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Information Feedback, Behaviour and 'Smart Meters'

Using behavioural economics to improve our knowledge about the potential effectiveness of Smart Meters to use electricity efficiently

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Acknowledgements

At the end of a road it seems proper to reflect back on the journey that brought you there. In a sense, this is the end of not only my graduate studies, but the end of my formal educational journey as such; a journey that began an August morning in a suburb to Copenhagen about 21 years ago and comes to an end with this thesis. It has taken me from math to languages, from Denmark to Canada, from Geography as a subject to geography as a reality, with friends and family located in different parts of the world. It would be impossible to thank all of the people who deserve credit for my being here. I therefore have to restrain myself to the people whom I can thank for making this last part of the journey all the more remarkable. For the last year or so, I have had my daily life at the International Institute for Industrial Environmental Economics at Lund University, and a warm thank you must go to all the students and staff at the place. Being able to discuss with and learn from all of you, and to be part of your lives, has been a privilege. Although it was challenging at times, there is strength and opportunities in bringing students from all over the world and from different academic and cultural backgrounds together to embark on a shared journey. Thanks guys!

For my thesis, I wanted to explore how insights from behavioural economics could be utilised in the energy business. Using behavioural insights is challenging in itself, and doing so in the energy and utility business, notoriously reluctant to share knowledge and information, is all the more difficult. Therefore, special thanks must go to those people who showed me a way into the business and gave me valuable information. Especially Christian von Scholten at NorthQ, who not only shares my passion for applying new forms of knowledge to the business, but also agreed to let me use a number of his products to test some of my ideas. Although the project encountered a number of difficulties, I am extremely grateful for your cooperativeness, openness, and generosity. Without your help, this project would have been even harder to conduct. I look forward to further exploring with you the ideas presented here. Thank you!

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Copenhagen, Summer 2014.

Simon Bager

Abstract

As part of the development of the European electricity grid, the EU has decided that 'Smart Meters' should be installed in 80% of the households of the EU by 2020. It is expected that this will lead to a reduction of energy use in the residential sector in the order of 10%. Driven by the so-called 'Information-Deficit' model, a critical assumption in this policy development is that provision of information, via 'Smart Meters', enables energy end-users to make more informed, and thus better, decisions in relation to their energy service demands (e.g. lighting). However, even if there is some evidence that feedback to consumers stimulate an efficient use of energy, the magnitude of this reduction is debated. In fact, findings from behavioural economics suggest that behavioural biases (e.g. loss aversion) and cognitive limitations restrict end-users from displaying purely rational behaviour, which in turn limits the effect (and policy expectations) of policies applying the information-deficit model. The thesis at hand addresses these issues explicitly and provides empirical analyses of how behavioural biases affects consumers' response to energy-related information. To that end, experimental research covering eight field exercises and a Smart Meter experiment was conducted. The thesis aimed to generate knowledge about the applicability and implications of using behavioural economics to deliver feedback to electricity consumers. With due limitations, the experiments illustrate that a knowledge-gap exists, and that information can help correct consumer behaviour, but that the framing and salience of this information can affect the magnitude of the response. The Smart Meter experiment on loss aversion took place in a real-life setting where consumers actually used and paid for the electricity. Results show that the intervention group reduced its electricity use, and that those reductions were larger than those found for the reference group (for both daily and standby consumption). Compared to related research, findings revealed that reductions in electricity use were also larger than the average electricity reduction found in other studies of feedback on electricity use. As a whole, it is concluded that feedback information can contribute to efficient electricity use and thus contribute to meeting EU policy targets. However, the (expected) effects depend on how feedback is designed, framed and presented. The Smart Meter experiment indicates an enhanced effect on electricity use reduction as a result loss aversion, but further research (e.g. large scale trials) is needed for more conclusive and statistically significant results.

Keywords: Feedback, Electricity, Smart Meter, Behavioural Economics, EU policy

Executive Summary

The amount of carbon dioxide (CO_2) and other greenhouse gases (GHG) in the atmosphere is increasing, which is leading to global climate change. The increasing levels of GHG are attributed largely to human activities, such as the consumption of fossil fuels. As the world's energy system still largely relies on the consumption of fossil fuels, a significant part of global anthropogenic GHG emissions stem from energy and electricity demand, a significant part of which arise from energy demand in buildings and residential areas. Emissions from this sector reached 9.18 gigatonne CO_2 equivalent ($GtCO_2e$) in 2010, equal to 19% of all global emissions, more than a third of which (3.5 $GtCO_2e$ in 2010) can be directly attributed to electricity use in residential buildings (IPCC, 2014). To mitigate climate change, the European Union (EU) and its Member States have introduced numerous policy efforts to reduce GHG emissions. Due to the significant energy demand from buildings and residential areas, reductions in this sector is expected to play a key role in meeting the EU policy targets of a 20% reduction in GHG emissions, a 20% share of renewable energy use, and a 20% increase in energy efficiency (EE) by 2020.

