004, Spraggon *et al.*, 2015) that such social norms can increase contributions in collective action games. In other experiments, social approval has been shown to reduce optimal behaviour (Noussair and Tucker, 2007, Brent *et al.*, 2017).

The social approval used in this experiment does not come from the other subjects, but from the regulator who informs subjects via a happy or sad face whether they are consuming more or less than the optimal amount.

3.1.3 Theory of Common Pool Resources

In economics, goods are classified based upon their degree of excludability and rivalry. Table 3.1 provides a general framework of the classification of goods according to these two criteria. A common pool resource is both rivalrous and non-excludable; once it has been consumed by an individual, another individual cannot consume it, and it is costly to exclude individuals from consuming it. Such goods face a problem of over consumption as individuals wish to consume more than the amount which is sustainable.

	Excludable	Non-excludable
Rivalrous	Private goods	Common pool resources
Non-rivalrous	Club goods	Public goods

Table 3.1: A classification of goods

Formally, a common pool resource is defined as a stock of a natural or man-made resource system from which a flow of resource units can be withdrawn. The stock of a CPR is renewable and so the stock can be sustained so long as average withdrawal rates do not exceed average replenishment rates. The social dilemma of CPRs is that

individuals would like to withdraw more than the sustainable amount of resource units from the stock and as such there is a conflict between personal interest and collective interest.

A game of common pool resource extraction can be modelled as follows: a group of n players share a common resource. They each have an endowment e which can be used to invest in the extraction of the common resource. The amount invested in resource extraction by individual i is x_i with Σx_i the amount invested by the group. Extraction of the resource earns each player a for every unit extracted personally, minus b for every unit extracted by the group regardless of who extracts it. The parameter a represents the utility of consuming electricity in terms of increased comfort, the use of appliances without constraint, whereas the parameter b represents the disutility of all subjects' consumption of electricity in terms of voltage reductions and brief power cuts. The cost of investing in the extraction of the resource is c . Each player's profit depends on his own investment in extraction as well as the group investment:

$$\pi_i = e - cx_i + x_i(a - b\Sigma x_i) \quad (3.1)$$

A rational, self-interested player invests an amount x_i which maximises their profit:

$$\max_{x_i} \pi(x_i, \Sigma x_i) = e - cx_i + x_i(a - b\Sigma x_i) \quad (3.2)$$

The first order condition is:

$$-c + a - bx_i - b\Sigma x_i = 0 \quad (3.3)$$

Supposing that all agents are equal, a symmetric Nash equilibrium can be found such that $x_i = x_j = x$ for all players i, j .

$$x_i = \frac{(a - c)}{b(n + 1)} \quad (3.4)$$

This level of extraction maximises individual profits regardless of the effects of an individual's extraction on the group.

The socially optimal investment in resource extraction is the amount x which maximises the collective profit. Assuming symmetry, the player maximises:

$$\max_x n\pi(x) = n[e - cx + x(a - bnx)] \quad (3.5)$$

The first order condition is:

$$-cn + an - 2bn^2x = 0 \quad (3.6)$$

which gives an optimal investment where:

$$x_i = \frac{(a - c)}{2bn} \quad (3.7)$$

This level of extraction takes into consideration the effect of each individual's consumption on the resource system.

The Nash equilibrium results in a higher level of extraction than the socially optimal amount, hence the social dilemma. One option to align private earnings with the social optimum, is to increase the cost of extraction c such that the Nash equilibrium and socially optimal level of extraction are equal. The cost of extraction c is increased by an amount d and its value is found by equating the Nash equilibrium and the socially optimal solution.

$$\frac{a - c - d}{b(n + 1)} = \frac{a - c}{2bn} \quad (3.8)$$

$$d = \frac{(a - c)(n - 1)}{2n} \quad (3.9)$$

This theoretical framework has been applied to residential electricity consumption (Bäckman, 2011, Goldthau, 2014, Gollwitzer *et al.*, 2018). The electricity network (power stations, distribution centres, transmission lines) represents a man-made resource system and the resource units are the kilowatt hours which can be consumed. In the short run, it can be considered that this system provides a stock of electricity units available to households. The stock of electricity is renewable in the sense that once electricity has been consumed it must be immediately reproduced in order to maintain supply and demand balance. Currently, generated electricity cannot be stored so the amount generated needs to correspond to the amount being consumed. There is limited storage capability in generators which are able to maintain electricity supply for under a minute. Beyond a minute, the supply is unstable and there is a risk of blackouts due to drops in frequency and voltage (Pratt and Fuller, 2016).

Given this, on on days of extreme weather, or when renewable energy resources supply electricity, there is risk of demand outstripping supply which implies a need to reduce the demand for electricity.

Individuals wish to consume electricity without constraint which is represented by the Nash equilibrium level of extraction described above. However, on days in which demand response is required, it would be better collectively if all individuals lowered their consumption. This level of consumption is represented within the CPR framework as the socially optimal amount.

3.2 Experimental Design

This section details the experimental design beginning with the parametric protocol and the different experimental treatments, followed by the hypotheses to be tested and a description of the participants and the procedure.

3.2.1 Experimental Parameters

The game concerns electricity consumption during 10 peak periods when demand can be greater than production. In the experiment, subjects form groups of four ($n = 4$) for 10 peak periods ($t = 10$). Subjects remain in the same groups for the duration of the experiment. Each group makes up an electricity consumption system of four households which represent a neighbourhood or small society. In this context, the demand response challenge is represented as a repeated CPR game.

At the start of each period, each subject receives an endowment $e = 100$ ECU²⁹ which they can use to consume electricity (measured in energy units (EU)). In the control and nudge treatments each EU costs 1 ECU ($c = 1$). The cost of each EU changes in the price treatment ($c = 3$) as discussed below in section 3.2.1.2. Any ECU that the subject does not use to consume electricity is kept by the subject and included in their profit function. For every EU consumed, the subject receives $a = 13$ and every EU consumed costs $b = 0.1$ for all subjects in the group regardless of who consumed it. Subjects' profit function is as follows:

$$\pi_i = 100 - cx_i + x_i(13 - 0.1\Sigma x_i) \quad (3.10)$$

²⁹ECU = Experimental Currency Units. The exchange rate is communicated to all subjects during the instruction phase and is 150 ECU = 1€.

Individually, subjects maximise their profit at the Nash equilibrium, $x^{NE} = 24$ for an individual profit of 158 ECU. This level of consumption is greater, and the payoff is lower than if subjects maximised the collective gains. Collectively subjects should each consume $x^{SO} = 15$ for an individual profit of 190 ECU. This represents the collective interest of lowering consumption by demand response.

In each period, subjects must decide how much of their endowment to spend on consuming electricity by choosing whether or not to use five different electrical items. Table 3.2 details the different levels of consumption that subjects can choose from. Subjects are told that their electricity consumption brings them comfort (via a monetary gain) of 13 ECU for every unit consumed. The total consumption of their group leads to a reduction in personal comfort of 0.1 ECU for every unit consumed regardless of who consumes it. This value represents the disutility of increased collective consumption due to voltage reductions and brief power cuts when demand is greater than supply. The greater the total consumption of the group, the greater the reduction in comfort.

Item	Consumption levels	Consumption amount (EU)
Electric heating	Unchanged	15
	1°C reduction in heating	10
	2°C reduction in heating	5
Electric water heater	On	5
	Off	0
Washing machine/ dishwasher	On	10
	Off	0
Cooking equipment	On	10
	Off	0
Television/ Computer	On	5
	Of	0

Table 3.2: Electricity consumption choices

When deciding whether or not to use the different electrical appliances proposed, subjects are choosing to consume energy units in increments of 5. The choice of electricity consumption is made discrete to reflect that in real life individuals consume electricity by turning appliances on or off. There are three levels of consumption for the heating choice; the same, 1°C cooler, or 2°C cooler. Given the discretisation of the consumption amount, the Nash equilibrium is $x_i = 25$ EU and the social optimum is $x_i = 15$ EU. To assist subjects in deciding how many EU to consume, a

simulator³⁰ is available as well as a printed profit table. At the end of each period, subjects see how much they have consumed and their profit for the period.

3.2.1.1 Nudge treatment

In the nudge treatment, subjects are told that one way to avoid power cuts is to ask consumers to lower their consumption during peak periods. This implies a lower level of comfort (as the individual may lower their heating or use their washing machine at a different time, for example) but allows all individuals, including oneself, to avoid a much lower comfort level, i.e. a power cut, or a reduction in the quality of electricity distribution.

At the end of each period, subjects receive additional feedback on their consumption. If their choice of consumption is less than or equal to the level of consumption which minimises the reduction in comfort for the group, i.e.: the socially optimal level, they see a picture of a smiley face. If their consumption is greater than this level, then they see a sad face.

3.2.1.2 Price treatment

In the price treatment, subjects are told that voltage reductions and brief power cuts can be avoided by increasing the price of electricity in order to incentivise consumers to consume less during peak periods. The price for this treatment is calculated with respect to the average level of consumption observed in the nudge treatment. The goal is to compare whether the price results in the same level of consumption as the nudge when the price implemented is designed to achieve the level of consumption observed in the nudge treatment. The average level of consumption observed in the nudge treatment is 19.07 across all periods. Given that subjects can only choose consumption in increments of 5, the price is calculated such that the Nash equilibrium consumption level in the price treatment is $x_i^{NE,P} = 20$.

$$\frac{a - c - d}{b(n + 1)} = 20 \quad (3.11)$$

$$\frac{13 - 1 - d}{0.1(4 + 1)} = 20 \quad (3.12)$$

³⁰The simulator is described to subjects during the explanation of the game phase.

$$d = 2 \tag{3.13}$$

The price increase required to incentivise subjects to consume 20 EU is equal to 2. The price of electricity for subjects in the price treatment is thus equal to 3 ECU. Subjects are told that each energy unit consumed during the peak period costs 3 ECU which is three times more expensive than in a normal period³¹.

In this treatment the subjects maximise:

$$\max_{x_i} \pi(x_i, \Sigma x_i) = 100 - 3x_i + x_i(13 - 0.1\Sigma x_i) \tag{3.14}$$

The feedback given at the end of each period is the subject's level of consumption and their earnings for that period.

3.2.2 Hypotheses

Under the assumption that subjects are rational and self-interested, it is expected that players will choose the Nash equilibrium consumption amount in all treatments, i.e.: 25 in the control and nudge treatment, and 20 in the price treatment. Such players would not be influenced by the nudge described above.

Previous experiments have shown that suggesting a course of action has a positive influence on socially optimal behaviour (Dal Bó and Dal Bó, 2014, Delaney and Jacobson, 2015, Boun My and Ouvrard, 2018). Other experiments have found that aligning the Nash equilibrium with the social optimum via the use of a tax (framed as a price increase in this experiment) is a first best policy for dealing with social dilemmas in public good and CPR games (Plott, 1983, Ballard and Medema, 1993, Cochard *et al.*, 2005). However, such interventions are not always well-received by the public. In the context of electricity consumption, varying price structures or dynamic pricing also has its opponents (Alexander, 2010). This leads to the main hypotheses:

Hypothesis 1 *Consumption choices in the nudge treatment will be lower than in the control treatment.*

Hypothesis 2 *Consumption choices in the price treatment will be lower than in the*

³¹This is comparable to tariffs proposed by EDF at the time of the experiment; the highest peak price is approximately 3.5 times the standard tariff (EDF, 2016).

control treatment.

Hypothesis 3 *As the price level is fixed according to the nudge result, consumption choices in the price treatment will be equivalent to those in the nudge treatment.*

Furthermore, the positive impact of suggested play or a nudge is increased when an element of social approval or disapproval is included (Dal Bó and Dal Bó, 2014). In the experiment, the nudge treatment is presented as an indication of what an individual's consumption is in relation to the level at which the loss in comfort is minimised for the whole group. The smiley and sad faces thus act as social approval or disapproval of a behaviour which affects the whole group. As such the following is hypothesised:

Hypothesis 4 *Subjects who receive 'happy face' feedback will not change their consumption in the following period (those who consume the optimal amount or less).*

Hypothesis 5 *Subjects who receive 'sad face' feedback will lower their consumption in the following period (those who consume more than the optimal amount).*

It has been shown in a previous experiment (Boun My and Ouvrard, 2018) that subjects' reaction to a nudge in an environmental setting depends on their environmental sensitivity. In addition, due to the nature of the CPR game and the interlinked effects of an individual's actions on the others in their group, altruism may also influence a subject's choice of consumption. This leads to the following hypotheses:

Hypothesis 6 *More environmentally sensitive and altruistic subjects will consume less than less environmentally sensitive and altruistic subjects in all treatments.*

Hypothesis 7 *The difference in consumption between more and less environmentally sensitive subjects will be greater in the nudge treatment than in the price treatment.*

3.2.3 Participants and Procedure

240 subjects took part in the experiment, during 12 sessions³² in March and April 2017 at Grenoble Applied Economics Laboratory (GAEL). Each session lasted one

³²During the 8th session a technical problem occurred and so the results of this session are excluded from the analysis. The excluded session would have been in the price treatment.

and a half hours.

Table 3.3 shows the number of subjects, groups, and sessions per treatment. The experiment was programmed using zTree software (Fischbacher, 2007). For participating in the experiment, subjects received a 10€ show-up fee. In addition, subjects earned 7€20 to 18€00, with average earnings across sessions of 12€30. The majority of subjects were undergraduate students in various disciplines (67%), 59% were female subjects, and the average age across subjects was 22 years.

Treatment	Number of subjects	Number of groups	Number of sessions
Nudge	100	25	5
Price	80	20	4
Control	60	15	3
Total	240	60	12

Table 3.3: Number of subjects per treatment

At the beginning of each session, subjects randomly chose a subject number and a computer post. Once the subjects were seated, the experimenter read aloud all instructions³³. These were also displayed on two screens at the front of the room which all subjects could see. After general instructions concerning confidentiality, anonymity of data and the code of conduct were given, the experimenter described the context of the game. Subjects were told that the experiment would include several phases. The first phase of the experiment was the CPR game. The second phase involved a risk aversion test³⁴. (Holt *et al.*, 2002). In the third and final phase, subjects completed three questionnaires: the General Ecological Behaviour (GEB) Scale³⁵ (Kaiser, 1998), an altruism questionnaire (Costa and McCrae, 1992) and finally a demographic questionnaire. The GEB questionnaire is used to determine an individual’s level of environmental sensitivity as this may impact their consumption choices in the game. A questionnaire on altruism is included as the nature of the game requires making a decision that affects other people, thus altruistic tendencies can be controlled for in the analysis.

The instructions for each phase were read aloud then the subjects completed the phase before listening to the instructions on the following phase. Before the begin-

³³An English translation of instructions is available in Appendix B.

³⁴Analyses on risk attitudes were not conclusive and so are not discussed further in the rest of the analysis.

³⁵Following Boun My and Ouvrard (2018), a shorter version of the GEB scale is used including 28 items. See Appendix B for details of the GEB and altruism questionnaires.

ning of the CPR game phase, subjects completed a questionnaire to determine their understanding of the game. Subjects were informed of any wrong answers and had to correct them before advancing to the first period of the game.

3.3 Results and Discussion

In this section, the results are described and discussed, beginning with descriptive statistics and a graphical analysis of group level consumption decisions, followed by non-parametric testing. Next, subjects' individual choices analysed, for all treatments and specifically for the nudge treatment according to the message received. The effect of treatment on subjects' welfare is also considered. Then, the results of the questionnaires used at the end of the experiment are described and the consumption decisions by type as identified by the questionnaires. Finally, the equipment choices made by subjects are assessed.

3.3.1 Average Consumption at the Group Level

The dynamics of average group consumption by treatment for each period is represented in fig. 3.1. Table 3.4 summarises the average group consumption by treatment overall and in periods 1 and 2, as this is pre- and post- initial feedback. To further analyse the results, non-parametric tests on average group level consumption between and within treatments compared to the corresponding Nash equilibrium and to the social optimum are performed. The second part of table 3.4 gives these results.

In the absence of any policies, the control groups consume 23.49 on average. Though this level of consumption is close to the Nash equilibrium level of the initial game, it is significantly different from 25 EU (p-value=0.0355, Wilcoxon signed-rank test). When average consumption per period is tested, average consumption in the control group is not significantly different from the NE in all but 3 periods. In periods 1, 5 and 9, average consumption is at its lowest and significantly different from 25 for the control groups (p-values<0.05, Wilcoxon signed-rank test).

Result 1: In the absence of policy, subjects do not achieve the socially optimal level of consumption.

Treatment	Period 1	Period 2	Overall
Nudge	21.80 (4.43)	18.20 (3.08)	19.07 (4.45)
Price	21.56 (3.71)	22.00 (3.17)	21.09 (3.66)
Control	21.67 (3.67)	23.58 (4.11)	23.49 (4.18)
Wilcoxon rank-sum test (Between treatment p -values)			
Nudge = Price	0.9083	0.0004	0.0046
Nudge = Control	0.9216	0.0005	0.0001
Price = Control	0.9194	0.2027	0.0035
Wilcoxon signed-rank test (Within treatment p -values)			
Nudge = Social optimum (15 EU)			0.0000
Nudge = Nash equilibrium (25 EU)			0.0000
Control = Social optimum (15 EU)			0.0007
Control = Nash equilibrium (25 EU)			0.0355
Price = Nash equilibrium (20 EU)			0.0057

Standard deviations in brackets

Between treatment p -values are p -values of Wilcoxon rank-sum tests.

Within treatment p -values are p -values of Wilcoxon signed rank tests.

Table 3.4: Mean group consumption by treatment

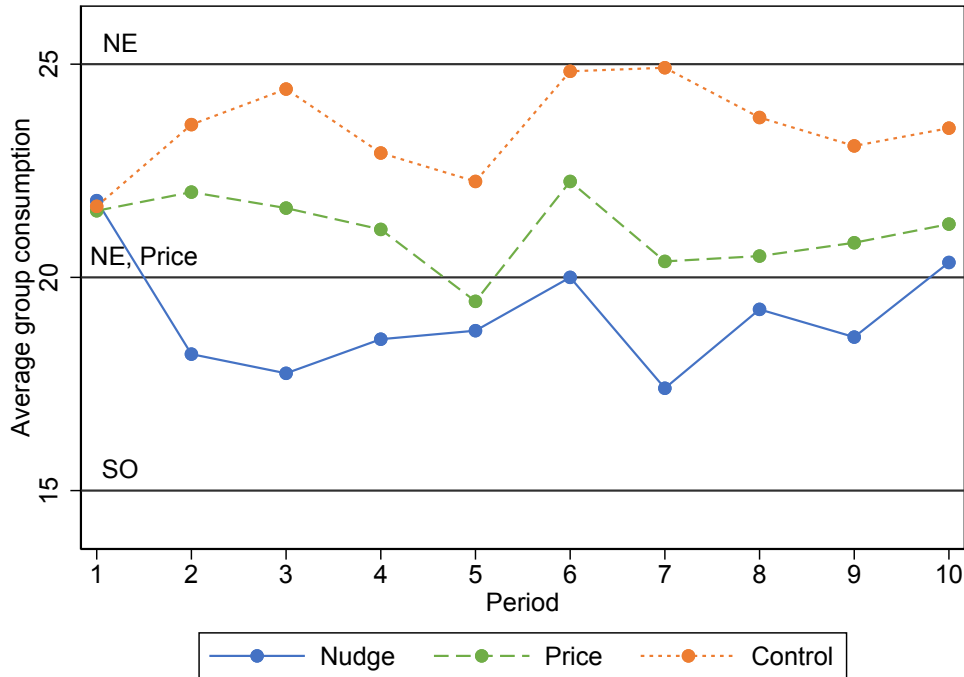


Figure 3.1: Dynamics of average consumption by treatment

The use of a nudge results in the lowest level of consumption of 19.07 on average across all 10 periods. This is to be expected given that the objective of the nudge is to encourage subjects to consume the optimal level of consumption of 15. In the first period, all treatments start at a similar level of average consumption³⁶. Given that in the nudge treatment, subjects do not receive feedback until after having made their consumption decision, it is to be expected that average group consumption in the first period will be similar between the nudge and control groups. In the nudge treatment, post-feedback, consumption is consistently lower compared to the control groups ($p < 0.01$, Wilcoxon rank-sum test), thus supporting hypothesis 1. In fig. 1. it can be seen that after the initial feedback, the average consumption immediately decreases and from period 2, there is a significant and permanent effect of the nudge policy as the average level of consumption under the nudge treatment is significantly different to those of control groups.

Result 2: Average consumption in the nudge treatment is significantly lower than in the control groups.

³⁶This difference is insignificant as tested non-parametrically using the Kruskal-Wallis test ($p = 0.9899$).

In the price treatment, when the price is increased such that consumers are incentivised to consume 20, (i.e. the observed level of consumption in the nudge treatment), the average group level of consumption is 21.09. This observed level of consumption is lower than that of control groups thus providing evidence to support hypothesis 2. In this treatment, subjects are aware of the price change prior to any decision making. Therefore, a significant difference between consumption decisions in the price treatment compared to control groups in the first period should be expected, but this difference is not significant (p-value = 0.9194, Wilcoxon rank-sum test). The average group consumption is only consistently and significantly different from the seventh period. It is also significantly different in periods 3 and 5 (p-value < 0.05, Wilcoxon rank-sum test). This suggests that it takes several periods for the subjects to integrate the price increase into their decision making and that it is not until the seventh period that the price is fully integrated into their decision making process.

Result 3: Average consumption in the price treatment is significantly lower than in the control groups from the seventh period.

Given that the price increase is designed to incentivise subjects to consume the amount observed under the nudge treatment, there should not be significant differences between the average group consumption decisions from the second period onwards between the nudge and price treatments. However, significantly different levels of consumption in periods 2 and 3 ($p < 0.01$, Wilcoxon rank-sum test) are observed. This suggests that subjects do not immediately integrate the price increase into their decision making. They require a few periods of play before they take into consideration the effect of the price increase on their consumption level. This result provides partial support for hypothesis 3, as consumption under the price increase is greater initially, and consumption choices in the two treatments are at similar levels from period 4.

Result 4: Consumption in the nudge and price treatments are statistically similar from the fourth period.

Finally, for all 10 periods, consumption across the three treatments is significantly

different ($p < 0.01$, Kruskal-Wallis test). In both the nudge treatment and the control groups, the observed average levels of consumption are significantly different from both the Nash equilibrium of 25 and the social optimum of 15 ($p < 0.05$, Wilcoxon signed-rank test). Groups in the nudge and price treatments have an average level of consumption that is significantly different from the control groups ($p < 0.01$, Wilcoxon rank-sum test). Moreover, the average consumption observed in the nudge treatment is significantly different from that observed in the price treatment ($p < 0.01$, Wilcoxon rank-sum test).

The results described in this section are robust to panel data estimation as shown in table 3.5 which presents regression estimates of treatment effects. The specifications have been estimated using panel data random effects estimation. Panel data methods are used as there are n subjects making a consumption decision in t periods. Random effects estimation is preferable to OLS or fixed effects estimation as it is more efficient than fixed effects estimation, and given that the experiment uses a between-subject design, random effects estimation allows for the estimation of the time-invariant treatment variables (Moffatt, 2015).

The value of the constant represents the average group contribution controlling for different variables. All specifications show a clear significant effect of both the nudge and price treatments compared to the control groups. In specifications 2 and 4, a period variable is included to control for variation during the game, however, the coefficient is not significant. In specifications 3 and 4, dummy variables are added to specify whether the group under or over consumed compared to the optimal consumption in their treatment³⁷. At the group level, there is no significant effect on consumption due to under or overconsuming in the previous period. Given that feedback on under or over consumption is provided at the individual level and in the nudge treatment, this effect is explored in more detail in the following section.

3.3.2 Average Consumption at the Individual Level

Table 3.6 shows the regression estimates of random effects specifications of treatment and covariates on individual consumption choice. Specification 1 shows a significant treatment effect for both the nudge and the price treatment at the individual level. In even numbered specifications, profit in $t-1$ is included and has a significant but small positive effect on average individual consumption. As the amount earned in

³⁷The share of each type of group (under, optimal or overconsuming) is shown in table B.1 in Appendix B

	(1)	(2)	(3)	(4)
Nudge	-4.427*** (0.830)	-4.427*** (0.830)	-4.740*** (0.807)	-4.731*** (0.808)
Price	-2.398*** (0.702)	-2.398*** (0.703)	-2.272*** (0.716)	-2.254*** (0.718)
Period		-0.018 (0.052)		0.058 (0.055)
Group under consumed (t-1)			-0.757 (0.683)	-0.744 (0.681)
Group over consumed (t-1)			0.288 (0.590)	0.340 (0.609)
Constant	23.492*** (0.607)	23.588*** (0.670)	23.415*** (0.795)	23.015*** (0.935)
Observations	600	600	540	540
R ² Overall	0.153	0.154	0.208	0.210
R ² Within	0.000	0.000	0.002	0.001
R ² Between	0.362	0.362	0.471	0.474

Standard errors in parentheses

Robust standard errors clustered by group.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: Average group consumption (random effects estimation)

$t-1$ increases, subjects increase their consumption in t . This could be indicative of a rebound effect where subjects who earn more, increase their consumption.

Specifications 3, 4 and 7 show that individuals who underconsumed in $t-1$, reduce their consumption in t compared to optimally consuming individuals. Those who overconsume in $t-1$ continue to do so compared to optimally consuming individuals. Once individual consumption type is controlled for, the significant effect of the price treatment falls out as the price treats all individuals equally and does not differentiate according to how an individual consumes (under, optimally, or over).

Finally, in specifications 5-7, variables concerning subjects' sensitivity towards the environment and their level of altruism³⁸ are included. Individuals who are more sensitive to environmental issues consume less. Given the context of the CPR game as an electricity consumption decision, such individuals may have additional motivation to choose a lower level of consumption so as to decrease their hypothetical impact on the environment. There is no significant effect of altruism on individual consumption choice.

³⁸The construction of these variables is explained in section 3.3.4

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Nudge	-4.427*** (0.829)	-5.655*** (0.952)	-3.899*** (0.720)	-4.802*** (0.840)	-4.275*** (0.835)	-5.515*** (0.955)	-3.794*** (0.720)
Price	-2.398*** (0.701)	-1.799** (0.901)	-0.843 (0.636)	-0.062 (0.872)	-2.318*** (0.759)	-1.742* (0.943)	-0.802 (0.677)
Profit in t-1		0.033*** (0.005)		0.037*** (0.007)		0.032*** (0.005)	
Individual under consumed (t-1)			-2.091*** (0.584)	-1.619*** (0.572)			-2.013*** (0.575)
Individual over consumed (t-1)			3.589*** (0.496)	3.342*** (0.483)			3.572*** (0.497)
High Environmental sensitivity					-1.545** (0.655)	-1.447** (0.669)	-1.314** (0.552)
High Altruism					-0.856 (0.652)	-0.603 (0.651)	-0.492 (0.527)
Constant	23.492*** (0.606)	18.682*** (1.189)	21.294*** (0.672)	15.785*** (1.494)	24.732*** (0.800)	19.807*** (1.366)	22.229*** (0.851)
Observations	2400	2160	2160	2160	2400	2160	2160
R ² Overall	0.042	0.090	0.147	0.169	0.053	0.098	0.153
R ² Within	0.000	0.014	0.001	0.001	0.000	0.014	0.001
R ² Between	0.099	0.185	0.559	0.570	0.125	0.202	0.550

Standard errors in parentheses

Robust standard errors clustered by group.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Individual consumption (random effects estimation)

The effect of the nudge on individual consumption decisions is also examined³⁹. The estimates are shown in table 3.7. Specification 1 includes only the feedback type, and subjects' level of environmental sensitivity and altruism is also included in specification 2. There is a significant negative effect of the happy face feedback, and a significant positive effect of the sad face feedback in both specifications.

Subjects who under consume receive happy face feedback and subjects who over consume receive sad face feedback. Compared to optimally consuming groups, this feedback has the effect of reinforcing an individual's behaviour in the previous period. With regard to the feedback received by subjects in the nudge treatment, both hypotheses 4 and 5 are rejected, as rather than nudging subjects towards the socially optimal level of consumption, the nudge employed in this experiment reinforces subjects' existing behaviour. Subjects who under (over) consume in the previous period tend to decrease (increase) their consumption in the present period. This suggests that while the nudge shows a decrease in average consumption at the group level, at the individual level the nudge may serve to reinforce behaviours that are already present. Individuals who overconsume and see a sad face in their feedback may feel that the nudge is a threat to their freedom to consume as they wish and so react to the feedback by demonstrating the behaviour that the nudge was trying to discourage (Brehm, 1966, Steindl *et al.*, 2015).

Result 5: The feedback in the nudge treatment reinforces subjects' existing consumption behaviour.

At the individual level in the nudge treatment, environmental sensitivity and level of altruism have a significant negative effect on consumption choice. More environmentally sensitive and altruistic individuals consume less compared to less environmentally sensitive and altruistic individuals.

3.3.3 Welfare Analysis

In this section we analyse the effect of the different treatments on subjects' welfare, at both the group and the individual level. Table 3.8 compares the average observed welfare by treatment at the group and individual level.

We can see that both individually and at the group level, subjects are worst off in

³⁹Table B.3 in Appendix B shows the distribution of feedback types in the nudge treatment.

	(1)	(2)
Under consumption :- (t-1)	-2.317*** (0.791)	-2.241*** (0.792)
Over consumption :- (t-1)	4.067*** (0.765)	3.753*** (0.846)
High Environmental sensitivity		-2.453*** (0.673)
High Altruism		-1.732** (0.846)
Constant	17.203*** (0.408)	19.770*** (1.021)
Observations	900	900
R ² Overall	0.115	0.142
R ² Within	0.004	0.004
R ² Between	0.825	0.601

Standard errors in parentheses

Robust standard errors clustered by group.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Effect of feedback on individual consumption in nudge treatment

price treatment, and better off in the nudge treatment. The increase in the peak price of electricity consumption results in a loss of welfare for individual subjects, or households, and for the group of subjects, or neighbourhood or society. Given that in the nudge treatment, there is no change in price, subjects' welfare is not affected. As such subjects are nudged towards the optimum and so their welfare, both individually and at the group level, is greater than for control groups.

Treatment	Average observed welfare	Welfare at social optimum	Welfare at Nash equilibrium	Welfare at a consumption of 20
Group level				
Nudge	702	760	600	720
Price	510	-	-	560
Control	617	760	600	720
Individual level				
Nudge	175	190	150	180
Price	128	-	-	140
Control	154	190	150	180

We do not provide a welfare level for the price treatment for the socially optimal and Nash equilibrium levels of consumption as the price is designed such that the Nash equilibrium level of consumption is equal to 20 as observed in the nudge treatment. We provide the welfare associated with this level of consumption in the final column.

Table 3.8: Welfare analysis at the group and the individual level

3.3.4 Questionnaire Results

In this section, the results of the questionnaires completed after the CPR game regarding environmental sensitivity and altruism are detailed.

3.3.4.1 General Ecological Behaviour Scale

The GEB questionnaire measures an individual's environmental sensitivity (Kaiser, 1998). Of the 28 items in the questionnaire, the mean score per item is 3.34 (std. dev. = 0.22). Cronbach's $\alpha = 0.73$ ⁴⁰. The GEB scale is therefore acceptable.

The average environmental sensitivity level of subjects overall, and per treatment is presented in table 3.9a, followed by the between treatment Wilcoxon rank-sum

⁴⁰Boun My and Ouvrard (2018) found a Cronbach's $\alpha = 0.74$.

tests in table 3.9b. The p -values indicate that the levels are statistically different from one another between the nudge and the price treatments, and the nudge and control groups. Subjects are slightly more environmentally sensitive in the nudge treatment compared to the price treatment and control groups.

Nudge	Price	Control	Overall			
108.8 (10.25)	106.5 (10.64)	107.1 (9.61)	107.6 (10.00)	Price	Control	
				Nudge	0.0001	0.0000
				Price		0.7534

Standard deviations are in brackets.

(a) Average environmental sensitivity (b) Between treatment p -values

Table 3.9: Environmental sensitivity questionnaire results

Table 3.10a shows the average consumption decisions of individuals in each treatment according to their sensitivity to environmental issues. High environmental sensitivity is classed as greater than the average of the sample⁴¹. As can be seen from the table, overall and for each treatment, more environmentally sensitive subjects choose to consume less. The difference in consumption level by environmental sensitivity is the greatest in the nudge treatment. This difference is statistically significant as shown in table 3.10b ($p < 0.01$, Wilcoxon signed-rank test).

Treatment	Low	High	Total			
Nudge	20.68	17.90	19.07	High		
Price	21.38	20.86	21.09	Nudge	Price	Control
Control	24.14	22.88	23.49	Nudge	0.0000	
Total	21.85	20.04		Low	Price	0.2036
					Control	0.1770

(a) Average individual consumption by treatment and by level of altruism (b) Between treatment p -values

Table 3.10: Average individual consumption by treatment and by environmental sensitivity

In line with Boun My and Ouvrard (2018), subjects’ consumption choices in the nudge treatment vary according to their level of environmental sensitivity. When comparing behaviour under each treatment by level of environmental sensitivity, in the nudge treatment subjects consume less than in the price treatment. These results provide support for hypotheses 6 and 7.

⁴¹In the nudge, price and control groups, 58%, 55% and 52% of subjects have high environmentally sensitivity, respectively.

Result 7: Individuals are affected differently by the nudge according to their level of environmental sensitivity. In the price and control groups, there is no difference according to environmental sensitivity.

3.3.4.2 Altruism Questionnaire

The altruism questionnaire is used to measure how altruistic subjects are. The mean score per item is 3.28 (std. dev. = 0.33). Cronbach's α is 0.68. The altruism questionnaire is moderately acceptable.

The average altruism scores are reported in table 3.11a across all subjects and by treatment and the associated p -values of Wilcoxon rank-sum tests in table 3.11b. The average scores on the altruism tests are significantly different across the nudge and price, and the nudge and control treatments. They are not significantly different between the price and control treatments.

Nudge	Price	Control	Overall		Price	Control
32.89	31.76	32.35	32.38	Nudge	0.0000	0.0000
(4.35)	(4.56)	(3.44)	(4.24)	Price		0.5779

(a) Average individual altruism score

(b) Between treatment p -values

Table 3.11: Altruism questionnaire results

Table 3.12a shows the average individual consumption by treatment according to level of altruism and table 3.12b the associated Wilcoxon signed-rank tests. High altruism is greater than the average of the sample⁴². In the nudge treatment highly altruistic individuals choose to consume less than less altruistic individuals. The levels are similar across altruism types in the control groups, and the opposite is observed in the price treatment. With regard to statistical significance, the differences are only significant in the nudge treatment. As with environmental sensitivity, it appears that a nudge based policy can separate subjects based upon their level of altruism, thus providing further support for hypothesis 6.

⁴²In the nudge, price and control groups, 58%, 55% and 52% showed a high altruism level, respectively.

Result 8: Individuals are affected differently by the nudge treatment according to their level of altruism. In the price and control groups, there is no difference according to their level of altruism.

Treatment	Low	High	Total	High		
Nudge	20.57	17.97	19.07			
Price	20.88	21.27	21.09			
Control	23.66	23.34	23.49			
Total	21.51	20.32				

		Nudge	Price	Control
Low	Nudge	0.0000		
	Price		0.6936	
	Control			0.6117

(a) Average consumption by altruism level

(b) Between treatment p -values

Table 3.12: Average individual consumption

3.3.5 Equipment Choices

This section looks at the hypothetical choices of subjects with regard to which electricity consuming activities they are willing to shift during peak periods. The consumption choices available to subjects are presented above in table 3.2. Figure 3.2 shows the share of subjects willing to lower the temperature of their heating by treatment type across periods. Figure 3.3 shows the percentage of subjects willing to turn off each of the other appliances, by treatment, in each period. The results in this section reflect the results found in the field, namely that individuals are willing to shift their use of appliances for which consumption is not at the point-of-use, and unwilling to shift their use of appliances for which consumption is at the point-of-use (Goulden *et al.*, 2014).

Figure 3.2 shows that the majority of subjects are willing to lower their heating by 2°. In the nudge treatment, after feedback has been received, there is an increase in the number of subjects choosing to lower their consumption by 2° from 47% to 59%, and a decrease in those lowering the temperature by 1°. The same can be observed for control groups but to a lesser extent. Of the subjects who choose to keep their heating at the same temperature, a greater percentage are present in the control groups and fewer in the nudge treatment.

In fig. 3.3, across all treatments, subjects are most willing to shift their use of washing machines or dishwashers. Across the 10 periods of the game, just under 80% of subjects choose to turn off these machines across treatments. This share is

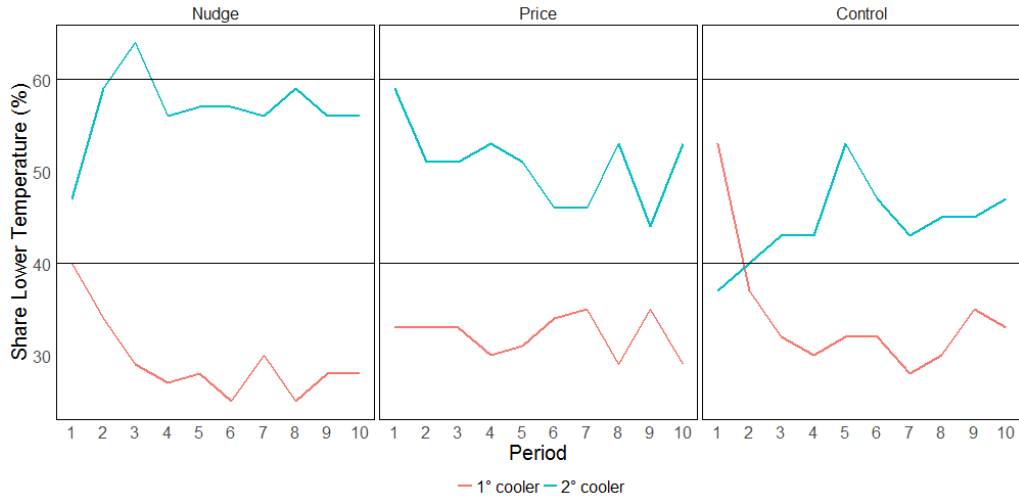


Figure 3.2: Dynamics of heating usage by treatment

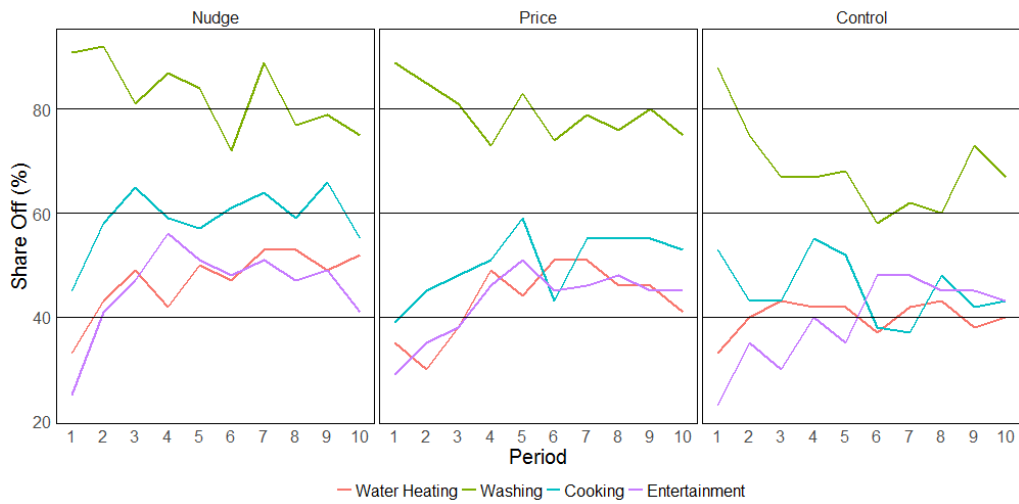


Figure 3.3: Dynamics of appliance usage by treatment

slightly higher for the nudge and price treatment compared to control groups. There appears to be a small effect of treatment on washing equipment use. In the control groups, there is a large decrease in the share of subjects who decide to shift their use of such equipment during the course of the game, compared to the treatment groups.

Figure 3.3 shows electricity consuming entertainment activities to be the activity that subjects are least willing to shift, at least initially with three-quarters of subjects choosing to turn on their televisions and computers in the first period, across all treatments. However, as the game progresses this appliance choice sees an increase in the share of subjects shifting its use.

The share of subjects willing to shift their use of cooking equipment is greater in the nudge treatment than in the price treatment and control groups, and remains around the 60% mark post initial feedback.

Concerning subjects use of water heating, there is an increase in the share of subjects who turn off their water heater in the nudge and price treatments. Whereas, the share remains lower in the control groups.

Across treatments, the shift in use of appliances is most apparent in the nudge treatment. With a marked increase in the share of subjects turning off appliances post feedback in period 2. This trend is also visible to a certain extent in the price treatment, and much less so in the control groups.

3.4 Conclusion and Policy Implications

The experiment described in this chapter explored subjects' responses to a nudge and a peak price based intervention in a contextualised CPR game. The experimental design allowed for a comparison of behaviour under a nudge policy and an equivalent price increase to an absence of policies. The nudge policy experimented concerned feedback on an individual's consumption choice in the form of a happy face if they consume the socially optimal amount or less, and a sad face if they consume more than the socially optimal amount. In addition, the experimental design provided an opportunity to examine subjects' consumption choices regarding their use of different appliances as subjects were asked to decide whether or not to use five different appliances when deciding upon their level of consumption. The results of the experiment may be of interest to policy makers when considering the imple-

mentation of a nudge or a price based intervention designed to reduce households' energy consumption during peak periods.

In the absence of energy conservation policies, individuals do not achieve the socially optimal level of consumption. When a policy is introduced, a nudge or price increase, individuals significantly reduce their consumption and it remains lower than that of individuals who do not experience any policy measures. Both the nudge and price increase result in a level of consumption that is halfway towards the optimal level compared to no policies. However, the nudge does so without the loss of both individual and group welfare that is associated with the price increase. Therefore, while both the nudge and price increase lead to a lower level of comfort due to the reduction in consumption, it can be concluded that although the nudge in itself is not sufficient to achieve the social optimum, it performs as well as an equivalent price increase without the implied loss of welfare.

The experiment showed that the nudge was quickly and easily understood, and resulted in an immediate reduction in consumption in the period following initial feedback. On the other hand, individuals took longer to understand the effect of the increased price on their consumption and so took longer to integrate it into their decision making process.

The advantage of a nudge policy is that, at the group level, it results in an immediate and significant reduction in consumption, however caution must be taken as the nudge in the present experiment reinforces the existing behaviour of individuals and divides the population into those who under or over consume, or who are more or less environmentally sensitive or altruistic.

In response to a happy face, individuals who under consumed previously tended to further decrease their consumption compared to individuals who consumed optimally, whereas, those who received a sad face tended to increase their consumption. Collectively, these individuals compensate for one another's behaviour and so the nudge has an effect on average consumption. However, individually the nudge appears to encourage those who already under consume to consume less, and those who over consume to consume more. In practice, this could lead to a situation where low consuming households are further reducing their consumption to compensate for the increasing consumption of high consuming households. While this result has been obtained in a hypothetical consumption game, it is worth consideration when implementing such nudges in the field.

It may be that overconsuming individuals see the nudge as a threat to their freedom

to consume as they wish and so they react by demonstrating the discouraged behaviour. The nudge in the present experiment could be considered as an exogenous nudge; it is an outsider (the experimenter) who provides feedback in relation to an exogenously optimal level of consumption. The experimenter defines the parameters of the game and thus the optimal amount. Whereas in field experiments an endogenous nudge (household consumption in relation to the average of the neighbourhood) is often tested. Given that nudges are a tool of "libertarian paternalism" and that it is a third party who is nudging individuals towards a decision that is in their best interest, further research could look into how individuals respond to exogenous and endogenous nudges.

In addition to reinforcing existing consumption behaviour, the nudge had a greater reduction effect on individuals who are environmentally sensitive and show altruistic traits. Such individuals consumed less than their less environmentally sensitive and less altruistic counterparts. The price increase showed no such effect. It would appear that the increase in price crowds out any existing motivation to reduce consumption due to environmental or altruistic tendencies.

Finally, the appliances that subjects are willing to shift their use of in order to reduce their consumption are considered. Subjects are most willing to turn off their washing appliances and prefer to continue to use their entertainment devices. Subjects are also willing to lower their heating in order to reduce their total consumption. Further research could look into specialised nudges according to the types of electric appliances in each household.

Chapter 4

Gain and Loss Framing of Incentives: Encouraging Individuals to Provide an Effort for Small Rewards

Joint with Béatrice Roussillon⁴³ and Sabrina Teyssier⁴³.

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⁴⁴See <https://ecosesa.univ-grenoble-alpes.fr/>

Abstract

When trying to save energy, households are required to perform small, repetitive tasks, e.g.: turning off lights, or turning appliances off standby. Each individual action has little effect on energy consumption and on household bills, however, they can add up to sizeable savings. This paper explores different methods of framing incentives to motivate subjects to perform a simple yet repetitive, real-effort task for a piece-rate payoff. Each individual effort does not earn much for the individual, but combined the payoff is significant. A 2 by 3 design is used: either gain framed or loss framed incentives, crossed with either a control treatment with a fixed payoff, an ex-ante treatment with a low or high payoff with equal probability, revealed to individuals prior to the task, or an ex-post treatment where the low or high payoff with equal probability is revealed after completing the task. Individuals are expected to perform better under loss-framing. Results show little difference in performance across treatments. Knowledge of the higher payoff improves performance in the gain-framed, ex-ante treatment, and subjects perform significantly better when the payoff is higher in both ex-ante treatments.

4.1 Introduction

Smart meters are a key piece of technology in the implementation of various incentives used to encourage households to lower their consumption. An in-home display (IHD) retrieves data from a smart meter and provides households with feedback on their energy consumption in relation to the various incentives that can be implemented. Without such an interface between the consumer and the smart meter, it is difficult for households to act upon the information that the smart meter can provide (Dütschke and Paetz, 2013).

For the data displayed on IHDs to have the desired effect of reducing residential household consumption, an important consideration in the design of IHD interfaces is how to frame the incentives to make them more effective. Should households be incentivised with the carrot - shown how much they are saving, or with the stick - shown how much they are paying?

Previous experiments exploring the effect of feedback provided by IHDs typically present information factually and consider the units of measurement of consumption information, whether to use energy units (kilowatt-hours) (Parker *et al.*, 2008, Van Dam *et al.*, 2010, Nilsson *et al.*, 2014), combined with monetary units (Schleich *et al.*, 2013, Alahmad *et al.*, 2012, Carroll *et al.*, 2014), or whether to use normative information by comparing a household's consumption to that of other similar households (Schultz *et al.*, 2007, Allcott, 2011b, Schultz *et al.*, 2015). This information is presented factually, in terms of amount consumed or amount spent on consumption, however, little research has compared the framing of energy consumption information in terms of salient losses and gains.

To date, and to the best of the author's knowledge, two studies have explored the effect of explicitly framing expenditure on energy consumption as a loss. Bager and Mundaca (2017) find that households under salient loss framing make more effort to shift their consumption than households under factual feedback. They reduce their overall demand by 7-11% compared to households without framed feedback. Bradley *et al.* (2016) create a loss frame by creating an incentive account for each household in their study in which an amount of money representative of each household's monthly budget is held. Households must then shift their energy consumption from peak to off-peak periods in order to retain as much of the incentive account as possible. The authors find that households in the incentive account treatment shifted more consumption during the experimental period compared to the pre-experiment period

when they paid for consumption as normal and had no incentive account. Both of these studies have used salient, loss-framed feedback to incentivise households to shift and/or lower their energy consumption compared to either groups with a factual presentation of consumption feedback, or to a pre experimental period.

A characteristic of residential energy consumption is that efforts made to save energy often result in small savings. Indeed, households using IHDs have found that the information on daily expenditure is too small to encourage energy consumption reduction as a single behavioural change has a small impact on daily expenditure (Goulden *et al.*, 2014). It is the accumulation of many small actions which amount to a larger effect on monetary savings. For some individuals the small individual monetary savings are not enough to encourage them to provide an effort (Hargreaves *et al.*, 2010), whereas others appreciate that many, repeated actions can add up to significant monetary savings (Murtagh *et al.*, 2014).

In the more general (non energy related) experimental literature on gain and loss framing, there is evidence showing that individuals provide more effort under loss framing than under gain framing in both the laboratory (Hannan *et al.*, 2005, Goldsmith and Dhar, 2011, Armantier and Boly, 2015, Imas *et al.*, 2016), and the field (Fryer Jr *et al.*, 2012, Hossain and List, 2012, Armantier and Boly, 2015), to name a few.

Larger or lump-sum payoffs encourage greater effort provision under loss framing than under gain framing. In both hypothetical (Hannan *et al.*, 2005) and real-life (Hossain and List, 2012) contract tasks, subjects perform better under a loss-framed lump-sum payoff for meeting a target. In an artificial, real-effort task, Imas *et al.* (2016) find that endowing subjects with a t-shirt and taking it back if they do not meet a certain target is more effective than receiving the t-shirt after having met the target.

Similar results have also been found in the field: in experiments in education, Fryer Jr *et al.* (2012) find that endowing teachers with an incentive of \$4000 has a larger effect on increased student grades than offering teachers the incentive at the end of the school year. In an experiment incentivising graders to grade papers, Armantier and Boly (2015) find that penalties out perform bonuses, and that a combination of both is most successful. They find a U-shaped relationship between framing and effort; their subjects increase their effort initially for both bonuses and penalties, but provide less effort when penalties are large. A large penalty has the effect of discouraging effort.

On the other hand, recent studies exploring the effect of gain and loss framing to motivate effort for small payoffs are less conclusive. [De Quidt *et al.* \(2017\)](#) and [Essl and Jaussi \(2017\)](#) do not find significant effects on effort provision due to framing. This is of particular interest for the present experiment as, as discussed above, encouraging residents to lower their energy consumption means motivating small efforts for small rewards.

Both of these studies provide subjects with immediate feedback on their performance akin to the real-time feedback that IHDs provide on energy consumption. While [De Quidt *et al.* \(2017\)](#) and [Essl and Jaussi \(2017\)](#) do not find significant effects of framing with feedback, other experiments using immediate feedback have found a significant effect of loss-framing on effort compared to gain framing ([Goldsmith and Dhar, 2011](#)).

A further characteristic of residential energy consumption is that many variables affect household consumption, such as building characteristics, appliance characteristics, external factors (location, weather, temperature, etc.) in addition to occupant behaviour ([Kavousian *et al.*, 2013](#)). This can mean that similar sized households, in buildings with similar characteristics can have substantially different levels of electricity consumption ([Gram-Hanssen, 2013](#)). Given the multitude of variables that affect energy consumption, when households make efforts to lower their demand, their efforts may not necessarily have the intended effect.

For example, a household may decide to lower their thermostat in order to save energy on heating during winter. However, factors outside of the households control may affect the payoff of such an action. Suppose the household in question lives in an apartment surrounded by other apartments. They may save energy, and money, as a result of lowering their consumption, yet the temperature of their apartment may not fall drastically due to the residual heat from neighbouring apartments. On the other hand, suppose the household lowers the thermostat on a day which is colder than forecast. The household may not save as much energy as hoped. While these examples are admittedly anecdotal, they highlight that when acting to lower energy consumption, there is an element of risk as to whether the action will result in the desired monetary savings.

Furthermore, with the increasing share of renewable energy sources in the production mix, the future price of electricity is set to become more variable than at present. These differing prices for consumption at different times of the day vary in the amount of risk households will bear and the reward they provide households

(Faruqui, 2012).