As part of their climate and energy policy portfolio, the EU has mandated the rollout of Smart Meters in all European households by 2020, where deemed economically a net-benefit as assessed by cost-benefit analysis (Directive 2009/72/EC). Smart Meters provide information on electricity use, which is expected to overcome the market failure generated by asymmetric information and other transaction costs on the part of the consumers. The EU expects the introduction of Smart Meters to result in a reduction in electricity use as a result of better information to consumers; a policy approach classified as an information-deficit model, which assumes rationality on the part of the consumer. This thesis argues that information alone will not necessarily be sufficient to induce changes to consumer behaviour, as certain cognitive and emotional factors preclude humans from displaying perfectly rational behaviour, as understood in neoclassical economics. Taking insights from behavioural economics as a starting point, this thesis argues that the way information is presented to households has an impact on how it is perceived and acted on.

Aim

The objective of the thesis at hand is to explore how theoretically and empirically grounded biases from behavioural economics work in a real-life setting, which can help determine the role of behavioural economics for increasing the effectiveness of Smart Meters. It is argued that there is a lack of knowledge on if and how findings from behavioural economics can inform the provision of feedback to consumers, and what the effects of this would be. By conducting a number of field-based preference-choice exercises and a Smart Meter experiment, and subsequently analysing data, an effort is made to determine what the effect is on electricity consumption of using different types of framing and biases in information provision and feedback. Using the installation of Smart Meters in Denmark as a case study, the aim of this thesis is to point at the importance of carefully considering how feedback on electricity is designed. In turn, the thesis aspires to contribute to improving energy efficiency policies, primarily in the EU, by informing policymakers of the need to look beyond the simple information-deficit model when designing policies.

The *research questions* that this thesis sets out to answer are:

- Which behavioural biases, as suggested by behavioural economics, are applicable when consumers are faced with energy-related decisions or provided with information on electricity consumption?

- Using insights from behavioural economics, what may be the expected energy efficiency improvements on electricity use as a result of Smart Meter deployment, particularly in the field of controlled customer feedback?
- To what extent can research findings support and be utilized in public policy design?

Methodology

Different methods of data collection and analysis were used to conduct this research. Data was collected across various sources to increase objectivity, and the collected material was analysed using both qualitative and quantitative methods. An extensive literature review of related or applicable research was also carried out. The choice exercises and experiments conducted aim to test the effect of a number of behavioural biases on consumer behaviour with regards to electricity use and energy-related decisions. The preference-choice exercises tested five specific biases; above-average bias, information overload, salience, loss aversion, and defaults, while the Smart Meter experiment focused on two of biases: salience and loss aversion. The knowledge generated from these experiments is used to determine which biases could be applicable, when providing consumers with information using Smart Meters.

The aspects analysed in this thesis departs heavily from behavioural economics. However, the research and findings are also framed and supported by different schools of economics, including neoclassical, institutional, and energy economics. From a methodological point of view, it is expected that the application and use of different disciplines facilitates more comprehensive insights on how the provision of information affect end-use behaviour with regards to energy and electricity use, and what implications this could have for related EU policy goals.

Main findings

The results shows that humans are prone to several behavioural biases when faced with decisions relating to energy and electricity use, which have implications for the way in which information is understood and acted upon.

It is found that consumer knowledge of electricity is low, confirming that a knowledge gap is likely to exist. It is also confirmed through conducting several preference choice exercises that making information salient can lead to behaviour change. In one exercise, information salience had a significant effect on purchase decision, which led to selecting goods that consumed on average 7% less electricity per year. The exercises also show that implicit discount rates are not static, but changes depending on framing and salience of information. Contrary to expectation, it was revealed that the incumbent plan had no effect on electricity plan selection, leading to speculation that Smart Meters can be used to increase the amount of consumers on variable tariff plans. The loss aversion choice exercise revealed that framing an EE decision as avoiding a loss rather than obtaining a gain increases the willingness to undertake an EE investment with an uncertain rate of return. As perceived riskiness possibly contribute to presence of the EE gap, understood as the slow diffusion of profitable EE technologies that fail to achieve market success, this indicates that changing the frame in these decisions can help narrow this gap.