Abeler *et al.* (2011) explore the effect of risk on effort provision in the gain domain. Abeler *et al.* manipulate subjects' reference points by proposing a payoff in the form of either a piece-rate payoff or higher/lower fixed amount (with equal probability) in order to influence subjects' expectations of earnings. In a similar task to the present experiment, subjects provided more effort when the possible fixed amount is higher. However, regardless of the size of the fixed payoff, subjects provide effort up to the level of the fixed amount though they could earn more under the piece-rate payoff. The authors find that expectations of payoffs form individuals' reference points such that if individuals expect to receive a low payoff when they receive it, it is not perceived as a loss.

In two mixed frame experiments where subjects faced risky payoffs, subjects received a piece-rate for performing simple additions to which a known amount was either added or taken away, with equal probability. Both Sloof and Van Praag (2010) and Corgnet and Hernán-González (2018) find that subjects provide more effort when the additional gain/loss is higher, i.e.: when there is greater variability in the payoff. According to expected utility theory, there is no difference in framing incentives positively (savings) or negatively (amount spent) as under isomorphic framing, the two incentives types should motivate the same provision of effort. On the other hand, prospect theory predicts that individuals make more effort when faced with negatively framed incentives than with positively framed ones as "losses loom larger than gains" (Kahneman and Tversky, 1979, p.279). This can be explained by the endowment effect (Thaler, 1980) or reference point bias (Kahneman *et al.*, 1991), whereby an individual considers a gain or a loss relative to their current endowment or reference point.

Prospect theory suggests that individuals derive greater utility from avoiding a loss than they do from gaining the same amount. Furthermore, the theory posits that individuals are risk-averse in gains and risk-seeking in losses (Kahneman and Tversky, 1979). In a meta-analysis of 136 experimental papers, Kühberger (1998) corroborates the theory. Kühberger finds that risk aversion in gains and risk seeking in losses is particularly strong when reference points rather than outcomes are manipulated, i.e.: when starting points rather than final earnings are manipulated. In the present experiment, starting points are manipulated by giving individuals in loss treatments an endowment from which their losses are subtracted.

These experiments have highlighted that individuals provide a greater level of effort

under loss-framing when payoffs are relatively large. When piece-rate payoffs are used the evidence is less clear. The particularity of energy consumption is that an individual, energy saving action has little impact on overall consumption (as such it is akin to a piece-rate payoff), yet together many repeated energy saving actions can amount to more substantial savings. When risk is added to payoff structures, individuals provide more effort when the additional amount that they can gain or lose is greater.

The present experiment contributes to this literature by exploring how individuals respond to riskless, and risky payoffs under both gain and loss framing, when they can earn small payoffs for small efforts in an artificial, real-effort, number counting task. Subjects are provided with immediate feedback which highlights the cumulative gains or losses as a result of subjects' effort. The present experiment captures some of the principal characteristics of residential energy consumption feedback via an IHD: small payoffs for small efforts which cumulate to sizeable earnings, direct feedback on performance, and both riskless and risky payoffs to reflect outside factors which can affect the reward of a particular effort.

The results of the present experiment suggest that framing has little effect on effort provision when small efforts are rewarded with small payoffs. Under riskless payoffs, subjects provide more effort for larger payoffs regardless of the treatment frame. Concerning subjects' effort throughout the game, their performance is lowest at the beginning of the game, then improves towards the end. Subjects' effort provision increases most significantly in the riskless treatments when payoffs are revealed to subjects prior to effort provision.

Given that reducing energy consumption through changes in residential behaviour requires small, repetitive efforts for small rewards, the present experiment has shown that in order for subjects to provide an effort, any risk on the realisation of payoffs should be reduced, in particular under loss framing.

The rest of the chapter is organised as follows: in section 4.2 describes the real-effort task and experimental treatments, followed by a presentation of the hypotheses in section 4.3. Section 4.4 provides the results of the experiment and finally section 4.5 concludes.

4.2 Experimental Design

The experiment was designed to allow for a precise measure of effort provision which is exogenously influenced by gain and loss framing, and by risky payoffs. A tedious, artificial, real-effort task was used. Subjects counted the number of ones in 9 by 9 tables of randomly ordered ones and zeros (Abeler *et al.*, 2011, Essl and Jaussi, 2017). The number of ones in each table varied between 28 and 45 (with 36 ones per table on average), and was randomly drawn prior to the first experimental session and was the same for all subjects. All subsequent experimental sessions faced the same order of tables. The advantages of this task are that no special knowledge is required, learning possibilities are limited, and effort is easily measurable. In addition, experimenter demand effects are minimised as the task is artificial and the outcome is of no intrinsic value to the experimenter.

The experiment consisted of 2 stages. At the beginning of the first stage, instructions⁴⁵ were read aloud to subjects, and subjects answered control questions. Prior to beginning the first stage, subjects were informed that the second stage of the experiment involved answering a questionnaire.

In the first stage of the experiment, subjects played 28 periods in each of which they had 80 seconds to count the number of ones in five tables. Once subjects had entered a number for the table on display, a new table appeared whether their answer was correct or not. If subjects ran out of time before completing the fifth table of the period, then the period was over. Subjects were not informed of the current period number and nor was there a timer present. In total, subjects saw up to 140 tables.

After each period of five tables, subjects received feedback on their performance for the period: how many tables they correctly counted and how much they earned, and feedback for the game so far: how much they earned. The number of tables which subjects correctly completed is used as a proxy for their effort provision.

In the second stage subjects completed a questionnaire containing socio-demographic questions.

4.2.1 Treatments

A 2x3 experimental design was used to create six treatment groups. The treatments were divided into two frames: incentives were framed as either a gain or a loss. In

⁴⁵An English translation of instructions can be found in Appendix C.

the gain treatments subjects increased the size of their pot of earnings by correctly counting the number of ones in each table. In loss treatments subjects were endowed with the maximum earnings possible and their pot decreased for every incorrect or incomplete table. In other words, they maintained their pot if they correctly counted the number of ones in each table. The experimenter in each loss-framed session distributed the maximum earnings of 21€ to each subject in real money and this was left on their table throughout the duration of the task. Within each frame, there were three payoff structures: a fixed payoff known prior to effort provision, a low or high payoff (with equal probability) known prior to effort provision, and a low or high payoff (with equal probability) known after effort provision. Each of these payoff structures will be described below.

Control

In the control treatments subjects could earn a fixed payoff for each correct table. In the gain-control (GC) treatment subjects began with a pot of 0€ and earned 15 cents per correct table. In the loss-control (LC) treatment, subjects began with a pot of 21€ and lost 15 cents for each incorrect or incomplete table. Subjects gained or avoided losing money by counting the correct number of ones in each table.

Ex-ante

In the gain-ex-ante (GEA) treatment subjects earned either 5 cents or 25 cents per correct table, with equal probability. In the loss-ex-ante (LEA) treatment subjects lost either 5 cents or 25 cents per incorrect or incomplete table, with equal probability. The per table payoff remained the same for the 5 tables in a given period. The payoff for a given in period was randomly drawn for each subject before subjects completed the tables and was displayed on the *task* screen.

In the ex-ante treatments, subjects were informed of the payoff for the period *before* counting the number of ones. They knew the possible payoff *before* making any effort.

Ex-post

In the gain-ex-post (GEP) treatment subjects earned either 5 cents or 25 cents per correct table, with equal probability. In the loss-ex-post (LEP) treatment subjects lost either 5 cents or 25 cents per incorrect or incomplete table, with equal probability. The payoff stayed the same for all 5 tables in each period. The payoff for a given period was randomly drawn for each subject before subjects completed the tables and was displayed on the *feedback* screen at the end of each period.

In the ex-post treatments, subjects were informed of the payoff for the period *after* counting the number of ones, once the period had ended. They knew the payoff *after* having made an effort.

Table 4.1 summarises the different payoffs in each treatment.

	Gain	Loss
Endowment	0€	21€
Control	0.15€	-0.15€
Ex-Ante risk	0.05 or 0.25€	-0.05 or -0.25€
Ex-Post risk	0.05 or 0.25€	-0.05 or -0.25€

Table 4.1: Payoffs by treatment

4.2.2 Participants and Procedure

The experiments took place during April and May 2018 at Grenoble Applied Economics Laboratory. 259 students took part in experiments across 16 sessions. There were 13-20 students per session and each session lasted one and a half hours. The experiment was programmed using zTree software (Fischbacher, 2007). Table 4.2 details the characteristics of subjects in each treatment. In addition to the amount earned during the experiment, subjects received a 5€ show-up fee.

Treatment	n	Average age	Female (%)	Undergraduate (%)	Average earnings
GC	31	21	55	71	13€55
LC	29	21	66	79	12€86
GEA	48	21	54	79	14€13
LEA	48	21	58	69	13€20
GEP	52	21	58	81	13€27
LEP	51	21	43	73	12€70

Table 4.2: Description of subjects per treatment

At the start of their session, subjects chose a subject number at random and a computer post. All instructions were read aloud by the experimenter and were displayed on two screens at the front of the room. Subjects were told that the experiment would consist of two phases: (1) the experimental task, (2) the questionnaire. The first phase began with a comprehension questionnaire which was corrected collectively before subjects started the experimental task. Instructions for the second phase were read aloud once all subjects had completed the first phase.

4.3 Hypotheses

According to expected utility theory, if subjects were rational and unaffected by the framing of incentives and the risk associated to payoff, then the above differences in treatments would result in no significant differences in effort. The gain or loss framing would have no effect as the expected outcome is the same under each frame. The different payoff structures would have no effect on effort as the expected outcome is the same under each structure. The risk on payoffs in the ex-post treatments would have no effect as the expected payoff is the same as in the control groups.

That being said, the above discussion of the literature has shown that individuals are influenced by framing. Previous experiments have confirmed this idea ([Hannan *et al.*, 2005](#), [Goldsmith and Dhar, 2011](#), [Fryer Jr *et al.*, 2012](#), [Hossain and List, 2012](#), [Armantier and Boly, 2015](#), [Imas *et al.*, 2016](#)). However, some more recent studies have found no evidence of framing effects ([Hong *et al.*, 2015](#), [De Quidt *et al.*, 2017](#), [Essl and Jaussi, 2017](#)).

Prospect theory predicts that individuals behave differently when faced with a gain or a loss; individuals attach a greater utility to avoiding a loss than they do to receiving an equivalent gain ([Kahneman and Tversky, 1979](#)).

Loss aversion may explain why framing incentives as gains and as losses affects behaviour differently ([Kahneman and Tversky, 1979](#)). When an incentive is negatively framed, an individual is given a payment from which an amount is withdrawn if their performance is not up to standard. This initial increase in income or utility provides the individual with an endowment. When faced with losing part or all of that endowment, prospect theory predicts that individuals will work harder to retain their endowment than if they were to begin with nothing and to make an effort to increase their endowment through bonuses. The loss of utility from moving away from the endowment amount is greater than the increase in utility of moving towards the same amount. This behavioural bias is known as the endowment effect ([Kahneman *et al.*, 1990](#)).

With positively and negatively framed incentives the reference point is different; individuals start from nothing or little and increase their income by making an effort. Or they start with a certain endowment and make an effort to not lose it. The individual's point of reference for making their decision to make an effort or not is different under each incentive type. Each individual will also have a different reference point with regard to the base payment and the bonus or penalty ([Kahneman,](#)

1992).

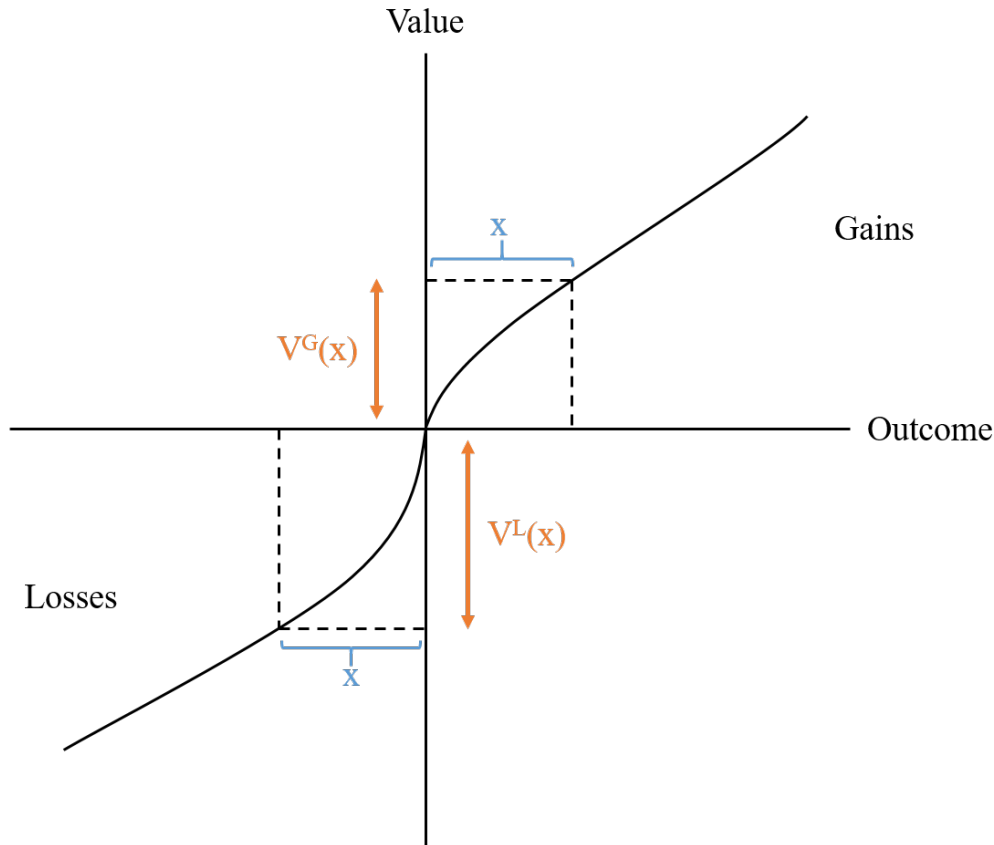


Figure 4.1: A hypothetical value function (Kahneman and Tversky, 1979, p.279)

Figure 4.1 provides a visual representation of a hypothetical value function⁴⁶. The centre of the graph represents the reference point and x a movement away from that point in both the gain and loss domain. The change in utility due to the gain or loss of x is not equal in the two domains. The disutility of losing x is greater than the utility of gaining x : $V^L(x) > V^G(x)$. As such, prospect theory predicts that individuals will expend more effort to avoid a loss of x than they will to gain x .

This leads to hypothesis 1:

Hypothesis 1: *Subjects provide more effort under loss framing than under gain framing: subjects' effort provision will be greater in LC compared to GC, LEA compared to GEA, and in LEP compared to GEP.*

Given the design of the present experiment, the only difference in effort that a rational individual would provide is in the ex-ante treatments; individuals would

⁴⁶The value function used here is slightly modified from the original for explicative purposes (Kahneman and Tversky, 1979).

provide more effort when the payoff is higher. Indeed, the above studies which found significant treatment effects are predominately studies which use large, rather than piece-rate incentives. This is further supported in [Abeler *et al.* \(2011\)](#) whose subjects provided more effort for higher payoffs.

This leads to hypothesis 2:

Hypothesis 2: *Subjects provide more effort when payoff amounts are higher: subjects' effort provision will be greater for $GEA^{0.25}$ compared to $GEA^{0.05}$, and $LEA^{0.25}$ compared to $LEA^{0.05}$.*

[Kahneman and Tversky \(1979\)](#) posit that individuals are risk averse towards gains and risk seeking towards losses. As [Kühberger \(1998\)](#) shows, this framing effect due to risk preferences is greater when reference points are manipulated. In the present experiment, under gain framing, subjects' initial reference point is 0€ whereas under the loss frame, their initial reference point is an endowment of 21€.

This leads to hypotheses 3:

Hypothesis 3a: *Subjects will provide more effort under risky payoffs compared to fixed payoffs in the loss domain: subjects' effort provision will be greater in LEP compared to LEA and LC.*

Hypothesis 3b: *Subjects will provide less effort under risky payoffs compared to fixed payoffs in the gain domain: subjects' effort provision will be smaller in GEP compared to GEA and GC.*

4.4 Results and Discussion

This section presents and discusses the results of the experiment in relation to the hypotheses set out above in section 4.3. The presentation of the results begins with the global treatment effects by frame, payoff amount and by risk. This is followed by a discussion of the evolution of effort provision over time.

4.4.1 Effort Provision by Frame

The main variable of interest in the experiment is the number of correct tables in a given period. This variable is used as a proxy for the effort provided by subjects in the experiment.

Table 4.3 provides the average number of correct tables and standard deviation in

each treatment for all periods. The final column shows the associated p -values of Wilcoxon rank sum tests of the difference in the average number of correct tables between treatments over all periods⁴⁷.

Treatment	Average	Std dev.	p -value
GC	3.23	1.14	0.459
LC	3.06	1.32	
GEA	3.27	1.16	0.298
LEA	3.10	1.24	
GEP	3.10	1.18	0.349
LEP	3.01	1.11	

Table 4.3: Number of correct tables overall and across all periods

Across all periods, subjects correctly completed most tables in the GEA and GC treatments, and least in the LEP treatment. Comparisons of average effort provision within payoff structures and between framing show that there are no significant differences in effort provision due to framing.

Figure 4.2 shows the evolution of the average number of correct tables. A comparison is made between the payoff structures within a treatment frame: loss or gain. The difficulty as measured by the average distribution of ones in the five tables of a period is underlaid and represented in grey. The peaks and troughs in the average number of correct tables correspond to relatively easy (fewer ones) and difficult (more ones) periods.

There is no clear trend in the evolution of average number of correct tables across treatments. Graphically, the trend lines are more disparate in the gain treatments, and more similar in the loss treatments.

Figure 4.3 displays the cumulative distribution functions of the total number of correct tables by completed by subjects in each treatment. The best subjects in each treatment correctly complete between 85 and 94% of the tables. There is more variation at the lower end of effort: the fewest number of tables correctly completed varies from 10 - 35%. There is substantial overlap in the six CDFs, further indicating small differences in effort provision across treatments. Graphically, the CDF of the LEP treatment stands out most: fewer subjects complete higher number of tables compared to the other treatments.

⁴⁷The average number of correct tables, standard deviations and associated Wilcoxon rank sum tests for periods 1 and 28 and for the first and second half of the experiment are provided in Appendix C.

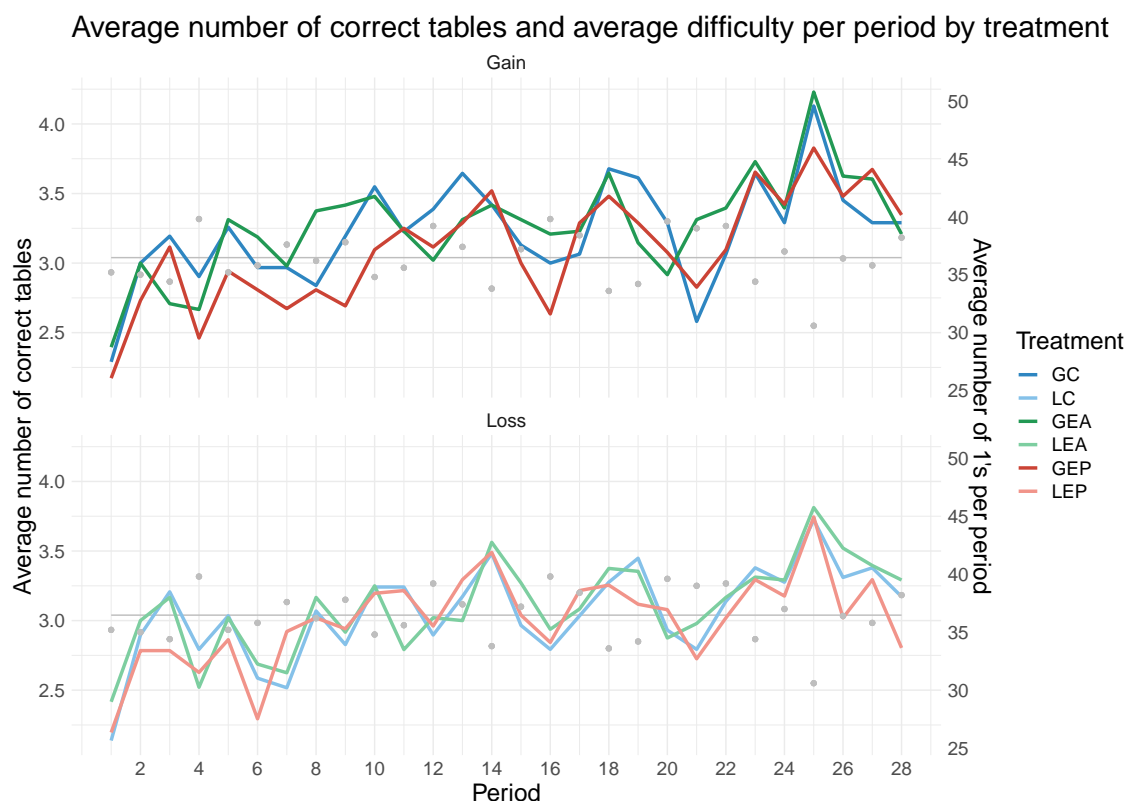


Figure 4.2: Evolution of average number of correct tables and average difficulty per period by treatment (comparison by frame)

Result 1: There is no framing effect: there are no significant differences between GC and LC, between GEA and LEA, nor between GEP and LEP (bar the final period).

4.4.2 Effort Provision by Payoff Amount

Given that there are two payoff amounts in each of the *Ex-Ante* and *Ex-Post* treatments⁴⁸, the average number of correct tables has been calculated for each payoff amount (standard deviations in brackets). Table 4.4 shows the averages and the standard deviations of the variable of interest by payoff amount for each of these treatments, as well as the results of Wilcoxon signed rank tests of significant differ-

⁴⁸The expected payoff in each of the four treatments with varying payoffs is ± 0.15 in either a gain or a loss frame. The expected payoff across all periods in each treatment is statistically indifferent from ± 0.15 .

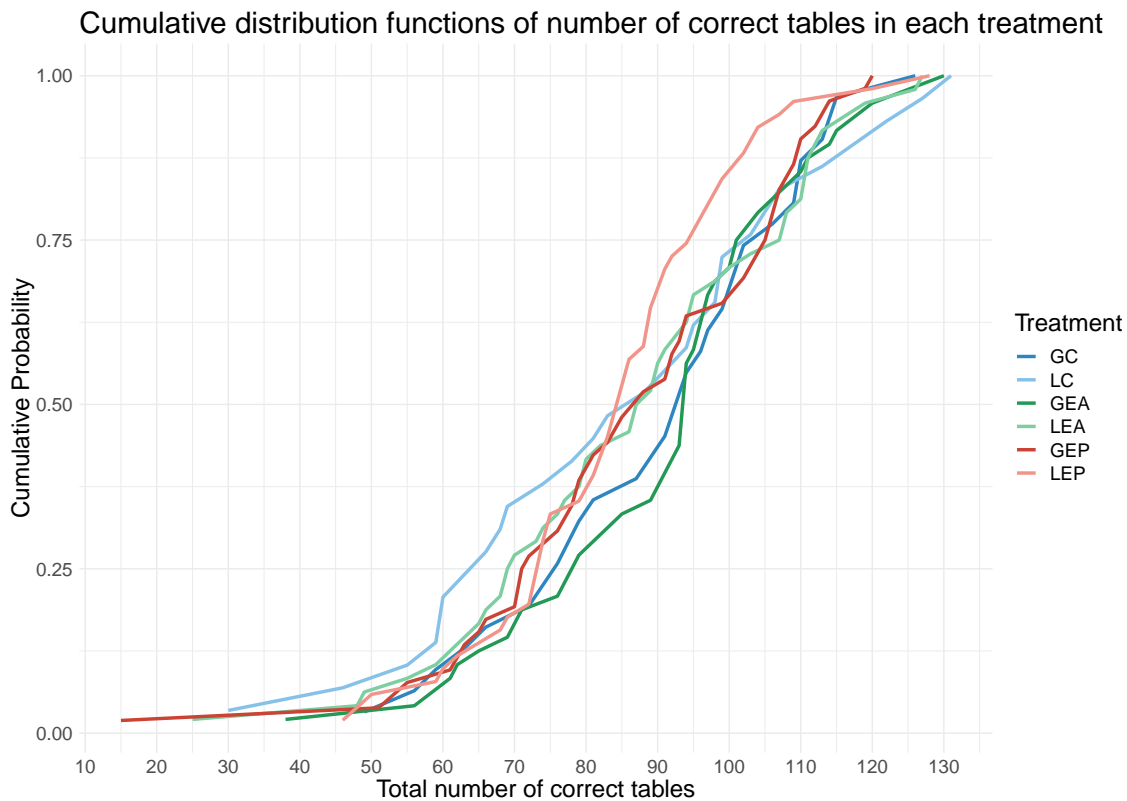


Figure 4.3: Cumulative distribution functions of number of correct tables in each treatment

ences between payoff amounts within each treatment.

Subjects perform better in the both GEA and LEA treatments when the gain or loss amount is greater. The difference in effort is significant ($p < 0.01$, Wilcoxon signed rank test) for both treatments. Subjects make more effort to earn, or to avoid losing, the larger payoff amount when it is known. As expected, there is no significant difference in performance in the GEP and the LEP treatments as subjects are only aware of the payoff amount after having made an effort. The difference in effort provision within the gain frame between payoff amounts is not significantly greater than that of the loss frame. Subjects in the GEA treatment do not provide significantly more effort for higher versus lower payoffs compared to the LEA treatment.

Result 2: Subjects provide more effort for higher payoffs than for lower payoffs (when payoffs are known prior to effort provision).

	Payoff amount		Difference ⁴⁹
	± 0.05	± 0.25	
GEA	3.15 (0.76)	3.38 (0.66)	0.23***
LEA	3.03 (0.85)	3.19 (0.80)	0.16***
GEP	3.06 (0.74)	3.13 (0.81)	0.07
LEP	2.99 (0.64)	3.02 (0.61)	0.03

Table 4.4: Average number of correct tables by payoff amount in Ex-ante and Ex-post treatments

4.4.3 Effort Provision by Risk

As described in Section 4.2.1, in treatments GEP and LEP subjects face risky payments of 5 or 25 cents per table in a given period with equal probability. The payoff is revealed to subjects after they have completed the task. In treatments GEA and LEA, subjects face the same payoff structure, however, the payoff amount is revealed at the start of each period.

Table 4.5 displays average effort per treatment over all periods. Subjects perform marginally better in each ex-ante treatment compared to its corresponding ex-post treatment. There are no significant differences in effort provision according to risk⁵⁰.

Treatment	Average	Std dev.
GEA	3.27	1.16
GEP	3.10	1.18
LEA	3.10	1.24
LEP	3.01	1.11

Table 4.5: Number of correct tables overall and across all periods

Result 3: Within a frame (gain or loss) there are no significant differences in effort provision between payoff structures due to risk.

⁴⁹The significance stars in the Difference column refer to Wilcoxon signed rank tests of significant differences in effort provision within a treatment by payoff amount.

⁵⁰Table C.6 in Appendix C gives the p -values of Wilcoxon rank sum tests of differences in these average between payoff structures

4.4.4 Evolution of Effort Provision

The above comparison of effort during the game shows few differences across treatments. In order to further assess subjects' effort during the experiment, the average number of correct tables is calculated for each block of 7 periods to provide 4 measures of effort across the experiment as shown in table 4.6.

Treatment	Periods 1 - 7	Periods 8 - 14	Periods 15 - 21	Periods 22 - 28
GC	2.94 (1.20)	3.32 (1.10)	3.19 (1.12)	3.45 (1.07)
LC	2.74 (1.26)	3.13 (1.30)	3.03 (1.31)	3.34 (1.35)
GEA	2.89 (1.15)	3.32 (1.15)	3.25 (1.19)	3.60 (1.07)
LEA	2.78 (1.22)	3.10 (1.25)	3.12 (1.26)	3.40 (1.14)
GEP	2.70 (1.14)	3.11 (1.11)	3.09 (1.13)	3.50 (1.21)
LEP	2.64 (1.06)	3.16 (1.01)	3.04 (1.12)	3.19 (1.17)

Table 4.6: Number of correct tables across different stages of the game (standard deviations in brackets)

Figure 4.4 displays the average number of correct tables by treatment for a block of 7 periods, along with the associated confidence intervals. Across all treatments, subjects' effort provision is lowest in the first block of 7 periods and highest in the final block. In the second and third blocks, subjects' effort is relatively stable in treatments GEA, LEA and GEP, and decreases slightly in treatments GC, LC and LEP.

Table 4.7 provides regression estimates of the average number of correct tables in the blocks of 7 periods with respect to the second block.

The coefficients on *Periods 1-7* confirm the above discussion of fig. 4.4, subjects' effort is lower in periods 1-7 compared to periods 8-14. The coefficients on *Periods 15-21* are not significant in any of the treatments. There is no significant change in subjects' effort between these two blocks of 7 periods. In the final 7 periods, subjects' effort is significantly greater in treatments GEA, LEA, and GEP compared to periods 8-14. In the other treatments, GC, LC, and LEP, subjects' effort increases in the second block compared to the first, then remains at a similar level for the

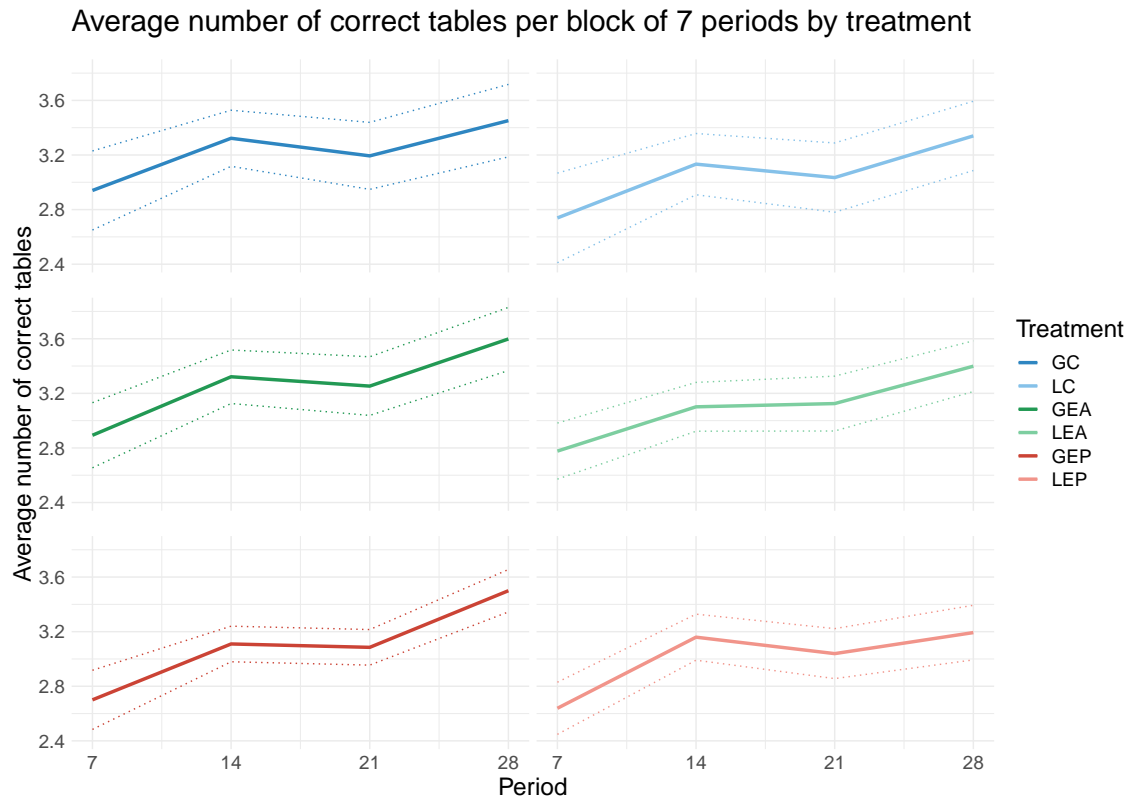


Figure 4.4: Evolution of average number of correct tables by block of 7 periods by treatment

duration of the experiment.

Subjects' improvement in correctly counting the number of ones in tables at the beginning and the end of the experiment, as well as across the two halves provides evidence of learning effects. As the experiment progressed, subjects became more adept at counting the number of ones in each table as the effort provision became routine.

Result 4: Subjects' performance increases between periods 1-7 and periods 8-14, before plateauing (GEA, LEA, GEP) or diminishing (GC, LC, LEP) in periods 15-21. Subjects' performance is highest in periods 22-28.

	(1) GC	(2) LC	(3) GEA	(4) LEA	(5) GEP	(6) LEP
Periods 1-7	-0.382*** (0.105)	-0.394*** (0.114)	-0.429*** (0.091)	-0.324*** (0.100)	-0.409*** (0.067)	-0.521*** (0.086)
Periods 15-21	-0.129 (0.079)	-0.099 (0.118)	-0.068 (0.065)	0.024 (0.103)	-0.025 (0.066)	-0.120 (0.082)
Periods 22-28	0.129 (0.089)	0.207 (0.126)	0.277*** (0.057)	0.298*** (0.086)	0.390*** (0.078)	0.034 (0.089)
Constant	3.323*** (0.138)	3.133*** (0.186)	3.321*** (0.111)	3.101*** (0.140)	3.110*** (0.112)	3.160*** (0.080)
R^2	0.028	0.027	0.047	0.032	0.057	0.039
Observations	868	812	1344	1344	1456	1428

Standard errors in brackets are clustered by subject

Table 4.7: Regression estimates of average effort provision over blocks of 7 periods

4.4.5 Individual Determinants of Effort Provision

This final results section discusses which individual and study design characteristics have a significant influence on effort provision. The dependent variable is the number of correctly counted tables in the period. For robustness, both a cluster-robust OLS regression (odd numbered specifications) and a panel data regression (even numbered specifications) using random-effects estimation are run. Clustering standard errors by subject adjusts for dependence in observations. Using a panel data specification accounts for the fact that in the present data, there are n subjects making decisions in t periods. A random-effects estimator is used in order to account for the influence of time-invariant variables on effort provision (Moffatt, 2015). Table 4.8 provides the regression estimates⁵¹

Specifications 1 and 2 control only for treatments. As seen in the descriptive analysis, there are no significant treatment effects. Specifications 3 and 4 include design and individual variables which may have an effect on the dependent variable.

As suggested in section 4.4.4, subjects' effort provision increases during the game; the period variable has a significant positive effect indicating that as subjects gain experience with the task, their performance improves. The average number of ones per period controls for the difficulty of the task; the more ones in the table, the harder the table. As expected, the coefficient on this variable is significantly negative; the harder, on average, the tables in a period are, the fewer tables subjects complete in

⁵¹A correlation table is provided in table C.7 in Appendix C.

	(1) Cluster spec.	(2) Panel spec.	(3) Cluster spec.	(4) Panel spec.
LC	-0.165 (0.207)	-0.165 (0.190)	-0.108 (0.158)	-0.108 (0.155)
GEA	0.039 (0.156)	0.039 (0.170)	-0.006 (0.131)	-0.006 (0.138)
LEA	-0.127 (0.168)	-0.127 (0.170)	-0.170 (0.144)	-0.170 (0.138)
GEP	-0.128 (0.161)	-0.128 (0.167)	-0.088 (0.131)	-0.088 (0.136)
LEP	-0.219 (0.149)	-0.219 (0.168)	-0.185 (0.128)	-0.185 (0.137)
Period			0.027*** (0.002)	0.027*** (0.001)
Average number of 1's per period			-0.073*** (0.005)	-0.073*** (0.005)
Ability (t=1)			0.391*** (0.036)	0.391*** (0.034)
Degree of risk taking			-0.043 (0.043)	-0.043 (0.040)
Female			-0.073 (0.076)	-0.073 (0.076)
Age			-0.015 (0.017)	-0.015 (0.015)
Constant	3.227*** (0.122)	3.227*** (0.132)	5.100*** (0.447)	5.100*** (0.409)
Observations	7252	7252	7252	7252
R ²	0.006		0.188	
R ² Overall		0.006		0.188
R ² Within		0.000		0.082
R ² Between		0.016		0.361

Standard errors in parentheses

Clustered regression: Robust standard errors clustered by subject. Panel regression: balanced panels by subject and period.

GC treatment used as reference level. Average number of ones per period: difficulty measure.

Ability: performance in first period. Degree or risk taking: from 1 risk averse to 5 risk lover.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8: Regression estimates of effect of individual characteristics on average effort provision

the period.

The final variables included in the regression refer to individual characteristics. Ability, as measured by subjects' performance in the first period, is a key indicator of performance throughout the game. Subjects who do better in the first period are more likely to correctly complete more tables in the rest of the experiment. Degree of risk taking is a subject's response, on a scale from 1 (I avoid taking risks) to 5 (I love taking risks). This variable has no significant effect on the number of correctly completed tables. Finally, gender and age of the subject are controlled for. Neither of these variables have a significant effect. These results show that there are no significant treatment effects due to framing. This may be due to the small sample sizes.

4.5 Conclusion

The objective of this chapter was to explore how incentives can be framed to encourage individuals to make small, repetitive efforts in a real-effort task, in a similar vein to encouraging households to make small, repetitive efforts to lower their energy consumption. Thus, the objective of this experiment was to better understand how the framing of incentives as either gains or losses affects subjects' effort provision under piece-rate and risky payoffs. Subjects were asked to complete a repetitive and tedious task which required no particular skills: counting the number of ones in a 9 by 9 table.

Under gain framing, subjects received a piece-rate payoff for each completed table. In the loss-framed groups, subjects were endowed with 21€ and lost a piece-rate amount for every incorrect or incomplete table. An element of risk on payoffs was added to four treatments. Payoffs were either high or low with equal probability and the true payoff was revealed to subjects either before or after effort provision according to the treatment. The different treatments presented subjects with identical payoffs under expected utility theory. However, they were framed in different ways in order to manipulate subjects' reference points via an endowment and via risk on the payoff amount.

Based on findings in previous experiments, and on prospect theory, subjects were expected to provide more effort under loss framing, in particular in the loss framed ex-post treatment, as individuals derive more utility from avoiding a loss than from gaining the same amount. In addition, individuals are more risk seeking in the loss

domain, and more risk averse in the gain domain.

Results show that there is no overall effect of framing on effort provision in the present experiment; subjects provide the same level of effort between framing types within a payoff structure. One explanation for such a result could be that most subjects are not susceptible to a loss frame as they realise it is a frame and so evaluate their earnings as a net payment rather than as a loss (Harrison *et al.*, 2016). Harrison *et al.* find that this is more apparent when subjects use "house money" rather than earned money.

In the present experiment, every effort was made to endow subjects with real money prior to beginning the loss-framed task; the money was left on subjects' tables throughout the duration of the experiment. Subjects were aware that the 21€ endowment would be exchanged for their actual earnings at the end of the experiment. Subjects' evaluation of payoffs as a net payment rather than an avoided loss may explain why there are no significant differences in effort between each gain and corresponding loss treatment in the present experiment. However, previous experiments have employed the same approach of endowing subjects with real money at the beginning of the experiment and have found that participants in loss-framed treatments provide significantly more effort (Hannan *et al.*, 2005, Goldsmith and Dhar, 2011, Imas *et al.*, 2016). Furthermore, experiments in which subjects in loss-framed treatments have not been endowed with real money have also found significantly more effort is provided under loss than under gain-framing (Hossain and List, 2012).

In line with previous research, subjects in ex-ante treatments provided more effort for the higher payoff when it was made known to them prior to effort provision than for the lower payoff. Subjects display rationality and so when faced with a higher payoff per table, they provided more effort and correctly counted more tables than when faced with a lower payoff, in both gain and loss-framed treatments.

Regarding subjects' behaviour under riskless and risky payoffs, the results of the present experiment do not show any significant differences in effort provision when payments are risky compared to when they are riskless under the same framing. Perhaps subjects correctly anticipated an expected payoff of 15 cents, or the difference in payoffs was not sufficient and so subjects did not provide additional effort under risky payoffs.

Finally, subjects demonstrated learning and improvement during the experiment as their effort provision increased during the course of the experiment. This is particularly true of the ex-ante and ex-post treatments. However, subjects' effort

provision plateaus or stagnates over the middle 50% of the game.

4.5.1 Implications, Limitations and Recommendations

The results of the present experiment have shown that there are limited framing effects on effort provision due to gain and loss framed incentives with and without risky payoffs. In particular, loss framing with risky payoffs is the least incentivising payoff structure, and gain framing with risky payoffs revealed prior to effort provision is the most incentivising. This suggests that in designing IHDs, the element of risk regarding the size of energy savings needs to be controlled for as much as possible. Households will make an effort for a higher payoff and so in the context of energy saving behaviours, subjects need to know whether a particular action will result in a lower or a higher payoff as this will affect their willingness to provide an effort.

The laboratory setting of the present experiment provides a high level of internal validity which allows the experimenters to focus solely on the variable they wish to manipulate in order to ascertain its effect on effort provision. Subjects concentrated solely on the task of counting the number of ones in each table, any outside factors were controlled for. The only variables which were different from one treatment to another, were the framing and the payoff structure.

In reality, when trying to save energy there are many other factors that will affect an individual's ability to provide the necessary effort to save energy. The use of risky payoffs attempted to reflect such situations. Given the differences in the laboratory setting and the context of energy consumption behaviour, it is difficult to generalise the results outside of the laboratory. That being said, if no significant results were found in a controlled environment where subjects were solely focused on the task at hand, will there be significant differences in effort due to framing in the context of energy saving when there are many additional factors at work? On the other hand, the task was the only activity for subjects to do for one and a half hours. Subjects' complete concentration on the task regardless of framing may explain the lack of significant treatment results.

The next steps for the present research are to increase the sample size in each of the treatments and to increase the saliency of the loss-frame by having subjects work for their endowment prior to completing the experimental task. By doing so, the hypothesis is that subjects will attach a greater utility to avoiding a loss of their endowment because they have had to work for it. This will avoid the possible issue

of subjects evaluating the net value of framing rather than seeing the loss-frame as a loss of their money.

Additionally, this experiment can be moved to the field to determine whether subjects make an increased effort to avoid spending their own money on energy consumption when the loss is salient. This can be compared to the effort made under a salient gain frame and to a factual presentation of consumption information.

Conclusion

This thesis has explored the different incentives that are used to encourage residential consumers to lower their energy consumption in order to determine whether households accept these incentives and the technologies that deliver them, and whether these incentives are effective at reducing their consumption. This subject is of particular importance given that human activity is causing the atmosphere of our planet to heat up considerably which is having disastrous impacts across the globe. To limit humankind's future impact, governments across the world have set objectives to lower emissions, to increase the share of renewable energies in the production mix and to achieve energy savings. Residential consumers can do their part by lowering their overall demand, and in particular, their peak demand.

In recent years there has been an increasing interest in the use of behavioural incentives to encourage households to lower their consumption. Given the recency of the application of such incentives to residential energy consumption, there is a smaller amount of research on such incentives in an energy consumption context compared to traditional, financial incentives. What's more, there are fewer studies which have collated the existing evidence on behavioural incentives. Furthermore, there are concerns as to the efficacy of behavioural incentives to motivate significant and lasting changes to consumer behaviour. The present thesis has added to this body of research by exploring the previous literature and assessing the effectiveness of traditional and behavioural incentives on consumption, and by more closely scrutinising behavioural incentives in the laboratory.

To answer the central question, how do residential consumers respond to incentives used to encourage them to lower their consumption, the thesis was divided into four chapters. Firstly, a qualitative review of the existing literature answered the question of what are the main barriers to the acceptance and adoption of smart meters and the incentives that they can deliver. Secondly, a meta-analysis provided an updated exploration of the effectiveness of incentives at encouraging households to lower their consumption, and an examination of how the design of experiments can influence the results. Given the findings of the first two chapters, the third chapter sought to further analyse consumer responses to both financial and behavioural incentives in a controlled, laboratory setting in order to ascertain whether such incentives are able to encourage more socially optimal behaviour, and to quantify the response to a behavioural incentive. The fourth and final chapter built on findings from previous research which suggest that individuals make more effort to avoid losses than to receive gains, and looked at whether this is applicable to effort provision for saving energy which is characterised by small efforts for small rewards. This experiment

explored ways in which information can be framed in order to incentivise effort provision.

In response to the research questions, Chapter 1 found that there exist many barriers to encouraging households to lower their consumption through incentives delivered via smart meters. These barriers need to be overcome in order for households to accept the installation of smart meters and associated technology in their home in the first instance, and in the second, in order for them to be effective at motivating consumers to reduce their energy demand. If these barriers remain, households will not engage with smart meters and incentives, and the cost of investing in this technology will not be recuperated through energy and monetary savings.

Chapter 2 looked in detail at the effectiveness of different incentives using a meta-analysis approach to combine the results of recent field experiments and pilot studies which have tested the effect of various incentives on residential energy consumption. The meta-analysis found that accounting for sample size in primary studies provides more accurate estimates of the effect of incentives, and as such, on average, an incentive will show a reduction in consumption of the order of 2%. Incentives such as pricing strategies, which are primarily aimed at reducing peak demand, can also be effective at reducing overall demand so long as the incentive to reduce consumption during peak periods is not offset by the incentive to increase consumption during off-peak periods. Reductions in peak demand are necessary to avoid the use of higher cost, polluting generators, however, if overall demand increases as a result of pricing strategies, the objectives of energy savings may not be met. Incentives based upon behavioural economics such as social feedback are also effective at encouraging a reduction in consumption on average. Such incentives are effective whether they are merely descriptive, or whether injunctive norms are also used. However, the latter shows a slightly larger reduction effect.

The estimate of the effectiveness of incentives was found to be greatly influenced by the design of the study. In particular, the exclusion of a control group provides inflated estimates of reductions in consumption than if a control group is present. Studies without control groups compare the consumption of a same group of households before and after the implementation of an incentive and so do not perform a simultaneous control for additional factors which may affect consumption. Studies which use a control group provide both a comparison between households' consumption before and after the implementation of an incentive, and a comparison of a group of households during the same time period whose consumption is not influenced by

an incentive. The use of a control group provides a more robust estimate of the effectiveness that incentives would have in a natural, non-experimental setting.

Additionally, it is important to note that the findings of field experiments and pilot studies may overstate the effect that particular incentives would have in the case of a nation-wide roll-out. In particular, when there are small samples of households who opt-in to the study, these households may be particularly disposed to make an effort to lower their consumption, whether this be for monetary, or environmental reasons, or even due to an interest in the enabling technology offered as part of the study. As [Spence *et al.* \(2014\)](#) have suggested, the type of incentive used, or the choice of unit used for the presentation of consumption information affects individuals' stated motivations to lower their consumption, and as shown in Chapter 3, this can also affect their consumption decisions.

In Chapter 3, individuals were either nudged to lower their consumption, or incentivised to do so by an increase in the price of hypothetical consumption within an experimental CPR game. The price incentive was most effective relative to the level of consumption each incentive was designed to encourage. However, the nudge had an immediate effect as the information was immediately understood by individuals. In the price treatment, individuals took longer to integrate the price into their decision making. This is reflective of findings from the literature discussed in Chapter 1 that pricing strategies such as dynamic pricing are complex for individuals to comprehend ([Layer *et al.*, 2017](#)).

While both of these incentives were more effective at encouraging consumers to lower their consumption than an absence of policies, ex-post evaluations of individual characteristics including concern for the environment showed that such characteristics were affected by the incentive used to encourage individuals to lower their consumption. The consumption choices in the nudge treatment differed according to individual environmental sensitivity; those who were more sensitive to environmental issues had previously chosen to consume less. The use of a monetary incentive had no such effect and appeared to crowd out environmental characteristics, as individuals who were more sensitive chose to consume the same amount as those who were less sensitive to environmental issues. This finding, along with the discussions of Chapters 1 and 2, highlights how incentives can affect motivations and individual characteristics to lower energy consumption. If the use of monetary incentives crowds out any environmental characteristics or motivations to lower consumption, then this is of concern as Chapter 1 showed that consumers find monetary displays

of energy savings to not be particularly motivating as the monetary savings are often small (Hargreaves *et al.*, 2010, Murtagh *et al.*, 2014).

The discussion and analysis of the literature in Chapters 1 and 2 highlighted potential problems with the use of behavioural incentives to encourage energy consumption reduction, namely that when told that they are consuming less than the average consumption of their neighbourhood, households increased their consumption (Schultz *et al.*, 2007). This boomerang effect was mitigated by the inclusion of a smiley face to confirm to individuals that consuming less than the average is socially desirable (Allcott, 2011b). The nudge experimented in Chapter 3, which is presented differently to the ones used in the field, found another concerning impact. The nudge was successful at encouraging a reduction in average consumption, however it reinforced individuals' existing behaviour such that those who underconsumed compensated for those overconsumed. This is of particular concern as the use of such nudges may serve to divide consumers: those who are low-consumers make increased efforts to lower their consumption and those who are high-consumers do not.

As discussed above, monetary savings are not necessarily sufficient to encourage energy saving efforts. With this in mind, Chapter 4 explored experimentally how the framing of information on earnings can encourage a greater provision of effort and found that individuals provide, on average, the same level of effort when incentivised to make a small effort for a small reward, however the earnings information is framed. When possible rewards are relatively larger, framing does not affect the effort provided by individuals in one direction or the other. When individuals are not sure of how much they will earn after an effort is made, i.e.: when earnings are risky, they tend to provide slightly less effort under loss framing. These findings have shown that in order to encourage individuals to make small efforts for small rewards, as is typical of energy saving behaviours, the framing of the reward is not of utmost importance, rather it would be more effective to focus on the size of the amount that can be saved. In order to encourage, households to make an effort to lower their consumption, emphasis should be put on the fact that several efforts lead to a larger saving, as individuals provided more effort when the potential earnings were relatively higher. In addition, efforts should be made to minimise the risk on earnings so that households know that by doing a certain action they are sure to earn a fixed amount.

The findings of the present research have helped to respond to the central research

question: how do residential consumers respond to incentives used to encourage them to lower their consumption? Despite barriers to the implementation of smart meters and the incentives that they can deliver, residential consumers do respond to incentives and they are effective at encouraging a reduction in consumption. The different incentives are more or less effective depending on the reduction objective. Monetary incentives, namely pricing strategies, are more suited to reducing peak demand than overall demand. In order for them to be truly effective, there needs to be an effort to better explain the tariffs so that perceived complexity does not slow their adoption, nor consumers' responsiveness. Behavioural incentives are another effective incentive, especially when injunctive norms are used alongside social norms. These incentives have the advantage over pricing strategies of being quickly understood but there may be unwanted consequences. When individuals are aware that they are being nudged towards a socially optimal behaviour, then they may react by performing exactly the behaviour that is undesirable. Information on energy and monetary savings is also effective, at least initially. However, there are limits to monetary motivation. Efforts to save energy result in small monetary rewards which are not necessarily sufficient to be motivating. Different methods of framing small monetary rewards for small efforts does not increase effort provision.

4.5.2 Limitations

When undertaking this research, certain limitations were met. The methodology of meta-analysis used in Chapter 2 means being exhaustive in including all studies on the topic yet is limited by the availability of studies and the potential for available studies to only be those which show significant effects. If studies which do not show significant effects are not included in the meta-analysis, then the results of the analysis are biased. This limitation was overcome by analysing the extent to which publication bias was an issue in the sample of studies used, and by using methods to correct for it. The method of giving more weight in statistical analyses of those studies with larger samples was found to significantly mitigate the publication bias issue.

Chapter 3 concerned energy consumption choices in a contextualised CPR game. Subjects made decisions in a computer laboratory, and although their decisions had monetary consequences designed to reflect the utility and disutility of consumption choices, their decisions did not impact actual consumption. On the other hand, in Chapter 4 an entirely decontextualised game mimicking in a stylised manner certain

characteristics of energy consumption and saving was used. Laboratory experiments benefit from high internal validity - individuals make decisions in a highly controlled setting, however, they can lack external validity.

The findings of the laboratory experiments presented in this thesis have provided an insight into behaviours in response to nudges and prices, and in response to the framing of information. They are not a substitute to the field experiments and pilot studies analysed in Chapter 2, but rather, are a complementary approach to better understanding individual behaviour. The experiment in Chapter 3 highlighted an unexpected consequence of a nudge on different groups on individuals, and showed how responses to incentives can influence individual characteristics. The experiment in Chapter 4 explored the provision of effort for small rewards in a less complex environment compared to real-life where efforts to save energy have wider impacts including impacts on comfort and on other individuals. The lack of framing effects in the laboratory environment raises the question of whether such framing effects will be found when the provision of effort is more complex. However, subjects in the experiment had only to focus on the task of counting the number of ones in a series of tables and so may not have been susceptible to framing as they were focused only on the task in hand.

An important requirement to verify the robustness of laboratory experiment results is replication. While, the experiment in Chapter 4 has replicated aspects of previous experiments and has drawn similar conclusions, namely that framing effects are not always found when earnings are small, the results of the experiment in Chapter 3 should be further researched. In particular, the effect of the nudge of reinforcing existing behaviour.

4.5.3 Implications

The implications of the present research are three-fold. Firstly, the different incentives are effective at encouraging households to lower their consumption to varying degrees. When policy makers decide which incentive or incentives to implement, they must first consider the objective: overall demand reduction or peak demand reduction. The incentives should then be adapted to that objective bearing in mind that pricing strategies are most effective at reducing peak demand and that additional incentives should be used to counter any extraordinary increases in demand during the off-peak periods. Additionally, policy makers should consider that information on consumption in the form of nudges is quickly understood by consumers and so

can have an immediate effect on consumption whereas prices take a little longer to be integrated into individuals' decision making. This is of interest to policy makers as increased prices may cause individuals to be worse off for a time if they are unable to lower their consumption immediately in response to the price. Consumers may suffer welfare losses before they are fully able to adjust their consumption in response to the price increase.

Secondly, policy makers should be aware of the barriers to the implementation of the different incentives and their potential undesirable consequences. In particular, they should be concerned by the individual effect of nudges typically used: as seen in the previous literature, descriptive comparisons may encourage low-consuming households to increase their consumption to the average amount, or, as seen in the present research, the inclusion of injunctive norms may reinforce existing behaviours such that low-consuming households reduce their consumption, compensating for high-consuming households who continue to increase their consumption.

Finally, the present research also has implications for the design of devices which display consumption information to households: the presentation of earnings in terms of gains or losses does not encourage greater effort provision under one or other framing. It is the size of potential earnings and the reduction of risk on earnings which is of importance. This lack of framing effect for small earnings also has implications for theory, as it would seem that loss aversion does not cause individuals to provide greater effort under loss framing in the case of small earnings. The amount that the individual can earn is simply too small to be affected.

4.5.4 Future research

The opening chapter of this thesis identifies barriers to the use of incentives to encourage demand reduction of which some are then further analysed in the following chapters. Given that several barriers were identified, there is much scope for further research into the topic of this thesis.

Individuals are generally unaware of their consumption, or of the electricity tariff that they are on. In turn this affects their decisions to opt-in into dynamic pricing contracts as individuals prefer to have a simpler contract as they are unaware of whether such a tariff would be beneficial to them and how they can change their behaviour to take advantage of the cheaper off-peak prices. An avenue for future research could be to see how individuals' tariff choices change upon being informed

of their own consumption and how they can make use of the different pricing levels, building on the research of [Dütschke and Paetz \(2013\)](#), [Buryk *et al.* \(2015\)](#) and [Layer *et al.* \(2017\)](#).

Monetary motivation has not been found to be a strong driver of changing consumption behaviour as the savings are generally small ([Hargreaves *et al.*, 2013](#), [Murtagh *et al.*, 2014](#)). Furthermore, the choice of different presentations of information awakens different motivations to save energy ([Spence *et al.*, 2014](#)). Another avenue for further research could be to provide individuals with displays of energy consumption information presented in different ways (monetary savings, energy savings, environmental savings, ...) then, via a choice experiment, measure their preferences for the different displays. This could then be further researched in the field by comparing responses to incentives to lower consumption which are based on non-monetary calculations of the impact of saving energy on the environment, or on health, or other.

In addition to the barriers identified in Chapter 1, the experiments carried out in this thesis also opened up avenues for further research. In Chapter 3, the nudge resulted in the unintended effect of reinforcing existing behaviour. A possible explanation was found in reactance theory: individuals feel that their freedom to do as they wish is threatened and so they do the behaviour that is not encouraged ([Brehm, 1966](#)). Yet, this effect was not found in the field experiments reviewed in Chapters 1 and 2. There is a difference in the creation of the nudge used in the field, and the one used in the present experiment. In the field, behaviour is compared to an endogenous level, the average consumption of the neighbourhood, whereas in the laboratory experiment, behaviour is compared to an exogenously defined optimal level of consumption which is calculated by the experimenter. Individual responses to endogenous and exogenous nudges merits further research.

This thesis set out to explore how residential consumers respond to incentives used to encourage them to lower their consumption. Residential consumers respond positively to the various incentives used in that they result in average reductions in peak or overall demand. The research highlighted that there may be unwanted consequences of various incentives on consumption at the individual level, and that different incentives trigger different characteristics which can affect how consumers respond to the incentives.

Appendix A

Appendix to Chapter 2

Included studies

Author	Year	Publication Information
Alahmad et al.	2012	IEEE Transactions on Industrial Electronics 59(4), 2002-2013
Allcott	2011	Resource and Energy Economics 33(4), 820-842
Allcott	2011	Journal of Public Economics 95(9), 1082-1095
Ayres et al.	2013	Journal of Law, Economics and Organization 29(5), 992-1022
Benders et al.	2006	Energy Policy 34(18), 3612-3622
Carroll et al.	2014	Energy Economics 45, 234-243
Costa and Kahn	2013	Journal of the European Economic Association 11(3), 680-702
Department of Energy & Climate Change	2015	Department of Energy & Climate Change
Dougherty	2013	Opinion Dynamics Corporation
DNV KEMA Energy and Sustainability	2014	DNV KEMA Energy and Sustainability
D'Oca et al.	2014	Energy Research and Social Science 3, 131-142
Faruqui and Sergici	2011	Journal of Regulatory Economics 40(1), 82-109
Gleerup et al.	2010	Energy Journal 113-132
Grønhøj and Thøgersen	2011	International Journal of Consumer Studies 35(2), 138-145
Harries et al.	2013	European Journal of Marketing 47(9), 1458-1475
Houde et al.	2013	Energy Journal 34(1), 87-102
Kendel and Lazaric	2015	Journal of Strategy and Management 8(3), 231-244
Kua and Wong	2012	Energy Policy 47, 49-56
Martin and Rivers	2015	(working paper)
Mizobuchi and Takeuchi	2013	Energy Policy 63, 775-787

Author	Year	Publication Information
Mountain	2006	Hydro One Network Inc.
Mountain	2008	Hydro One Networks Inc.
Mountain	2012	Research Institute for Quantitative Studies in Economics and Population
Nilsson et al.	2014	Applied Energy 122, 17-23
Parker et al.	2008	Florida Solar Energy Center
Provencher et al.	2015	Navigant
Raw and Ross	2011	Energy Demand Research Project: Final Analysis
Schleich et al.	2013	Energy Policy 61, 1097-1106
Schultz et al.	2015	Energy 90, 351-358
Schumatz and Dimetrosky	2014	NMR Group Inc and Tetra Tech
Shen et al.	2016	Energy Policy 98, 19-32
Sullivan et al.	2013	Freeman, Sullivan & Co.
Sullivan et al.	2016	Nexant
Torrìti	2012	Energy 44(1), 576-583
Ueno et al.	2006	Applied Energy 83(2), 166-183
Van Dam et al.	2010	Building Research and Information 38(5), 458-469
Van Elburg	2014	Dutch Energy Savings Monitor for the Smart Meter
Vassileva et al.	2012	Applied Energy 93, 575-582
Xu et al.	2015	Energy Procedia 75, 2694-2699

Table A.1: Studies included in analysis

Reasons for study exclusion

Reason for exclusion	Number of papers excluded
Different effect size measure (<i>e.g.: peak demand reduction, appliance level data, median % change</i>)	28
Non-residential sample	17
Not a field experiment or pilot study (<i>e.g.: a simulated study or laboratory experiment</i>)	11
Included under a different title	8
Gas and electricity consumption combined	4
Experimental issues leading to missing data	3
Secondary data	1
Total	72

Table A.2: Reasons for studies exclusion from the analysis

OLS estimation of treatment effects

	(1) Monetary	(2) Personal feedback	(3) Social feedback	(4) Study design	(5) All incentives
Pricing strategies	2.075 (1.354)				1.651 (1.055)
Monetary information	-0.333 (1.009)				1.980 (1.523)
Individual feedback		-1.754 (1.260)			-2.116 (1.273)
Real-time feedback		-1.253 (1.048)			-2.565* (1.310)
Savings tips		1.195 (1.338)			1.455 (1.292)
Personalised advice		-1.690 (1.993)			-2.252 (2.069)
Social norms			-1.161 (1.875)		-3.462* (1.976)
Injunctive norms			-3.113 (2.825)		-1.942 (2.557)
Control group	3.420 (3.131)	4.983 (3.116)	4.070 (3.026)	3.499 (3.201)	5.586* (2.854)
Weather controls	-0.003 (1.053)	0.294 (1.095)	0.380 (1.342)	0.405 (1.182)	-0.778 (1.339)
Demographic controls	-1.640 (1.623)	-1.665 (1.706)	-1.576 (1.802)	-2.419 (1.901)	0.094 (1.603)
Random assignment	-0.189 (0.990)	-0.343 (1.083)	0.154 (1.302)	0.135 (1.049)	-1.116 (1.299)
Opt-in recruitment	-1.441 (1.495)	-1.652 (1.470)	-3.063 (2.739)	-0.847 (1.038)	-4.224 (2.799)
Duration	0.144** (0.058)	0.164*** (0.038)	0.135*** (0.045)	0.117*** (0.043)	0.215*** (0.056)
Peer reviewed	1.982* (1.112)	2.302** (1.106)	2.301* (1.146)	1.601 (0.971)	3.603** (1.391)
Constant	-7.597** (3.395)	-7.410 (4.423)	-6.166 (4.082)	-6.732* (3.765)	-7.455* (4.016)
Observations	105	105	105	105	105
Adjusted R^2	0.132	0.157	0.114	0.109	0.194

Standard errors in parentheses

Standard errors are clustered by primary study.

A negative coefficient reads as a reduction in energy consumption.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: OLS estimation of treatment effects

Appendix B

Appendix to Chapter 3

English Translation of Experiment Instructions

In black are the instructions which are common to all treatments. In green are the instructions specific to control groups, in red are the instructions for the nudge treatment, and finally, in blue are the instructions for the price treatment.

Study

This study concerns individual electricity consumption. It is carried out by Grenoble Applied Economics Laboratory as part of a public research programme.

Confidentiality

In order to maintain your anonymity during any future data analysis, we will not ask for any personal information such as your name. The data collected during this study will remain anonymous and be used for research publications or other analyses. It will not be used for commercial purposes.

Code of conduct

Communication between participants is strictly forbidden. Including discussions of what should or should not be done during the study. Remain concentrated on your screen for the duration of the experiment. If you have any questions, or problems, raise your hand and an experimenter will come to you.

Payment and earnings

On your desk is an envelope containing 10€ in exchange for your participation in this study. This amount belongs to you. In addition to this amount, and according to the decisions you make in the game, you can earn more money. You will be informed of your final earnings at the end of the experimental session.

Organisation of the session

This session is composed of several phases. Before the start of each phase, instructions on the phase will be read aloud. A new phase will begin once all participants

have completed the preceding phase. The session will not last longer than 1 hour 30 minutes.

Are there any questions?

Phase 1: Electricity consumption behaviour

Electricity consumption

We consume electricity to satisfy our daily needs:

- To heat or to cool our homes via our central heating, or an air conditioner.
- To use our household appliances
- To use heat our meals or to keep them cool
- To recharge our electronic equipment (mobile phones, computers)

We are all electricity consumers, in particular in our homes, to a varying degree according to our daily needs and habits. To meet the demand for electricity, there are different actors in the electricity network, from production to distribution in residential homes. Regardless of the actors of production or distribution, there must always be a balance between production and consumption in order to maintain the functioning of the system. If there is an imbalance, then the system is interrupted and this could result in a power cut. For example, during the winter, the increased consumption by households could result in power cuts.

The study

This study focuses on such periods, known as peak periods when there is a risk that consumption is greater than the available production. These periods generally last for 4-8 hours, during the afternoon and evening.

Interruptions in the electricity network (voltage reductions, brown outs or black outs) equates to a reduction in comfort for all.

In order to avoid such interruptions in the electricity network (voltage reductions, brown outs or black outs), one solution is to ask consumers to reduce their consumption during the peak period. Of course, this reduction in consumption equates to a

reduction in individual comfort. However, it avoids a greater reduction in comfort for all due to greater interruptions in the system.

In order to avoid such interruptions in the electricity network (voltage reductions, brown outs or black outs), one solution is to incentivise consumers to reduce their consumption by increasing the price during the peak period. Of course, this reduction in consumption equates to a reduction in individual comfort. However, it avoids a greater reduction in comfort for all due to greater interruptions in the system.

For this study, imagine that you are in a situation where you must decide on how much electricity to consume during a peak period. You will have to make this decision during 10 peak periods. This decision is based on whether or not you use the different electricity consuming appliances during the peak period. For the 10 peak periods, you will be placed in a group with three other people which constitutes an electricity consumption system.

Your task during the period

In each period, you will decide how much electricity to consume using your initial endowment of 100 Experimental Currency Units (ECU). In order to do so, you must decide whether to use or not several electricity consuming appliances, to each of which is associated a certain level of consumption. The consumption levels of each appliance will be presented on the next screen.

Electricity consumption choices

In each period, you must choose whether to use, or not, the following appliances:

1. Electricity heating, with three levels of use:

- No change = 15 Energy Units (EU)
- Lower temperature by 1°C = 10 EU
- Lower temperature by 2°C = 5 EU

2. Water heating:

- On = 5 EU
- Off = 0 EU

3. Washing machine or dishwasher:

- On = 10 EU
- Off = 0 EU

4. Cooking equipment (oven, hot plate)

- On = 10 EU
- Off = 0 EU

5. Television or computer

- On = 5 EU
- Off = 0 EU

For each period, you can therefore consume between 5 and 45 EU.

Earnings per period

Regardless of appliance usage, each EU is billed at the price of 1 ECU for all peak periods.

Regardless of appliance usage, each EU is billed at the price of 1 ECU for all peak periods.

Regardless of appliance usage, each EU is billed at the price of 3 ECU, which is 3 times more expensive compared to normal periods. With your initial endowment, you can consume up to 30 EU.

Your electricity consumption provides you with comfort via a monetary gain for each period: 13 ECU per consumed EU. However, your consumption in addition to the consumption of the three other people in your group has an impact on the equilibrium of the electricity network and thus on potential interruptions in supply. The total consumption of the group results in a lower level of comfort for every one (including yourself). The greater the total consumption of the group, the greater the reduction in comfort. Your earnings for the period thus depend on your own consumption and the impact that the total consumption has on the system.

Earnings simulator

To assist you in making your decisions, you have at your disposal a simulator with which you can simulate your earnings. You have 1 minute to do as many simulations as you wish before making your final decision for the period. The use of the simulator is described in the following slide. In addition to the simulator, there is a table summarising all the possible earnings depending on your consumption choice (by column) and the total consumption of the other three people in your group (by row).

(Presentation of table)

(Presentation of simulator)

The end of the period

At the end of each period, your earnings will be displayed on the screen. The part of your endowment which was not used for your consumption is integrated in this amount. At the end of the period, your earnings will be saved and you will start a new peak period, with a new endowment of 100 EU.

At the end of each period, your earnings will be displayed on the screen. The part of your endowment which was not used for your consumption is integrated in this amount. You will also be informed of how your consumption compares to the level of consumption which minimises the reduction in comfort felt by the group. This level is the same for all people in the group and is used as a reference for your own consumption. At the end of the period, your earnings will be saved and you will start a new peak period, with a new endowment of 100 EU.

At the end of each period, your earnings will be displayed on the screen. The part of your endowment which was not used for your consumption is integrated in this amount. At the end of the period, your earnings will be saved and you will start a new peak period, with a new endowment of 100 EU.

Your consumption during the period

You will be informed via a smiley if your consumption for the peak period is:

- Equal or below the level which minimises the reduction in comfort felt by the

group: :-)

- Above the level which minimises the reduction in comfort felt by the group:
:-)

At the end of the period, your earnings will be saved and you will start a new peak period, with a new endowment of 100 EU.

At the end of the 10 peak periods

Phase 1 of the study is composed of 10 peak periods. In each period you have the same decisions to make with the same people in your electricity consumption group. At the end of the study, your earnings in ECU for the 10 peak periods, will be added together and converted into euros at the following exchange rate : 150 ECU = 1€ These earnings will be added to those of phase 2 and paid at the end of the study.

Are there any questions?

Before we begin, please answer a few questions to verify your understanding of the instructions.

Phase 2: Lottery

In phase 2, you can earn an additional sum. You will see on your screen a table with 10 rows. For each row, 2 options are presented: Option A and Option B. You will decide at which row you wish to move from Option A to Option B. You can see that for Option A the same earnings are possible at every row (2€ or 1€60), and for Option B (3€85 or 0.10€). Only the probabilities associated to each amount in each Option change.

Principle of the lottery

For each option, you know the probability associated to each amount. You must decide at which row you wish to move from Option A to Option B. For example, for decision 1 in row 1, choosing Option A gives a 1 in 10 chance of winning 2€ and a 9 in 10 chance of winning 1€60, whereas as choosing Option B gives a 1 in 10 chance

of winning 3€85 and a 9 in 10 chance of winning 0.10€. By clicking on the button associated with the chosen row, all the rows of Option A above your chosen row become green, and all the rows of Option B below your chosen row become blue. The colour, green or blue, indicates that if that row is chosen randomly, you will win according to the probabilities in colour. Once you have made and confirmed your decision, the computer will randomly choose a row among the 10 rows. Then the computer will randomly choose one of the winnings of the option chosen for that row, according to the probabilities presented in the table. Your earnings will be displayed on the screen.

Are there any questions?

(Questionnaires and organisation of payment)

Thank you for participating in this experiment.

General Ecological Scale Questions (Kaiser, 1998)

1. I use energy-efficient bulbs.
2. If I am offered a plastic bag in a store, I take it.
3. I kill insects with a chemical insecticide.
4. I collect and recycle used paper.
5. When I do outdoor sports/activities, I stay within the allowed areas.
6. I wait until I have a full load before doing my laundry.
7. I use a cleaner made especially for bathrooms, rather than an all-purpose cleaner.
8. I wash dirty clothes without pre-washing.
9. I reuse my shopping bags.
10. I use rechargeable batteries.
11. In the winter, I keep the heat on so that I do not have to wear a sweater.
12. I buy beverages in cans.
13. I bring empty bottles to a recycling bin.
14. In the winter, I leave the windows open for long periods of time to let in fresh air.
15. For longer journeys (more than 6h), I take a plane.
16. The heater in my house is shut off late at night.
17. I buy products in refillable packages.
18. In winter, I turn down the heat when I leave my house for more than 4 hours.
19. In nearby areas, I use public transportation, ride a bike, or walk.
20. I buy clothing made from all-natural fabrics (e.g. silk, cotton, wool, or linen).
21. I prefer to shower rather than to take a bath.

22. I ride a bicycle, take public transportation, or walk to work or other.
23. I let water run until it is at the right temperature.
24. I put dead batteries in the garbage.
25. I turn the light off when I leave a room.
26. I leave the water on while brushing my teeth.
27. I turn off my computer when I'm not using it.
28. I shower/bathe more than once a day.

Altruism Questionnaire (Costa and McCrae, 1992)

1. Some people think that I am selfish and egotistical.
2. I try to be courteous to everyone I meet.
3. Some people think of me as cold and calculating.
4. I generally try to be thoughtful and considerate.
5. I'm not known for my generosity.
6. Most people I know like me.
7. I think of myself as a charitable person.
8. I go out of my way to help others if I can.

Proportion of groups by consumption type (under, optimal or over-consuming)

		Group consumption			
		Under	Optimal	Over	Total
Treatment	Nudge	42	17	191	250
		16.8%	6.8%	76.4%	100.0%
	Price	66	26	108	200
		33.0%	13.0%	54.0%	100.0%
	Control	0	4	146	150
		0.0%	2.7%	97.3%	100.0%
Total		108	47	445	600
		18.0%	7.8%	74.2%	100.0%

For the nudge and control groups, the optimal consumption level is 60. In the price treatment, it is 80.

Table B.1: Number of groups by consumption level (across all periods)

Proportion of individuals by consumption type (under, optimal or over-consuming)

		Individual consumption			
		Under	Optimal	Over	Total
Treatment	Nudge	190	316	494	1,000
		19.0%	31.6%	49.4%	100.0%
	Price	234	295	271	800
		29.3%	36.9%	33.9%	100.0%
	Control	75	79	446	600
		12.5%	13.2%	74.3%	100.0%
Total		499	690	1,211	2,400
		20.8%	28.7%	50.5%	100.0%

For the nudge and control groups, the optimal consumption level is 15. In the price treatment, it is 20.

Table B.2: Number of groups by consumption level (across all periods)

Distribution of messages received in nudge treatment

Message received (t-1)	Period									
	2	3	4	5	6	7	8	9	10	Total
Under consumption :- (t-1)	9	18	22	19	18	20	24	20	24	174
	5.2%	10.3%	12.6%	10.9%	10.3%	11.5%	13.8%	11.5%	13.8%	100.0%
Optimal :- (t-1)	19	28	30	33	35	32	34	36	35	282
	6.7%	9.9%	10.6%	11.7%	12.4%	11.3%	12.1%	12.8%	12.4%	100.0%
Over consumption :- (t-1)	72	54	48	48	47	48	42	44	41	444
	16.2%	12.2%	10.8%	10.8%	10.6%	10.8%	9.5%	9.9%	9.2%	100.0%

Table B.3: Distribution of messages received in nudge treatment by period

Appendix C

Appendix to Chapter 4

English Translation of Experiment Instructions

In black are the instructions in common for all treatments.

In brown are the additional instructions for the Gain Control treatment.

In green are the additional instructions for the Loss Control treatment.

In red are the additional instructions for the Gain Ex-ante treatment.

In blue are the additional instructions for the Loss Ex-ante treatment.

In orange are the additional instructions for the Gain Ex-post treatment.

In purple are the additional instructions in the Loss Ex-post treatment.

Study

This study is carried out by Grenoble Applied Economics Laboratory. During the study you will be asked to make decisions. If you have any comprehension problems, please do not hesitate to let us know.

Confidentiality

In order to maintain your anonymity during the study and during any future data analysis, you were attributed a subject code. No personal data will be collected meaning it will be impossible to connect your answers during the study to your name. The data collected during this study will remain anonymous and be used for research publications or other analyses.

Code of conduct

Communication between participants is strictly forbidden. Including discussions of what should or should not be done during the study. Remain concentrated on your screen for the duration of the experiment. If you have any questions, or problems, raise your hand and an experimenter will come to you.

Organisation of the session

This study is composed of two phases. The first phase includes:

1. The reading of the instructions

2. The completion of the task
3. The display of your earnings.

The second phase includes:

1. A questionnaire
2. The organisation of the end of the session

The second phase will begin once all participants have completed the first phase. The session will not last longer than 1 hour 30 minutes.

Payment and earnings

On your desk is an envelope containing 5€ in exchange for your participation in this study. This amount belongs to you. In addition to this amount, and according to the decisions you make in the game, you can earn more money. Your earnings in this study will depend upon your pot of earnings in the first phase. At the end of the session, you will receive your earnings in a separate room in order to maintain confidentiality.

Phase 1

Your task

Your task is to count the number of 1's in a table similar to the one below.

A table is successfully completed if you count the correct number of 1's.

The phase

There are 28 periods in the first phase. In each period, you are asked to count the number of 1's in 5 consecutive tables. You have 80 seconds for each period. After each period, you must reply to the following question: How many tables do you think you successfully completed?

0	1	1	1	0	1	1	1	0
1	0	1	1	1	0	1	1	1
0	1	1	1	0	0	1	1	0
0	0	0	0	1	0	1	1	0
0	0	1	1	0	1	0	1	0
0	0	0	1	1	1	1	0	1
1	1	0	1	1	0	0	1	1
0	1	1	0	1	0	0	1	1
0	1	1	1	0	0	1	0	0

Figure C.1: Example table used in task

Your pot of earnings

At the start of the first phase, the total of your pot is 0€. For each period, the gain associated to each correctly completed table is 0€15. You win 0€15 when you correctly complete the table, i.e.: when you count the correct number of 1's in a table. You earn 0€ when you incorrectly complete the table, i.e.: when you have not counted the correct number of 1's or when you have not given an answer. Your earnings for the period are therefore: **Number of correct tables x 0€15**

At the start of the first phase, the total of your pot is 21€. For each period, the loss associated to each incorrectly completed table or table without an answer is 0€15. You lose 0€15 when you incorrectly complete the table, i.e.: when you have not counted the correct number of 1's or when you have not given an answer. You earn 0€ when you correctly complete the table, i.e.: when you count the correct number of 1's in a table. Your earnings for the period are therefore: **Number of correct tables x -0€15**

At the start of the first phase, the total of your pot is 0€. For each period, the gain associated to each correctly completed table is 0€05 with 50% probability, or 0€25, with 50% probability. The random draw of the gain is valid for the five tables within

a period. You win 0€05 or 0€25 when you correctly complete the table, i.e.: when you count the correct number of 1's in a table. You earn 0€ when you incorrectly complete the table, i.e.: when you have not counted the correct number of 1's or when you have not given an answer. Your earnings for the period are therefore, with 50% probability: **Number of correct tables x 0€05 OR Number of correct tables x 0€25**

At the start of the first phase, the total of your pot is 21€. For each period, the loss associated to each incorrectly completed table or table without an answer is 0€05 with 50% probability, or 0€25, with 50% probability. The random draw of the gain is valid for the five tables within a period.. You lose 0€05 or 0€25 when you incorrectly complete the table, i.e.: when you have not counted the correct number of 1's or when you have not given an answer. You earn 0€ when you correctly complete the table, i.e.: when you count the correct number of 1's in a table. Your earnings for the period are therefore: **Number of correct tables x -0€05 OR Number of correct tables x -0€25**

At the start of the first phase, the total of your pot is 0€. For each period, the gain associated to each correctly completed table is 0€05 with 50% probability, or 0€25, with 50% probability. The random draw of the gain is valid for the five tables within a period. You win 0€05 or 0€25 when you correctly complete the table, i.e.: when you count the correct number of 1's in a table. You earn 0€ when you incorrectly complete the table, i.e.: when you have not counted the correct number of 1's or when you have not given an answer. Your earnings for the period are therefore, with 50% probability: **Number of correct tables x 0€05 OR Number of correct tables x 0€25**

At the start of the first phase, the total of your pot is 21€. For each period, the loss associated to each incorrectly completed table or table without an answer is 0€05 with 50% probability, or 0€25, with 50% probability. The random draw of the gain is valid for the five tables within a period.. You lose 0€05 or 0€25 when you incorrectly complete the table, i.e.: when you have not counted the correct number of 1's or when you have not given an answer. You earn 0€ when you correctly complete the table, i.e.: when you count the correct number of 1's in a table. Your earnings for the period are therefore: **Number of correct tables x -0€05 OR Number of correct tables x -0€25**

Random draw

The random draw is done by the computer before each period (5 tables) in order to determine the gain associated to a correctly completed table. You are informed of the result of this random draw before doing the task.

The random draw is done by the computer before each period (5 tables) in order to determine the loss associated to an incorrect or incomplete table. You are informed of the result of this random draw before doing the task.

The random draw is done by the computer before each period (5 tables) in order to determine the gain associated to a correctly completed table. You are informed of the result of this random draw after doing the task.

The random draw is done by the computer before each period (5 tables) in order to determine the loss associated to an incorrect or incomplete table. You are informed of the result of this random draw after doing the task.

Feedback at the end of each period

At the end of each of the 28 periods, you will be informed of:

- The number of correctly completed tables
- The gain associated to each table (*if in gain treatments: GC, GEA, GEP*)

The loss associated to each table (*if in loss treatments: LC, LEA, LEP*)

- Your earnings for the period (*if in gain treatment: GC, GEA, GEP*)

Your losses for the period (*if in loss treatment: LC, LEA, LEP*)

- Your total earnings for all the previous periods

Are there any questions?

To start, please enter your subject code. Before we begin, please answer a few questions to verify your understanding of the instructions.

Answers to comprehension questions

Your task is to count the number of 1's in the table **TRUE**

There are 28 periods **TRUE**

A period lasts for 80 seconds **TRUE**

There are 5 tables in a period **TRUE**

You have 80 seconds to count the number of 1's in 5 tables **TRUE**

In each period, the gain associated to each correct table is 0€15 **TRUE**

In each period, the loss associated to each incorrect or incomplete table is 0€15 **TRUE**

In each period, the gain associated to each correct table is 0€05 with 50% probability, or 0€25, with 50% probability **TRUE**

The random draw is valid for the 5 tables in a period **TRUE**

You know the random draw before the start of a period **TRUE**

In each period, the loss associated to each correct table is 0€05 with 50% probability, or 0€25, with 50% probability **TRUE**

The random draw is valid for the 5 tables in a period **TRUE**

You know the random draw before the start of a period **TRUE**

In each period, the gain associated to each correct table is 0€05 with 50% probability, or 0€25, with 50% probability **TRUE**

The random draw is valid for the 5 tables in a period **TRUE**

You know the random draw after the start of a period **TRUE**

In each period, the loss associated to each correct table is 0€05 with 50% probability, or 0€25, with 50% probability **TRUE**

The random draw is valid for the 5 tables in a period **TRUE**

You know the random draw after the start of a period **TRUE**

Reminder

(This slide was on display throughout the duration of phase 1.)

- Count the number of 1's
- 28 periods
- 1 period = 5 tables during 80 seconds
- Gain associated to each correct table = 0€15

Loss associated to each incorrect or incomplete table = 0€15

Gain associated to each correct table = 0€05 or 0€25

Loss associated to each correct table = 0€05 or 0€25

Gain associated to each correct table = 0€05 or 0€25

Loss associated to each correct table = 0€05 or 0€25

Phase 2

(Questionnaires and organisation of payment)

Thank you for participating in this experiment.

Wilcoxon rank sum tests

	GC	LC	GEA	LEA	GEP
LC	0.459				
GEA	0.908	0.331			
LEA	0.498	0.817	0.298		
GEP	0.489	0.723	0.310	0.994	
LEP	0.098*	0.768	0.023**	0.452	0.349

Table C.1: Wilcoxon rank sum tests between treatments for all periods (p-values)

	GC	LC	GEA	LEA	GEP
LC	0.683				
GEA	0.778	0.376			
LEA	0.726	0.362	0.753		
GEP	0.705	0.874	0.453	0.305	
LEP	0.741	0.848	0.365	0.293	0.950

Table C.2: Wilcoxon rank sum tests between treatments in period 1 (p-values)

	GC	LC	GEA	LEA	GEP
LC	0.763				
GEA	0.652	0.991			
LEA	0.871	0.794	0.794		
GEP	0.670	0.513	0.375	0.582	
LEP	0.041**	0.175	0.060*	0.041**	0.015**

Table C.3: Wilcoxon rank sum tests between treatments in period 28 (p-values)

	GC	LC	GEA	LEA	GEP
LC	0.407				
GEA	0.790	0.418			
LEA	0.345	0.958	0.324		
GEP	0.260	0.914	0.231	0.839	
LEP	0.152	0.833	0.075*	0.674	0.840

Table C.4: Wilcoxon rank sum tests between treatments in period first (p-values)

	GC	LC	GEA	LEA	GEP
LC	0.739				
GEA	0.626	0.388			
LEA	0.752	0.821	0.344		
GEP	0.839	0.734	0.394	0.833	
LEP	0.120	0.531	0.027**	0.270	0.162

Table C.5: Wilcoxon rank sum tests between treatments in period last (p-values)

	All periods	Period 1	Period 28	First half	Second half
GC = GEA	0.908	0.778	0.652	0.790	0.626
GC = GEP	0.489	0.705	0.670	0.260	0.839
GEA = GEP	0.310	0.453	0.375	0.231	0.394
LC = LEA	0.817	0.362	0.794	0.958	0.821
LC = LEP	0.768	0.848	0.175	0.833	0.531
LEA = LEP	0.452	0.293	0.041**	0.674	0.270

Table C.6: Wilcoxon rank sum tests of significant differences in effort between payoff structure (p-values)

Correlation table

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Total number of correct tables in period	1.00						
(2) Ability ($t=1$)	0.36 (0.00)	1.00					
(3) At least one random answer	-0.09 (0.00)	-0.09 (0.00)	1.00				
(4) Degree of risk taking	-0.04 (0.00)	-0.01 (0.01)	-0.03 (0.00)	1.00			
(5) Hot hand fallacy	0.03 (0.00)	-0.02 (0.00)	0.02 (0.00)	0.07 (0.00)	1.00		
(6) Female	-0.01 (0.10)	0.04 (0.00)	-0.04 (0.00)	-0.17 (0.00)	-0.09 (0.00)	1.00	
(7) Age	-0.04 (0.00)	-0.01 (0.06)	-0.04 (0.00)	0.08 (0.00)	-0.09 (0.00)	-0.03 (0.00)	1.00

Table C.7: Cross-correlation table

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French Summary

Introduction

Transition énergétique et consommateurs résidentiels

L'un des principaux défis du XXI^e siècle est le passage à une société verte, neutre en CO₂, renouvelable et durable. En 2017 par rapport à l'ère préindustrielle, la température de notre planète a augmenté de 1,1°C et 2013-2017 ont été les cinq années les plus chaudes jamais enregistrées à ce jour. Ce réchauffement de la planète a eu des conséquences d'une portée considérable dans le monde entier, allant de violentes tempêtes et inondations, à des sécheresses mortelles et des incendies de forêt, avec des effets économiques majeurs sur la vie humaine. L'influence humaine est le principal facteur à l'origine de l'augmentation des températures mondiale et régionales ([World Meteorological Organization, 2018](#)).

Afin de lutter contre la hausse des températures, les gouvernements du monde entier se sont fixé des objectifs pour réduire notre impact sur la planète. L'Union européenne a proposé des objectifs à atteindre à certaines dates, à savoir une réduction de 20% des émissions de gaz à effet de serre (GES) par rapport aux niveaux de 1990, une part de 20% d'énergies renouvelables (EnR) dans le mix de production et une amélioration de 20% de l'efficacité énergétique⁵². L'UE dans son ensemble est en bonne voie pour les atteindre en 2020. D'ici 2030, l'UE poursuivra sa stratégie énergétique en visant à réduire ses émissions de GES de 40%, à avoir une part d'au moins 27% des sources d'EnR dans le mix de production et à réaliser des économies d'énergie d'au moins 25% dans tous les secteurs (industrie, commercial, transports, résidentiel)⁵³.

En ce qui concerne les émissions de GES, l'UE a atteint son objectif 2020 en 2014, et les estimations pour 2016 suggèrent que les émissions de GES dans l'UE sont de 23% inférieures aux niveaux de 1990. Cependant, l'UE est actuellement en deçà de sa trajectoire pour 2030 ([European Environment Agency, 2017c](#)). De même, la

⁵² Voir https://ec.europa.eu/clima/policies/strategies/2020_en

⁵³ Voir https://ec.europa.eu/clima/policies/strategies/2030_en

France est en bonne voie d'atteindre son objectif d'émissions de GES pour 2020, mais le rythme de réduction des émissions devrait ralentir. Il est ainsi peu probable que la France atteigne son objectif 2030 ([European Environment Agency, 2017d](#)).

En ce qui concerne les énergies renouvelables, l'UE est en bonne voie pour atteindre son objectif 2020. En revanche, la croissance de la part des EnR ralentit, ce qui rend l'objectif 2030 plus difficilement atteignable ([European Environment Agency, 2017b](#)). La France quant à elle s'est engagée à atteindre une part de 23% des EnR d'ici 2020. Cependant, en 2016, la part des EnR en France était de 15,6%, et au rythme actuel de progression, la France ne réalisera son objectif 2020 qu'en 2029⁵⁴.

En ce qui concerne les économies d'énergie, en 2014, dans l'UE-28, la consommation d'énergie du secteur résidentiel représentait le troisième secteur le plus consommateur avec 25% de la consommation finale d'énergie⁵⁵. Entre 2005 et 2014, la consommation finale d'énergie dans le secteur résidentiel a diminué de 14,8% ([European Environment Agency, 2017a](#)). Cependant, en France, la consommation d'électricité résidentielle est le secteur qui consomme le plus, représentant 36% de la consommation finale d'électricité. Entre 2001 et 2017, la consommation d'électricité du secteur résidentiel en France a augmenté de 12%, restant relativement stable à partir de 2011 ([Réseau de Transport d'Electricité, 2018](#)). En 2014, la France devait réduire sa consommation finale d'énergie (tous secteurs confondus) de 7,5% supplémentaires afin d'atteindre son objectif 2020 ([European Environment Agency, 2017a](#)).

Étant donné que le secteur résidentiel est le secteur qui consomme le plus et que la France est en bonne voie d'atteindre un seul des objectifs de l'UE 2020 d'ici l'année prochaine (celui des GES) ([European Environment Agency, 2017d](#)), il existe un potentiel clair de réduction de la consommation dans le secteur résidentiel en France afin d'atteindre les objectifs nationaux et européens de transition énergétique.

⁵⁴Ceci est calculé par rapport à la part des énergies renouvelables en France d'après la Commission Européenne (voir https://ec.europa.eu/info/business-economy-euro/economic-and-fiscal-policy-coordination/eu-economic-governance-monitoring-prevention-correction/european-semester_en)

⁵⁵Les secteurs de transport et de l'industrie sont les plus consommateurs avec respectivement 33% et 26% de consommation finale d'énergie.

Une façon de réduire les émissions de GES consiste à diminuer l'utilisation de générateurs coûteux, inefficaces et polluants et de privilégier plutôt les énergies provenant de sources renouvelables. Ces générateurs sont généralement utilisés pendant les périodes de pointe, lorsque la demande est particulièrement élevée. En 2008, en France, seulement 6% de la capacité de pointe a été utilisée pendant 1% des heures (Faruqui *et al.*, 2010a). L'augmentation de la part des EnR, qui est intermittente par nature, signifie que l'électricité ne sera disponible qu'à certaines périodes de la journée et de l'année (lorsque le soleil brille et que le vent souffle). Ces deux éléments impliquent un changement dans le fonctionnement traditionnel du marché de l'électricité, de sorte que la demande suit l'offre plutôt que l'offre suit la demande (Strbac, 2008).

A l'avenir, l'intégration croissante de l'électricité produite à partir des EnR sera stockée pour être utilisée pendant les périodes de pointe. Les consommateurs chargeront leurs véhicules électriques à des moments où l'électricité est abondante et moins chère, pour être utilisés à des moments où l'offre est limitée et où une forte demande signifie des prix élevés. Actuellement, les capacités de stockage de l'électricité sont limitées et coûteuses (Stephens *et al.*, 2015) et d'autres méthodes pour encourager la demande à suivre l'offre sont donc nécessaires.

En l'absence de stockage d'électricité, la maîtrise de la demande en énergie (MDE) est une méthode de redistribution de la demande des périodes de pointe aux périodes creuses. Dans le secteur résidentiel, les consommateurs peuvent être encouragés à réduire leur consommation pendant les périodes de pointe pour éviter de raccorder au réseau des générateurs inefficaces. Ils peuvent également être encouragés à augmenter leur consommation pendant les périodes creuses, lorsqu'il existe un approvisionnement en EnR. La méthode de la MDE dans le secteur résidentiel exige que la demande des consommateurs soit flexible et qu'ils réagissent aux incitations mises en place pour modifier leur comportement. Des économies significatives, tant monétaires qu'environnementales, peuvent être réalisées si les ménages sont incités à réduire leur demande en période de pointe.

L'intégration des EnR dans le système de production d'énergie et la réduction de la demande en période de pointe sont importants pour atteindre les objectifs de réduction de GES, et pour l'intégration des ER. En revanche ces deux facteurs n'entraînent pas nécessairement une réduction de la demande globale. Or celle-ci est nécessaire pour atteindre le troisième objectif de l'UE, à savoir les économies d'énergie. L'effet sur la demande globale dépendra des retombées de l'utilisation d'incitations pour réduire la demande en période de pointe. C'est-à-dire, s'il y aura une réduction prolongée sur les périodes quand la demande est plus faible (Allcott, 2011a), ou si au contraire, les consommateurs augmentent leur demande pendant les périodes creuses après avoir été encouragés à réduire leur demande en période de pointe (Torriti, 2012).

Une réduction de la demande globale fait référence à une diminution de la consommation totale d'énergie à tout moment de la journée ou de l'année. Bien que de telles réductions puissent être réalisées grâce à l'amélioration de l'efficacité énergétique (normes pour les bâtiments à énergie zéro, modernisation des vieux bâtiments et utilisation d'appareils à basse consommation), le comportement des occupants est un facteur important de réduction de la consommation d'énergie en secteur résidentiel. Les caractéristiques des bâtiments peuvent représenter 42% de la consommation d'énergie d'un bâtiment, tandis que les caractéristiques et le comportement des occupants ne représentent que 4,2% (Santin *et al.*, 2009). Même si cela ne semble pas être une grande proportion, la consommation d'électricité des ménages vivant dans des maisons similaires (selon les caractéristiques du bâtiment) peut varier d'un facteur 5 et la consommation de chauffage peut varier d'un facteur 2-3 (Gram-Hanssen, 2013). En outre, il existe un écart d'efficacité énergétique lorsque les gains d'efficacité réalisés sont inférieurs aux gains prévus. Cet écart est dû d'une part aux barrières comportementales (Hirst and Brown, 1990), et d'autre part, aux effets de rebond. C'est-à-dire, lorsque la consommation augmente à la suite d'une amélioration de l'efficacité énergétique (Greening *et al.*, 2000). Compte tenu de la variation de la consommation d'énergie et de l'augmentation de la consommation après les gains

d'efficacité, il est nécessaire d'influencer le comportement des consommateurs et de les encourager à réduire leur consommation énergétique. Sur le marché traditionnel de l'électricité, les consommateurs sont passifs et ignorent leur consommation. Ainsi, influencer leur comportement est un défi significatif. Toutefois, l'introduction des compteurs intelligents dans le secteur résidentiel constitue un progrès technologique important qui permet la mise en place d'incitations pour encourager les ménages à réduire leur consommation d'énergie.

[European Commission \(2014a, p.8\)](#) L'Union européenne a déclaré que dans des "secteurs comme le logement [...], il sera nécessaire d'intensifier considérablement les efforts actuellement déployés pour tirer parti des nombreuses possibilités inexploitées. Cela nécessitera d'importants investissements dans le secteur de la construction (en vue d'abaisser les frais d'exploitation), des conditions générales et une information des consommateurs propres à les inciter à adopter des produits et services innovants, ainsi que des instruments financiers appropriés pour faire en sorte que tous les consommateurs d'énergie bénéficient des changements ainsi occasionnés. » Dans toute l'UE, les États membres ont investi dans l'installation de compteurs intelligents dans les foyers résidentiels. La fig. C.2 montre les stratégies de déploiement des États membres d'ici 2020. [Faruqui et al. \(2010a\)](#) estiment que le déploiement des compteurs intelligents dans l'UE coûtera 51 milliards d'euros et que les avantages opérationnels⁵⁶ représenteront de 26 à 41 milliards d'euros. L'investissement manquant de 10 à 25 milliards d'euros dans la technologie des compteurs intelligents peut être récupéré par une réduction de la demande d'énergie du secteur résidentiel, en particulier en période de pointe. Les compteurs intelligents constituent un progrès technologique clé pour un marché de l'électricité dans lequel les consommateurs jouent un rôle plus actif dans la gestion de la consommation d'énergie. Cependant, les compteurs intelligents seuls ne suffisent pas à eux seuls à encourager les consommateurs à réduire leur demande. Pour motiver un changement de comportement,

⁵⁶Les avantages opérationnels comprennent : le relevé à distance des compteurs, la détection plus rapide des pannes d'électricité et la détection des fraudes, entre autres.

les consommateurs doivent être incités de manière appropriée.

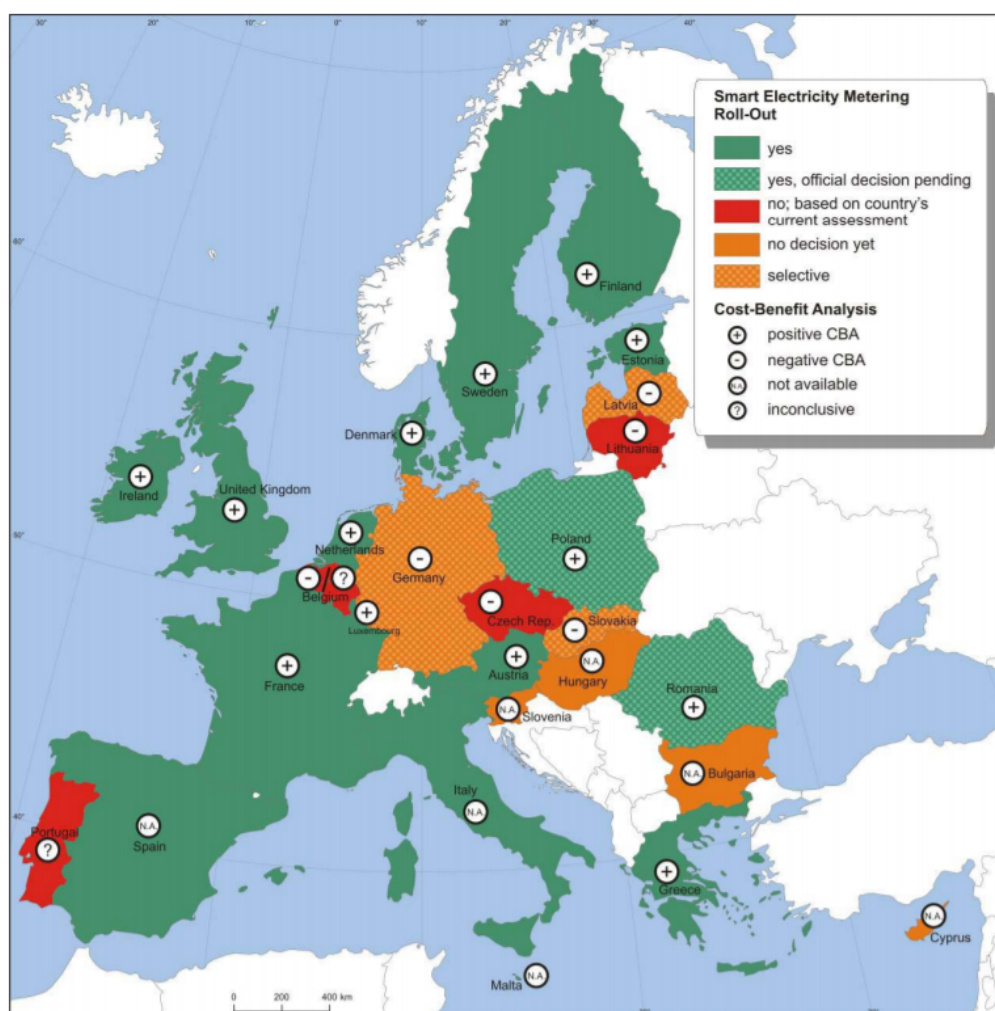


Figure C.2: Stratégies de déploiement de compteurs intelligents dans l'UE-27 d'ici 2020 à compter de juillet 2013, (European Commission, 2014b)⁵⁷

⁵⁷ La carte présente les résultats des analyses coûts-avantages (ACB) des États membres, qu'elles soient positives, négatives, non disponibles ou non concluantes, ainsi que l'état d'avancement du déploiement des compteurs intelligents. A partir de 2013, les pays en vert foncé ont officiellement commencé l'installation de compteurs intelligents, ceux en vert hachuré prévoient d'installer des compteurs intelligents (une fois une décision officielle a été prise), ceux en rouge ont décidé de ne pas installer des compteurs intelligents après une ACB négative ou non concluante, ceux en orange foncé n'ont pas encore pris une décision et ceux en orange hachuré ont commencé une installation sélective. Par exemple, en Allemagne, l'installation des compteurs intelligents se limite aux maisons neuves ou rénovées, aux « consom'acteurs » et aux ménages à forte consommation (Edelmann and Kästner, 2013).

Technologies et mesures incitatives

Grâce à l'utilisation de compteurs intelligents, différentes incitations peuvent être offertes aux consommateurs en fonction de mesures précises de la consommation. Les incitations qui ciblent la réduction globale de la demande sont traditionnellement basées sur l'information (Darby *et al.*, 2006) - informations sur la consommation historique ou de feedback en temps réel - ou, plus récemment, sur les connaissances de l'économie comportementale (Allcott, 2011b). Les compteurs intelligents facilitent l'utilisation d'incitations financières tels que la tarification dynamique qui est utilisée pour encourager une baisse de la demande en période de pointe (Faruqui and Sergici, 2013). Les sections suivantes donnent un aperçu de la littérature sur ces différentes mesures incitatives.

Feedback

L'un des principaux avantages des compteurs intelligents est la possibilité de communiquer des données de consommation en temps réel aux consommateurs. En fournissant aux ménages des informations sur leur consommation d'énergie, ils deviendront plus conscients de leurs habitudes de consommation et feront des efforts pour la réduire. Sensibiliser les ménages à leur consommation d'énergie est le premier pas vers un changement des habitudes de consommation (Attari *et al.*, 2010). La facture papier est la méthode de feedback traditionnellement utilisée pour informer les consommateurs de leur consommation et de leurs dépenses énergétiques. Darby *et al.* (2006) soulignent qu'un tel feedback est utile pour évaluer l'impact sur la consommation des investissements dans l'efficacité énergétique plutôt que pour évaluer les effets dus aux changements de comportement. Ce genre d'information ne fournit pas de feedback approprié sur les efforts déployés pour réduire la consommation d'énergie, car les données sont reçues trop longtemps après le changement de comportement. Pour que le feedback ait un effet, la relation entre l'action et l'effet doit être claire pour les ménages afin qu'ils puissent voir comment les changements

de comportement affectent la consommation d'énergie (Fischer, 2008).

Pour que les consommateurs puissent vraiment bénéficier des informations sur leur consommation fournies par le compteur intelligent, ils doivent pouvoir accéder à celles-ci peu de temps après la mise en œuvre du changement de comportement. Les données disponibles en ligne fournissent des informations plus détaillées sur les niveaux de consommation et peuvent potentiellement combler l'écart d'action et d'effet, mais elles exigent que les consommateurs disposent d'un appareil avec une connexion Internet et qu'ils se connectent pour accéder aux données. Des études évaluant ce type de feedback et son effet sur la consommation d'énergie révèlent que peu de personnes se connectent aux portails en ligne et que le nombre de connexions diminue au cours de l'étude (Benders *et al.*, 2006, Vassileva *et al.*, 2012, Schleich *et al.*, 2013).

Pour combler l'écart action-effet, les ménages peuvent utiliser un dispositif capable de s'interfacer avec leur compteur intelligent qui peut leur fournir des informations en temps réel et accessibles sur la consommation. Ces dispositifs sont communément appelés moniteurs d'énergie. Ce sont des plates-formes dédiées qui fournissent des données de consommation en temps réel, assurant ainsi un lien direct entre l'action et l'effet. L'utilisation de ces moniteurs peut encourager une réduction de la consommation à condition qu'ils soient placés dans des endroits visibles de la maison pour un accès facile et rapide aux données disponibles. Cependant, ce n'est pas toujours le cas et le facteur nouveauté de consulter sa consommation en temps réel tend à s'atténuer au fil de l'utilisation (Hargreaves *et al.*, 2010, 2013). Afin de faire participer les ménages à l'utilisation des données fournies, il faut prêter attention à la façon dont les données sont présentées, qu'il s'agisse de termes monétaires ou énergétiques (Buchanan *et al.*, 2014), d'affichages numériques ou graphiques (Chiang *et al.*, 2012), de dépenses présentées de façon factuelle ou sous forme de perte (Bager and Mundaca, 2017). Ces présentations et leurs effets sur l'effort sont examinés plus en détail au chapitre 4.

Tarification dynamique

La tarification dynamique fait référence à l'ajustement des prix de détail de l'électricité pour mieux refléter les coûts de la production d'énergie. En période de pointe, les coûts de production sont plus élevés, ce qui entraîne une hausse des prix de détail qui incite les ménages à réduire leur demande pendant les périodes de pointe et, dans certains cas, à augmenter leur demande pendant les périodes creuses, afin de maintenir l'équilibre entre l'offre et la demande (Faruqui *et al.*, 2009). Il existe différentes structures tarifaires plus ou moins dynamiques, allant d'une tarification variable dans le temps, mais statique, les tarifications heures pleines-heures creuses, à une tarification dynamique en temps réel. Ces différents programmes de tarification diffèrent selon le degré de risque et le rendement possible (Faruqui and Palmer, 2011). Un tarif standard dans lequel les prix sont fixés quel que soit le moment de la consommation est "sans risque" car tous les kWh sont consommés au même prix. Le risque associé à une tarification heures pleines-heures creuses est légèrement plus élevé, mais le risque demeure beaucoup plus faible que celui d'une tarification de pointe critique ou d'une tarification dynamique en temps réel. La fig. C.3 montre l'arbitrage risque-rendement des tarifications dynamiques où le risque fait référence à l'exposition des consommateurs à la volatilité des prix du marché de gros de l'électricité (Faruqui, 2012).

Les tarifications dynamiques sont efficaces pour réduire la consommation d'énergie, en particulier les tarifications du type Critical Peak Pricing ou Real-time Pricing lorsqu'ils sont combinés à des moniteurs d'énergie (Faruqui and Sergici, 2013). En effet, pour que les ménages puissent réagir avec succès à une tarification dynamique, les consommateurs ont besoin d'un moniteur pour les informer de l'évolution des prix (Dütschke and Paetz, 2013), en particulier dans le cas de tarification en temps réel. Toutefois, les opposants à une tarification dynamique défendent qu'il ne faut pas demander aux consommateurs du secteur résidentiel de soutenir la volatilité des prix de l'électricité, en particulier les consommateurs vulnérables aux changements de l'offre

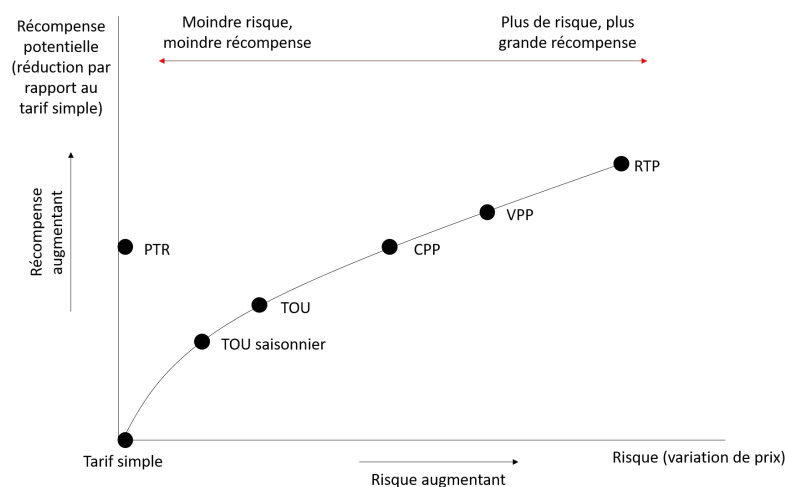


Figure C.3: Trade-off risque/récompense en matière de tarification dynamique (adapté de Faruqi (2012, p.17))

d'électricité (jeunes enfants, personnes âgées, personnes handicapées) (Alexander, 2010). De plus, les pics de demande sont naturels, en raison de l'organisation de la vie quotidienne, difficilement déplaçables (Naus *et al.*, 2014, Hall *et al.*, 2016).

Nudging

L'installation de compteurs intelligents et de moniteurs n'est pas suffisante pour inciter les consommateurs à modifier leurs comportements. La majorité des ménages montrent un manque d'intérêt pour les moniteurs. On constate que ce sont souvent seulement ceux qui sont déjà concernés par leur consommation d'énergie qui s'y intéressent le plus (Buchanan *et al.*, 2015). La tarification dynamique a tendance à n'avoir un impact que sur les consommateurs qui sont pleinement informés et attentifs aux changements de prix (Jesso *et al.*, 2016). Ainsi, les outils d'économie comportementale sont de plus en plus utilisés pour accroître la réaction des consommateurs aux mesures incitatives. Ces mesures incitatives sont appelées des nudges ou des coups de coude et reposent principalement sur les travaux des lauréats du prix Nobel Richard Thaler (2017) et Daniel Kahneman (2002).

Thaler and Sunstein (2008) définissent un nudge comme suit : " Un nudge (...) est tout aspect de l'architecture de choix qui modifie le comportement des gens

d'une manière prévisible sans interdire aucune option ou modifier sensiblement leurs incitations économiques. Pour compter comme un simple nudge, l'intervention doit être facile et peu coûteuse à éviter. Les nudges ne sont pas des mandats."

Le nudging est basé sur l'idée du paternalisme libertaire qui est une approche qui oriente les individus vers des choix qui sont dans leur meilleur intérêt et qui augmenteront leur bien-être sans limiter leur liberté de choix. Le nudging reconnaît que les individus font des choix qui ne sont pas dans leur meilleur intérêt, des choix qu'ils ne feraient pas s'ils avaient une information complète et des capacités cognitives illimitées (Thaler and Sunstein, 2003).

Les ménages ont été encouragés à réduire leur consommation d'énergie par le biais de normes sociales et injonctives. Les normes sociales sont un type de feedback qui compare la consommation d'énergie d'un ménage à celle de ses voisins (Schultz *et al.*, 2007, Nolan *et al.*, 2008). Les normes injonctives ajoutent de l'approbation sociale de la consommation d'un ménage par rapport à celle de ses voisins (Schultz *et al.*, 2007). Par exemple, Opower⁵⁸ met cela en pratique avec des factures papier qui compare la consommation d'un ménage avec la consommation moyenne des ménages voisins (norme sociale). On y trouve également un visage content (norme injonctive) si le ménage consomme moins que ses voisins (Allcott, 2011b). La fig. C.4 fournit un exemple de l'utilisation de normes sociales et injonctives dans un facture d'Opower.

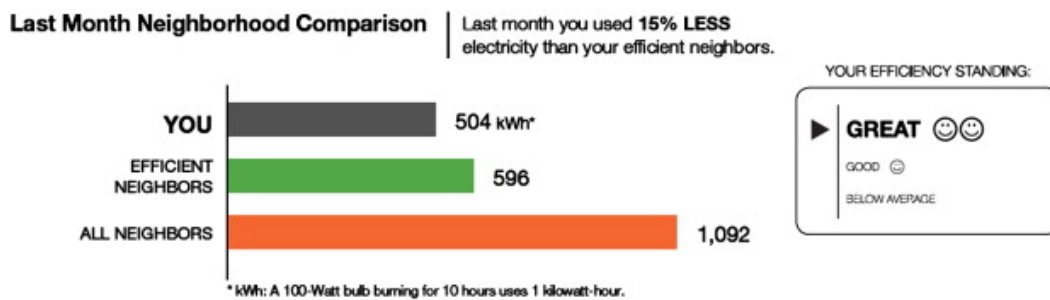


Figure C.4: Une facture "Home Energy Report" d'Opower

En absence de normes injonctives, c'est-à-dire avec uniquement des comparaisons

⁵⁸Opower était une société américaine qui fournissait des logiciels aux compagnies d'énergie pour analyser les données de consommation afin d'encourager la réduction de la demande. La société a été acquise par Oracle Corporation en 2016.

descriptives de la consommation, les ménages qui consomment moins que la moyenne ont tendance à augmenter leur consommation. [Schultz et al. \(2007\)](#) suggèrent que l'utilisation d'une norme sociale descriptive fournit un niveau auquel il n'est pas souhaitable de s'écarter. Ce niveau devient le niveau normal de comportement et donc, être au-dessus ou en-dessous n'est pas désiré. Ceci conduit à une convergence vers la moyenne que [Schultz et al.](#) appellent un effet boomerang. Un tel comportement peut également être décrit par un effet de compensation morale lorsque l'engagement dans une bonne action, c'est-à-dire en réduisant sa consommation, permet à un individu de s'engager ultérieurement dans une mauvaise action, c'est-à-dire en augmentant sa consommation ([Khan and Dhar, 2006](#)). L'inclusion de visages contents est utilisée pour contrecarrer ces effets en fournissant une approbation sociale du comportement désirable : la réduction de la consommation.

Si de tels nudges relativement peu chers sont efficaces pour réduire la consommation d'énergie, ils peuvent être utilisés comme alternatif à des incitations plus coûteuses comme la tarification dynamique. Avant de prendre une telle mesure, il convient d'étudier l'effet des nudges et de la tarification afin de déterminer la valeur monétaire d'un tel nudge (voir chapitre 3).

Plan de la thèse

Les compteurs intelligents sont introduits dans les foyers pour inciter les consommateurs à jouer un rôle actif dans leur gestion de la consommation d'énergie et donc contribuer à la réalisation des objectifs nationaux et européens en matière de changement climatique. Actuellement, la France n'est pas en mesure d'atteindre tous ses objectifs d'ici un an. En outre, les incitations utilisées pour encourager les ménages à réduire leur demande en énergie présentent à la fois des avantages et des inconvénients, comme nous l'avons souligné dans la section précédente. La question centrale de cette thèse est donc :

Comment les consommateurs du secteur résidentiel réagissent-ils aux in-

citations utilisées pour les encourager à réduire leur consommation ?

Cette question est abordée en quatre chapitres dont une présentation de chacun suit ci-dessous.

Chapitre 1

Le premier chapitre de la thèse est une revue de la littérature existante sur la façon dont les consommateurs du secteur résidentiel interagissent avec les incitations décrites ci-dessus et les utilisent pour réduire leur consommation, que ce soit la consommation en période de pointe ou globale. L'objectif du premier chapitre est d'identifier tous les problèmes qui affectent le succès des différentes incitations à encourager les ménages à réduire leur consommation. Différents obstacles à l'acceptation et à l'adoption des compteurs intelligents, des moniteurs et des incitations qu'ils offrent sont identifiés.

L'objectif du chapitre 1 est d'analyser le potentiel des compteurs intelligents pour encourager les consommateurs résidentiels à réduire leur consommation par le biais d'incitations financières et non financières.

La question de recherche de ce chapitre est : **Quels sont les principaux obstacles à l'acceptation et à l'adoption des compteurs intelligents et les incitations qu'ils peuvent offrir ?**

La littérature référence deux principaux obstacles à surmonter pour pouvoir inciter les ménages à réduire leur consommation : les obstacles à l'acceptation et ceux à l'adoption. L'acceptation est le premier obstacle. Les ménages doivent d'abord être prêts à accepter l'installation de compteurs intelligents dans leur maison et à recevoir un feedback sur leur consommation, que ce soit par le biais de factures papier, de portails en ligne ou de moniteurs. L'installation de compteurs intelligents ouvre la voie de l'utilisation d'une tarification dynamique qui est mise en œuvre de manière à « opter pour » plutôt qu'à « opter contre ». Une fois que les ménages ont accepté les compteurs intelligents et les incitations associées, le prochain obstacle à surmonter

est l'adoption afin de savoir si ces dispositifs peuvent être efficaces. L'installation d'un compteur intelligent, la présence d'un moniteur et la tarification dynamique ne suffisent pas à elles seules à faire baisser la consommation des ménages. Ces derniers doivent s'engager à utiliser ces différentes mesures incitatives.

La littérature souligne que le principal obstacle à l'acceptation des compteurs intelligents est que les ménages ne font pas confiance aux compagnies d'énergie. Ils ne savent pas ce que sont les compteurs intelligents et comment ils peuvent être utilisés au profit des consommateurs. En ce qui concerne la tarification dynamique, les ménages trouvent que les tarifs sont complexes et lorsqu'ils ont le choix, peu de ménages optent pour une tarification dynamique. Ils préfèrent rester sur le tarif standard qui est plus simple et sans risque. En ce qui concerne l'adoption par les ménages de compteurs intelligents et de mesures incitatives, les résultats de la littérature suggèrent que tout effet sur la consommation est généralement de courte durée. Les ménages ont tendance à répondre au feedback au début, mais leur intérêt diminue après quelques semaines ou quelques mois. De plus, les ménages sont contraints de répondre au feedback selon leur niveau de confort personnel sur lequel ils ne sont pas prêts à faire des compromis, et selon les rigidités de la vie quotidienne. En outre, les économies monétaires résultant de la baisse de leur consommation sont rarement suffisamment élevées pour encourager des changements de comportement persistants.

La contribution de ce chapitre est une revue récente de la littérature expérimentale afin d'identifier les obstacles à l'utilisation des compteurs intelligents et des incitations associées comme moyen d'encourager les ménages à réduire leur consommation.

Chapitre 2

Il existe une richesse des expériences de terrain et des études pilotes explorant comment les consommateurs réagissent aux incitations (seuls ou en combinaison, dans de nombreux pays et les nombreux protocoles expérimentaux) et une attention crois-

sante accordée aux incitations comportementales telles que le nudging ces dernières années. Etant donné le deuxième chapitre utilise une approche méta-analytique pour analyser les résultats des études expérimentales récentes qui ont examiné l'effet des incitations sur la consommation énergétique du secteur résidentiel.

L'objectif du chapitre 2 est d'analyser quantitativement la littérature expérimentale existante pour obtenir des estimations précises de l'effet des différentes incitations sur la consommation du secteur résidentiel.

Les questions de recherche abordées dans le deuxième chapitre sont : **Quelles mesures incitatives sont les plus efficaces pour encourager les ménages à réduire leur consommation d'énergie ? Comment la conception de l'étude expérimentale influe-t-elle sur l'efficacité des différentes mesures incitatives pour réduire la consommation d'énergie du secteur résidentiel ?** La méta-analyse est une méthodologie qui consiste à combiner les résultats de nombreuses études qui explorent un même objectif (l'effet des incitations sur la consommation d'énergie du secteur résidentiel) afin d'obtenir une estimation plus précise de l'effet réel. L'idée est que la combinaison de nombreuses estimations d'un effet conduit à une meilleure estimation de l'effet réel ([Stanley and Doucouliagos, 2012](#)).

Ce chapitre se concentre sur les études menées à l'époque de l'« Ère des réseaux intelligents⁵⁹ ». La collecte des données est limitée à cette période afin d'éviter de fausser les estimations de l'ampleur de l'effet en utilisant les études des décennies précédentes, lorsque des effets plus importants des incitations sur la consommation d'énergie ont été constatés ([Ehrhardt-Martinez et al., 2010](#)). Dans le passé, on a constaté que l'effet était plus grand en raison des différents niveaux de connaissance de la consommation d'énergie par les consommateurs et en raison de la technologie et des méthodes de feedback disponibles. Ces dernières années, de plus en plus d'études ont expérimenté des mesures incitatives fondées sur la théorie économique comportementale. Dans le présent chapitre, ces incitations comportementales sont

⁵⁹[McKerracher and Torriti \(2013\)](#) propose un ère des réseaux intelligents à partir de 2005.

séparées en deux catégories : celles qui ne fournissent qu'une norme sociale (une comparaison descriptive), et celles qui comprennent également une norme injonctive (une approbation ou désapprobation sociale). Afin de déterminer s'il y a une différence de l'impact de l'effet dû à des effets de boomerang ou de compensation morale (Schultz *et al.*, 2007). De plus, la méta-analyse vise à fournir une meilleure estimation des effets réels des différentes mesures incitatives en incluant les résultats non seulement des revues à comité de lecture, mais également des rapports du gouvernement et des services publics.

Les résultats montrent que le biais de publication peut être limité en tenant compte de la taille de l'échantillon de l'étude originale. Ainsi, si l'on prend en compte la taille de l'échantillon, une étude mesurant l'impact des incitations sur la consommation énergétique du secteur résidentiel fera apparaître en moyenne une baisse de 2% de cette consommation. Il s'agit d'un effet beaucoup plus faible que celui estimé dans les méta-analyses précédentes. C'est le fait de fournir aux ménages un feedback sur leur consommation d'énergie en temps réel ou en termes monétaires qui a le plus d'impact, avec une réduction de la consommation s'élevant respectivement à 2,89% et 2,86%. Le protocole de l'étude (par exemple, la manière dont les participants sont recrutés) influence l'ampleur de l'impact mesuré. Les études reposant sur une participation volontaire des sujets font apparaître une réduction plus importante de la consommation énergétique. Ce résultat suggère que le déploiement d'une incitation particulière à l'échelle nationale sera probablement moins efficace que ce que les expériences de terrain et les études pilotes peuvent montrer. Cela revêt une importance particulière pour les décideurs politiques.

L'apport de ce chapitre est de proposer une analyse actualisée de l'impact des différentes mesures incitatives sur la consommation d'énergie du secteur résidentiel. En particulier, cette méta-analyse se concentre sur des études récentes et de ce fait, elle considère plus d'expériences utilisant des incitations comportementales. Elle limite le problème du biais de publication, souvent présent dans les méta-analyses, et enfin, elle tient compte de certaines caractéristiques des protocoles expérimentaux,

non prises en compte par les méta-analyses précédentes.

Chapitre 3

Dans les chapitres 1 et 2, on souligne l'idée que la tarification dynamique peut être politiquement difficile à mettre en œuvre (Alexander, 2010), et qu'elle est difficile à comprendre pour les consommateurs (Layer *et al.*, 2017, Schlereth *et al.*, 2018). De plus, les nudges sous forme de comparaisons sociales, avec ou sans normes injonctives, sont efficaces pour réduire la consommation. Ils peuvent néanmoins engendrer un effet de compensation morale ou de boomerang, lorsque les ménages qui consomment moins que la moyenne de leurs voisins estiment qu'ils peuvent augmenter leur consommation pour converger vers la consommation moyenne (Schultz *et al.*, 2007, Allcott, 2011b). Dans le troisième chapitre, ces incitations sont analysées dans un environnement de laboratoire afin de comparer leurs avantages et inconvénients respectifs en conditions contrôlées.

L'objectif du chapitre 3 est de comparer les réactions des individus à une incitation comportementale et à une incitation financière dans un jeu stylisé de consommation d'énergie.

Les questions de recherche posées dans ce chapitre sont les suivantes : **Quelles sont les mesures incitatives les plus susceptibles de favoriser un comportement socialement optimal ? Quel est le « prix » du nudge ?**

Le chapitre 3 décrit une expérience basée sur un jeu de ressources communes appliqué au contexte de la consommation d'énergie du secteur résidentiel. (Ostrom, 1990) décrit une ressource commune comme un système de ressources à partir duquel un flux de ressources peut être extrait. Le stock de ressources est renouvelable et peut être maintenu tant que la quantité extraite ne dépasse pas le taux de renouvellement. Collectivement, il est préférable que chacun ne dépasse pas sa part de la quantité renouvelable de la ressource. Cependant, chaque individu aimerait en extraire davantage. Des recherches antérieures ont porté sur la façon dont ce cadre

peut être appliqué à l'infrastructure énergétique (Bäckman, 2011, Goldthau, 2014, Gollwitzer *et al.*, 2018). Ce cadre est appliqué à la consommation d'énergie dans le secteur résidentiel en période de pointe, où la capacité maximale est utilisée. Chaque ménage aimerait consommer comme il l'entend, mais il serait bénéfique pour tout le monde que tous les ménages s'efforcent de réduire leur consommation afin d'éviter des chutes de tension et des pannes de courant.

Les résultats de l'expérience montrent que l'utilisation d'un nudge ou d'un prix encouragent les individus à adopter un comportement plus optimal socialement en réduisant leur consommation, comparé à une situation où il n'y a pas d'incitations. A la moyenne, le nudge est compris rapidement par les individus et a un effet immédiat sur la consommation dans la deuxième période du jeu après la première réception du feedback. Il faut plus de temps pour que le prix ait un effet, et ce n'est qu'au cours de la quatrième période de jeu que les individus intègrent le prix dans leur prise de décision. L'hypothèse sous-tendant le nudge est que les individus qui ne se comportent pas de manière optimale en absence d'incitation, c'est-à-dire qui surconsomment, seront encouragés à baisser leur consommation après avoir reçu le nudge. Cependant, les résultats montrent que les individus ne répondent pas au nudge de cette manière et continuent à surconsommer. Cette constatation revêt une importance particulière, car elle met en lumière un inconvénient potentiel des nudges.

La contribution de ce chapitre est l'application de la théorie des ressources communes au marché de l'électricité dans le cadre d'une expérience en laboratoire. La valeur monétaire du nudge est estimé en comparant le comportement des individus face au nudge au comportement face au prix équivalent. Le prix est fixé pour que les individus soient incités à choisir le même niveau de consommation que celui qu'ils choisissent dans le traitement nudge.

Chapitre 4

Le chapitre 1 montre que l'information fournie par le moniteur n'incite pas nécessairement les ménages à réduire leur consommation : lorsque cette information est affichée en unités énergétiques, elle est incompréhensible (Raw and Ross, 2011, Buchanan *et al.*, 2014) ; lorsqu'elle est en unités monétaires, les économies potentielles sont trop faibles. Certains ménages estiment que l'effort qu'ils font pour réduire leur consommation d'énergie n'en vaut pas la peine car il n'a qu'un faible effet sur la consommation et entraîne peu d'économies monétaires (Hargreaves *et al.*, 2010, 2013, Goulden *et al.*, 2014). Le dernier chapitre tient compte de ces obstacles et cherche à déterminer comment des mesures incitatives pourraient être formulées pour encourager un effort plus important, lorsqu'on demande aux individus de faire de petits efforts pour de petites récompenses. Ce cas de figure s'applique en effet particulièrement aux efforts visant à réduire la consommation énergétique.

L'objectif du chapitre 4 est d'explorer le cadre des mesures incitatives utilisées pour encourager les petits efforts lorsque les récompenses sont faibles.

La dernière question de recherche est la suivante : **Comment l'information (sur les moniteurs) peut-elle être formulée pour encourager la fourniture d'efforts ?**

Le chapitre 4 vise donc à déterminer comment l'information peut être structurée pour encourager les individus à faire un petit effort lorsque les récompenses sont faibles. Dans l'expérience, les individus sont incités à faire un effort pour réaliser une tâche artificielle à effort réel sur un certain nombre de périodes. L'incitation prend la forme de paiements, qui sont présentés aux individus de manière différente (sous forme de gains ou de pertes) et dont la structure est différente (paiements sans risque ou à risque). L'expérience s'appuie sur les conclusions de la théorie des perspectives (Kahneman and Tversky, 1979) qui suggère que les individus font plus d'efforts lorsque les paiements sont présentés comme une perte (en particulier lorsque les pertes sont risquées), que lorsqu'ils sont présentés comme un gain.

Dans le cas des petites récompenses pour de petits efforts, la présente expérience ne révèle aucun effet significatif de la présentation des paiements sous forme de gains ou de pertes sur l'effort. En moyenne, les individus fournissent le même niveau d'effort quelle que soit la présentation. Toutefois, les individus fournissent plus d'efforts lorsqu'ils peuvent gagner ou perdre un montant élevé plutôt que faible. Cela suggère que lorsque les récompenses sont faibles, comme dans le cas des actions visant à réduire la consommation d'énergie, les individus font un effort équivalent dans le cadre d'une présentation sous forme de gains ou d'une présentation sous forme de pertes. Augmenter l'importance des récompenses associées à une action est essentiel pour encourager les individus à faire un effort.

Ce chapitre contribue à la littérature sur la présentation des paiements sous forme de gains ou de pertes en examinant comment la théorie de la perspective s'applique dans une situation où les individus doivent faire de petits efforts pour de petites récompenses, et en incluant un élément de risque dans la structure des paiements.

Enfin, la thèse se termine par une vue d'ensemble des quatre chapitres et de leurs conclusions en relation avec la question centrale de la recherche. Les limites de la recherche et ses implications pour les décideurs, les praticiens et les théoriciens sont examinées. La thèse se termine par une discussion sur les pistes de recherche futures.

Conclusion

Cette thèse a exploré les différentes mesures incitatives utilisées pour encourager les consommateurs du secteur résidentiel à réduire leur consommation d'énergie. L'objectif était de déterminer si les ménages acceptent ces mesures incitatives et les technologies qui y sont associées, et si ces mesures sont efficaces pour réduire leur consommation. Ce sujet revêt une importance particulière étant donné l'impact des activités humaines sur le réchauffement de l'atmosphère de notre planète, qui a des effets désastreux dans le monde entier. Pour limiter l'impact futur de l'humanité, les gouvernements du monde entier se sont fixé des objectifs de réduction des émissions,

d'augmentation de la part des énergies renouvelables dans le mix de production et d'économies d'énergie. Les consommateurs du secteur résidentiel peuvent contribuer à cet effort en réduisant leur demande globale et, en particulier, leur demande de pointe.

Ces dernières années, on observe un regain d'intérêt pour l'utilisation d'incitations comportementales pour encourager les ménages à réduire leur consommation. Compte tenu de l'application récente de ces incitations à la consommation résidentielle d'énergie, les recherches sur ces incitations dans le contexte de la consommation d'énergie sont moins nombreuses que celles portant sur les incitations financières traditionnelles. De plus, il y a peu d'études qui ont rassemblé les données existantes sur les incitations comportementales. En outre, se pose la question de l'efficacité des incitations comportementales pour motiver des changements significatifs et durables dans le comportement des consommateurs. La présente thèse contribue à ce corpus de recherche en explorant la littérature antérieure et en évaluant l'efficacité des incitations traditionnelles et comportementales sur la consommation, et en analysant plus finement les incitations comportementales en laboratoire.

Pour répondre à la question centrale de savoir comment les consommateurs du secteur résidentiel réagissent aux incitations utilisées pour les encourager à réduire leur consommation énergétique, la thèse a été divisée en quatre chapitres. Premièrement, une revue de la littérature a permis d'identifier les principaux obstacles à l'acceptation et à l'adoption des compteurs intelligents et aux incitations qu'ils peuvent offrir. Deuxièmement, une méta-analyse a permis d'actualiser les connaissances sur l'efficacité des mesures incitatives pour encourager les ménages à réduire leur consommation, et de prendre en compte le fait que la manière dont sont conçues les expériences influence les résultats. Compte tenu des conclusions des deux premiers chapitres, le troisième chapitre visait à analyser plus en détail les réactions des consommateurs aux incitations financières et comportementales dans un environnement contrôlé en laboratoire afin de déterminer si ces incitations sont capables d'encourager un comportement socialement plus optimal et à quantifier la réaction

à une incitation comportementale. Le quatrième et dernier chapitre s'appuie sur les résultats de recherches antérieures qui suggèrent que les individus font plus d'efforts pour éviter les pertes que pour recevoir des gains. Ce chapitre cherche à savoir si cela est applicable à la fourniture d'efforts pour économiser l'énergie, qui se caractérise par de petits efforts pour de petites récompenses. Cette expérience a permis d'explorer les moyens de présenter l'information afin d'encourager la fourniture de l'effort.

En réponse aux questions de recherche, le chapitre 1 a permis de constater qu'il existe de nombreuses barrières limitant les possibilités d'encourager les ménages à réduire leur consommation au moyen de mesures incitatives associées à des compteurs intelligents. Ces obstacles doivent être surmontés pour que les ménages acceptent l'installation de compteurs intelligents et de la technologie connexe à leur domicile dans un premier temps, et dans un deuxième temps, pour qu'ils soient en mesure de motiver efficacement les consommateurs à réduire leur demande énergétique. Si ces obstacles persistent, les ménages n'utiliseront pas de compteurs intelligents et n'adopteront pas les mesures incitatives, et le coût d'investissement dans cette technologie ne sera pas amorti par les économies énergétiques et monétaires qui pourraient être réalisées.

Le chapitre 2 a examiné en détail l'efficacité de différentes mesures incitatives à l'aide d'une méta-analyse combinant les résultats d'expériences récentes sur le terrain et d'études pilotes qui ont testé l'effet de diverses mesures incitatives sur la consommation énergétique résidentielle. La méta-analyse a révélé que la prise en compte de la taille de l'échantillon dans les études initiales fournit des estimations plus précises de l'effet des incitations et qu'en moyenne, une incitation entraînera une réduction de la consommation de l'ordre de 2%. Des mesures incitatives telles que les stratégies de prix, qui visent principalement à réduire la demande de pointe, peuvent également être efficaces pour réduire la demande globale tant que l'incitation à réduire la consommation pendant les périodes de pointe n'est pas compensée par une incitation à augmenter la consommation pendant les heures creuses.

Des réductions de la demande de pointe sont nécessaires pour éviter l'utilisation de générateurs coûteux et polluants, mais si la demande globale augmente en raison des stratégies de tarification, les objectifs d'économies d'énergie pourraient ne pas être atteints. Les mesures incitatives fondées sur l'économie comportementale, telle que la comparaison sociale, sont également efficaces pour encourager une réduction de la consommation en moyenne. De telles incitations sont efficaces, qu'elles soient simplement descriptives ou qu'elles fassent également appel à des normes injonctives. Toutefois, cette dernière montre un effet de réduction légèrement plus important.

L'estimation de l'efficacité des mesures incitatives a été grandement influencée par le protocole de l'étude. En particulier, l'absence d'un groupe de contrôle fournit des estimations gonflées des réductions de consommation par rapport au cas où un groupe de contrôle est présent. Les études sans groupe de contrôle comparent la consommation d'un même groupe de ménages avant et après la mise en œuvre d'une mesure incitative et n'effectuent donc pas un contrôle simultané des facteurs externes qui peuvent affecter la consommation au cours d'une expérience. Les études qui utilisent un groupe de contrôle fournissent à la fois une comparaison entre la consommation des ménages avant et après la mise en œuvre d'une mesure incitative, et une comparaison avec un groupe de ménages dont la consommation n'est pas influencée par une mesure incitative, pendant la même période. L'utilisation d'un groupe de contrôle fournit une estimation plus robuste de l'efficacité que les mesures incitatives auraient dans un cadre naturel et non expérimental.

De plus, il est important de noter que les résultats des expériences sur le terrain et des études pilotes peuvent surestimer l'effet que des incitations auraient dans le cas d'un déploiement à l'échelle nationale. En particulier, lorsqu'il y a de petits échantillons de ménages qui choisissent de participer à l'étude, ces ménages peuvent être particulièrement disposés à faire un effort pour réduire leur consommation, que ce soit pour des raisons monétaires ou environnementales, ou même en raison d'un intérêt pour la technologie offerte dans le cadre de l'étude. Comme l'ont suggéré [Spence *et al.* \(2014\)](#) le type d'incitation utilisé ou le choix de l'unité utilisée

pour la présentation de l'information sur la consommation influe sur les motivations déclarées des individus à réduire leur consommation et, comme le montre le chapitre 3, cela peut aussi influencer sur leurs décisions de consommation.

Au chapitre 3, les individus ont été encouragés à réduire leur consommation par le biais d'un nudge, ou incités à le faire par une augmentation du prix de la consommation hypothétique dans le cadre d'un jeu expérimental de ressources communes. L'incitation via le prix était la plus efficace pour atteindre le niveau de consommation que chaque incitation était conçue pour encourager. Cependant, le nudge a eu un effet immédiat puisque l'information a été immédiatement comprise par les individus. Dans le cas de l'incitation tarifaire, les individus ont mis plus de temps à intégrer le prix dans leur prise de décision. Cela reflète les constatations tirées de la littérature dont il a été question au chapitre 1, à savoir que les stratégies de prix, telle que la tarification dynamique, sont complexes à comprendre pour les ménages (Layer *et al.*, 2017).

Ces deux mesures incitatives ont été plus efficaces pour encourager les consommateurs à réduire leur consommation que l'absence de politiques. Cependant, les évaluations ex post des caractéristiques individuelles, y compris la sensibilité environnementale, ont montré que les caractéristiques déclarées par les individus diffèrent selon l'incitation utilisée pour les encourager à réduire leur consommation. Les choix de consommation dans le traitement nudge diffèrent selon la sensibilité environnementale individuelle ; ceux qui étaient plus sensibles aux questions environnementales sont ceux qui ont le plus réduit leur consommation. L'utilisation d'une incitation monétaire n'a pas eu cet effet différencié en fonction des caractéristiques environnementales, car les personnes plus sensibles ont choisi de consommer la même quantité que celles qui étaient moins sensibles aux questions environnementales. Cette constatation, ainsi que les discussions des chapitres 1 et 2, mettent en lumière l'existence d'un lien entre les incitations, et les motivations et les caractéristiques individuelles. Si l'utilisation d'incitations monétaires écarte toute influence des caractéristiques ou motivations environnementales sur la réduction de la con-

sommation, c'est préoccupant, car le chapitre 1 a montré que les consommateurs sont peu motivés par les économies monétaires liées à la réduction de leur consommation énergétique, celles-ci étant souvent faibles (Hargreaves *et al.*, 2010, Murtagh *et al.*, 2014).

La discussion et l'analyse de la documentation aux chapitres 1 et 2 ont mis en lumière les problèmes potentiels liés à l'utilisation d'incitations comportementales pour encourager la réduction de la consommation d'énergie, à savoir que lorsqu'on leur dit qu'ils consomment moins que la consommation moyenne dans leur quartier, les ménages augmentent leur consommation (Schultz *et al.*, 2007). Cet effet boomerang a été atténué par l'inclusion d'un smiley pour rappeler aux individus que consommer moins que la moyenne est socialement souhaitable (Allcott, 2011b). Le nudge expérimenté au chapitre 3, qui est présenté différemment de ceux utilisés sur le terrain, a conduit à un autre impact inquiétant. Le nudge a réussi à encourager une réduction de la consommation moyenne, mais il a renforcé le comportement existant des individus, de sorte que ceux qui sous-consommaient ont compensé pour ceux qui surconsommaient. Cela est particulièrement préoccupant, car l'utilisation de tels nudges peut diviser les consommateurs : ceux qui sont peu consommateurs font des efforts accrus pour réduire leur consommation et ceux qui sont gros consommateurs ne le font pas.

Comme expliqué dans le chapitre 1, les économies monétaires ne sont pas nécessairement suffisantes pour encourager les efforts d'économie d'énergie. C'est dans cette optique que le chapitre 4 a exploré expérimentalement la façon dont la présentation de l'information sur les gains peut encourager un plus grand effort. Le chapitre a également montré que les personnes fournissent, en moyenne, le même niveau d'effort lorsqu'elles sont incitées à faire un petit effort pour une petite récompense, quelle que soit la présentation des paiements (en gains ou en pertes). Lorsque les récompenses possibles sont relativement plus importantes, la présentation des paiements n'affecte pas l'effort fourni par les individus. Lorsque les individus ne sont pas sûrs du montant qu'ils gagneront après un effort, c'est-à-dire lorsque les gains sont risqués, ils

ont tendance à fournir un peu moins d'effort dans le cas d'une présentation sous forme de pertes. Ces résultats ont montré qu'afin d'encourager les individus à faire de petits efforts pour de petites récompenses, comme c'est le cas pour les économies d'énergie, la présentation des paiements n'est pas de la plus haute importance, il serait plutôt plus efficace de se concentrer sur le montant qui peut être économisé. Afin d'encourager les ménages à faire un effort pour réduire leur consommation, il convient de mettre l'accent sur le fait que plusieurs efforts combinés conduisent à des économies plus importantes, car les individus fournissent plus d'efforts lorsque les récompenses potentielles sont relativement plus élevées. En outre, il conviendrait de minimiser le risque sur les paiements afin que les ménages soient assurés du montant qu'ils gagneront en réalisant une certaine action.

Les résultats de la présente recherche ont permis de répondre à la question centrale de la recherche : comment les consommateurs résidentiels réagissent-ils aux incitations utilisées pour les encourager à réduire leur consommation énergétique ? Malgré les obstacles au déploiement des compteurs intelligents et des mesures incitatives qui y sont associées, les consommateurs résidentiels réagissent aux incitations et ces dernières sont efficaces pour encourager une réduction de la consommation. Les différentes incitations sont plus ou moins efficaces selon l'objectif de réduction. Les incitations monétaires, à savoir les stratégies de prix, sont plus appropriées pour réduire la demande de pointe que la demande globale. Pour qu'ils soient vraiment efficaces, il faut mieux expliquer les tarifs afin que la complexité perçue ne freine pas leur adoption, ni la réactivité des consommateurs. Les incitations comportementales sont une autre incitation efficace, en particulier lorsque des normes injonctives sont utilisées parallèlement aux normes sociales. Ces incitations ont l'avantage, par rapport aux stratégies de prix, d'être comprises rapidement, mais il peut y avoir des conséquences non désirées. Lorsque les individus se rendent compte qu'ils sont poussés vers un comportement socialement optimal, ils peuvent réagir en adoptant exactement le comportement qui n'est pas souhaitable. L'information sur les économies d'énergie et les économies monétaires est également efficace, du

moins au début. Cependant, il y a des limites à la motivation monétaire. Les efforts d'économie d'énergie se traduisent par de petites récompenses monétaires qui ne sont pas nécessairement suffisantes pour être motivantes. Les différentes méthodes de présentation des petites récompenses pour de petits efforts n'augmentent pas la fourniture d'effort.

Limites

Au cours de cette recherche, certaines limites ont été rencontrées. La méthodologie de la méta-analyse utilisée dans le chapitre 2 consiste à inclure de façon exhaustive toutes les études sur le sujet, mais elle est limitée par la disponibilité des études. Or, il est possible que les études disponibles ne soient que celles qui ont des effets significatifs. Si les études qui ne montrent pas d'effets significatifs ne sont pas incluses dans la méta-analyse, alors les résultats de l'analyse sont biaisés. Cette limite a été contournée en analysant les problèmes liés au biais de publication, et en utilisant des méthodes pour le corriger. La méthode consistant à donner plus de poids aux études portant sur des échantillons plus importants a permis d'atténuer de façon significative le biais de publication.

Le chapitre 3 portait sur les choix de consommation d'énergie dans un jeu de ressources communes contextualisé. Les sujets prenaient leurs décisions dans un laboratoire informatique et, même si leurs décisions avaient des conséquences monétaires conçues pour refléter l'utilité et la désutilité des choix de consommation, leurs décisions n'avaient aucune incidence sur la consommation réelle. D'autre part, au chapitre 4, un jeu entièrement décontextualisé imitant de manière stylisée certaines caractéristiques de la consommation et des économies d'énergie a été conduit. Les expériences de laboratoire bénéficient d'une validité interne élevée - les individus prennent des décisions dans un environnement hautement contrôlé, mais elles peuvent manquer de validité externe.

Les résultats des expériences de laboratoire présentées dans cette thèse ont permis

de mieux comprendre les comportements en réponse aux nudges et aux prix, et en réponse à la présentation des paiements. Ils ne se substituent pas aux expériences de terrain et aux études pilotes analysées au chapitre 2, mais constituent plutôt une approche complémentaire pour mieux comprendre le comportement individuel. L'expérience du chapitre 3 a mis en évidence une conséquence inattendue d'un nudge donné à différents groupes sur les individus, et a montré comment les réponses aux incitations et les caractéristiques individuelles sont liées. L'expérience du chapitre 4 a étudié la possibilité de fournir des efforts pour de petites récompenses dans un environnement moins complexe que dans la vie réelle, où les efforts d'économie d'énergie ont des impacts plus larges, notamment sur le confort et sur les autres individus. L'absence d'effets de la façon de présenter les paiements (sous formes de gains ou de pertes) en laboratoire soulève la question de savoir si de tels effets se manifesteront lorsque l'effort à fournir est plus complexe. Toutefois, les sujets de l'expérience n'avaient qu'à se concentrer sur une tâche qui consistait à compter le nombre de « 1 » dans une série de tableaux, et n'étaient donc peut-être pas sensibles à la présentation des paiements, car ils n'étaient concentrés que sur la tâche en cours. Une exigence importante pour vérifier la robustesse des résultats d'expériences en laboratoire est la réplication. Bien que l'expérience du chapitre 4 ait repris certains aspects des expériences précédentes et ait tiré des conclusions similaires, à savoir que les effets de présentation des paiements (sous forme de gains ou de pertes) ne se manifestent pas toujours lorsque les gains sont faibles, les résultats de l'expérience du chapitre 3 devraient faire l'objet de recherches plus poussées. En particulier sur l'effet du nudge consistant à renforcer le comportement existant.

Conséquences

Les implications de la présente recherche sont de trois ordres. Premièrement, les différentes incitations sont efficaces pour encourager les ménages à réduire leur consommation à des degrés divers. Lorsque les décideurs décident des mesures d'incitation

à mettre en œuvre, ils doivent d'abord tenir compte de l'objectif : réduction globale de la demande ou réduction de la demande de pointe. Les incitations devraient ensuite être adaptées à cet objectif en gardant à l'esprit que les stratégies de tarification sont les plus efficaces pour réduire la demande de pointe et que des incitations supplémentaires devraient être utilisées pour contrer les augmentations de la demande pendant les périodes creuses. En outre, les décideurs devraient tenir compte du fait que l'information sur la consommation sous forme de nudges est rapidement comprise par les consommateurs et peut donc avoir un effet immédiat sur la consommation, alors que les prix prennent un peu plus de temps à être intégrés dans le processus décisionnel des individus. Cela présente un intérêt pour les décideurs, car l'augmentation des prix peut aggraver la situation des individus pendant un certain temps s'ils ne sont pas en mesure de réduire immédiatement leur consommation en réaction à la hausse des prix. Les consommateurs peuvent subir une diminution de leur bien-être avant d'être pleinement en mesure d'ajuster leur consommation en réponse à l'augmentation des prix.

Deuxièmement, les décideurs politiques devraient être conscients des obstacles à la mise en œuvre des différentes incitations et de leurs potentielles conséquences indésirables. En particulier, ils devraient prendre en compte l'effet individuel des nudges habituellement utilisés. Comme le montre la revue de littérature, les comparaisons descriptives peuvent inciter les ménages consommant peu à augmenter leur consommation jusqu'au niveau moyen ou, comme vu dans la présente étude, l'inclusion de normes injonctives peut renforcer les comportements existants, de sorte que les ménages peu consommateurs réduisent leur consommation, compensant l'impact des ménages très consommateurs qui continuent à accroître leur consommation.

Enfin, la présente recherche a également des implications pour la conception de dispositifs qui affichent des informations sur la consommation aux ménages : la présentation des paiements en termes de gains ou de pertes n'a pas d'effet sur l'effort fourni. C'est le montant des paiements potentiels et la réduction du risque sur les paiements qui est importante. Cette absence d'effet de présentation pour les petites

récompenses a également des implications théoriques, car il semblerait que l'aversion aux pertes n'incite pas les individus à fournir plus d'efforts lorsque les paiements sont présentés sous forme de pertes (par rapport à une présentation sous forme de gains) dans le cas des petites récompenses. Le montant que la personne peut gagner est tout simplement trop petit pour que la présentation ait un effet.

Recherches futures

Le premier chapitre de cette thèse identifie les obstacles à l'utilisation d'incitations pour encourager la réduction de la demande énergétique, dont certains sont ensuite analysés plus en détail dans les chapitres suivants. Plusieurs obstacles ayant été identifiés, les possibilités de recherche sur le sujet de cette thèse sont vastes.

Les ménages ignorent généralement leur consommation ou ne connaissent pas le tarif de l'électricité qu'ils paient. Cela influe sur leur décision d'opter pour des contrats à tarification dynamique. En effet, les ménages préfèrent avoir un contrat simple car ils ne savent pas si un tarif dynamique serait avantageux dans leur cas, ni comment ils peuvent modifier leur comportement pour profiter des tarifs moins élevés en période creuse. Une piste de recherche future pourrait être d'étudier la manière dont les choix tarifaires des individus évoluent lorsqu'ils bénéficient d'informations sur leur propre consommation et sur l'utilisation qu'ils peuvent faire des différents niveaux de prix, en s'appuyant sur les recherches des autres.

La motivation monétaire ne s'est pas avérée être un facteur clé du changement des comportements de consommation, car les économies monétaires sont généralement faibles. De plus, la manière dont est présentée l'information peut être mise en regard des différentes motivations pour économiser de l'énergie. Une autre piste de recherche pourrait être de proposer aux individus différents affichages de l'information sur leur consommation d'énergie (économies monétaires, économies d'énergie, économies environnementales, ...) puis, à travers une expérience de choix, de mesurer leurs préférences pour ces différents affichages. Cela pourrait ensuite faire

l'objet de recherches plus approfondies sur le terrain en comparant les réponses aux incitations à la réduction de la consommation basées sur des calculs non monétaires de l'impact des économies d'énergie : sur l'environnement, la santé, ou autre.

Outre les obstacles identifiés au chapitre 1, les expériences menées dans le cadre de cette thèse ont également ouvert la voie à de nouvelles recherches. Au chapitre 3, le nudge a eu pour effet involontaire de renforcer le comportement existant. Une explication possible a été trouvée dans la théorie de la réactance : les individus estiment que leur liberté de faire ce qu'ils veulent est menacée et ils adoptent donc un comportement qui n'est pas encouragé. Pourtant, cet effet n'a pas été observé dans les expériences de terrain analysées aux chapitres 1 et 2. Il y a une différence entre la création du nudge utilisé sur le terrain et celui utilisé dans la présente expérience. Sur le terrain, le comportement est comparé au niveau de consommation moyen des ménages similaires (niveau endogène), alors qu'en laboratoire, le comportement est comparé à un niveau optimal de consommation défini de façon exogène, calculé par l'expérimentateur. Les réponses individuelles aux nudges endogènes et exogènes méritent des recherches plus approfondies.

Cette thèse avait pour but d'étudier la manière dont les consommateurs du secteur résidentiel réagissent aux incitations utilisées pour les encourager à réduire leur consommation énergétique. Les consommateurs résidentiels réagissent positivement aux diverses mesures incitatives utilisées : les incitations entraînent une réduction moyenne de la consommation de pointe ou globale. La recherche a mis en évidence que diverses mesures incitatives peuvent avoir des conséquences indésirables sur la consommation au niveau individuel et que les mesures incitatives déclenchent différentes caractéristiques qui peuvent influencer sur la façon dont les consommateurs réagissent à ces mesures.

Abstract

This thesis examines how consumers respond to incentives used to encourage a reduction in their energy consumption. This necessary reduction stems from the need to reduce greenhouse gas emissions, increase energy production from renewable energy sources and achieve energy savings. These objectives require that residential demand be more flexible in response to changes in supply and that energy savings be achieved by households. The first chapter explores the barriers to consumer acceptance and adoption of smart meters and the incentives that they provide. Significant barriers exist and consumption reductions are far from being achieved. Limited motivation, lack of understanding of information on consumption and the rigidity of daily life are the main barriers preventing households from acting upon the incentives delivered via smart meters. The second chapter analyses the results of field experiments and pilot studies on the impacts of different incentives on residential consumption. The results show that there are large variations and that, on average, an incentive will result in a 2% reduction in energy consumption. Real-time feedback and monetary information have the greatest effect. Finally, more robust studies report lower reduction effects. In the third chapter, a common pool resource game is used to explore individual responses to price and nudge-based incentives. Individuals are encouraged to reduce their consumption either by price increases or by smiles that reflect their overconsumption. The price is most effective at encouraging the target level of consumption but takes longer to have an effect. The nudge is quickly understood but tends to reinforce overconsumption behaviours. The fourth chapter examines the effect of framing on effort provision. Individuals are asked to complete a simple and repetitive task for which they receive a piece-rate payoff in the form of a gain or loss. Framing in the form of gains and losses is combined with three different payment structures: fixed gain, low gain or high gain with an equal probability revealed before or after the effort is made. The results show that framing has no effect on effort provision, except for a high gain context announced before making the effort.

Keywords: Common pool resources, demand response, framing, residential energy consumption, incentives, smart meters.

Résumé

Cette thèse examine comment répondent des consommateurs aux mécanismes visant à réduire leur consommation d'énergie. Ce besoin de réduction découle de la nécessité d'atteindre les objectifs de réduction d'émissions de gaz à effet de serre, d'augmenter la production d'énergie à partir d'énergie renouvelables et de réaliser des économies d'énergie. Ces objectifs exigent que la demande résidentielle soit plus flexible face à l'évolution de l'offre et que des économies d'énergie soient réalisées par les ménages. Le premier chapitre explore les barrières à l'acceptation et à l'adoption des compteurs intelligents et des incitations qu'ils peuvent fournir. D'importantes barrières existent et les réductions de consommation sont loin d'être réalisées. Le manque de motivation, l'incompréhension de l'information sur la consommation et la rigidité de la vie quotidienne sont les principales barrières qui limitent la réponse des ménages aux incitations fournies par les compteurs intelligents. Le deuxième chapitre analyse les résultats d'expériences de terrain et d'études pilotes portant sur les impacts des différentes incitations sur la consommation résidentielle. Les résultats montrent qu'il existe de grandes variations et qu'en moyenne, une incitation entraînera une réduction de 2% de la consommation d'énergie. Les incitations de *feedback* en temps réel ainsi que l'information monétaire ont le plus grand effet. Enfin, les études plus robustes font état d'effets de réduction plus faibles. Dans le troisième chapitre, un jeu expérimental de ressources communes est utilisé pour explorer les réponses individuelles aux incitations basées sur le prix et les *nudges*. Les individus sont encouragés à réduire leur consommation, soit par une augmentation de prix, soit par des *smiley* évoquant leur surconsommation. Le prix est le plus efficace pour encourager le niveau cible de consommation, mais il faut plus de temps pour qu'il fasse effet. Le *nudge* est compris rapidement mais tend à renforcer les comportements de surconsommation. Le quatrième chapitre examine l'effet du *framing* sur la disposition à l'effort. Les individus doivent accomplir une tâche simple et répétitive pour laquelle ils reçoivent un paiement à la pièce sous forme d'un gain ou d'une perte. Le *framing* sous forme de gains et de pertes est combiné à trois structures de paiement différentes : gain fixe, gain faible ou élevé avec une probabilité égale révélée avant ou après la réalisation de l'effort. Les résultats montrent que le *framing* n'a aucun effet sur la réalisation de l'effort, excepté pour un contexte de gain élevé annoncé avant de fournir l'effort.

Mots clés : Compteurs intelligents, consommation résidentielle d'énergie, framing, incitations, réponse à la demande, ressources communes.