The choice exercises were carried out in an artificial real-life setting, as participants' decisions had no influence on their real-life situation, meaning that the external validity of the results is fairly low. However, the exercises could easily be tested in real-life settings, where decisions had consequences, and the tentative indication of an effect calls for further testing.

Analysing consumption data from a number of Smart Meters installed in the greater Copenhagen region revealed that the average effect of installing a Smart Meter was a reduction in consumption of 6.6%. In the loss aversion experiment conducted, the group not subjected to loss aversion (reference group) reduced their daily electricity consumption with 7% on average, while those subjected to loss aversion (intervention group) reduced their consumption by 18%. The reduction in standby consumption was 3% for the reference group, but 25% for the intervention group. Reviewing literature on the effect of feedback indicate that providing feedback results in electricity reductions of 1-13%, though effects were found to be heterogeneous, and further research is needed to determine the effect of feedback.

The Smart Meter experiment on loss aversion took place in a real-life setting where consumers actually used and paid for their electricity. This means that the results have a high external and ecological validity, as the experiment took place in the home of the participants, indicating that this effect is likely to be found even if implemented in real life. The very specific context makes replicating the experiment difficult (low internal validity), which means that the effect found in this case cannot be assumed to be of the same magnitude once scaled to a population. If previous large-scale feedback trials are any indication, effects in a population of applying loss aversion feedback is assumed to be in the order of 4-6%. In any case, the clear indication of an effect in both instances (daily and standby consumption), and the likelihood of replication in real-life situations, calls for large-scale trials to further test this.

Conclusions and recommendations

It is concluded that a knowledge-gap exists, and that information can help correct consumer behaviour. However, the framing and salience of this information can affect the response of end-users and the resulting order of magnitude of efficiency improvements. The work conducted as part of this thesis confirms that behavioural biases exist when end-users are faced with electricity and energy-related decisions. In turn, these biases are likely to affect the decisions made by end-users. The experiments indicate that at least two of these biases; salience and loss aversion, can be utilised when providing feedback to consumers using Smart Meters, and that this is likely to increase the effectiveness of said feedback.

With due limitations, the thesis provides evidence that Smart Meters can lead to reduced electricity use, at least in the short to medium term, but that these meters alone are unlikely to lead to the sustained behaviour change required to meet EU policy goals. However, the results indicate that the right combination of behavioural insights, informative policy instruments and Smart Meter technologies can lead to significant reductions in energy use, which can help close the EE gap and potentially achieve or even surpass the EU policy target. These policy developments also need to take into account a much larger mix of policies, including market-based incentives and regulatory aspects.

The research has implications for policy makers, academia as well as industry. To policy-makers, because it highlights that information is not just about quantity, but that a policy prescribing the delivery of information to consumers need to take into account how the information is designed, framed, and presented. To academics, because it highlights that our knowledge on the effect of information on human (economic) behaviour with regards to energy consumption is incomplete, and that findings from behavioural economics can possibly contribute to filling this knowledge gap. Finally, the research is important to utility companies and others working with electricity end-users, as it demonstrates that behavioural insights can likely be employed to change consumer behaviour, e.g. inducing customers to save electricity overall and at peak hours, or increase the uptake of EE measures.

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Abbreviations

BE Behavioural Economics

BIT United Kingdom Behavioural Insights Team

CBA Cost-Benefit Analysis

CFL Compact Fluorescent Light bulb

CO_2 Carbon Dioxide

CO_2e Carbon Dioxide Equivalent

DSM Demand Side Management

DSO Distribution System Operator

DG Directorate General

DK Denmark

DKK Danish Kroner

EC European Commission

EE Energy Efficiency

EU European Union

GHG Greenhouse Gas

ICT Information and Communication Technologies

IEA International Energy Agency

IPCC Intergovernmental Panel on Climate Change

IHD In-Home Display

JRC European Union Joint Research Centre

kWh kilowatt-hour

MS European Union Member States

NPV Net Present Value

Q1 Questionnaire #1

Q2 Questionnaire #2

RQ Research Question

SM Smart Meter

TC Transaction Cost

WTA Willingness-to-Accept

WTP Willingness-to-Pay

1 Introduction

This chapter introduces the reader to the background for conducting this thesis, defines the research problem and outlines a relevant research gap worth exploring. The objectives of this thesis are presented along with the research questions that this thesis set out to answer, before the scope and delimitations are provided. Finally, a number of ethical considerations in relation to this thesis are outlined, before the audience to whom this work is relevant is presented. The chapter ends with a disposition that outlines the rest of this thesis.

1.1 Background

1.1.1 Climate change and energy use

Unsustainable patterns of production and consumption of energy has led to increasing emissions of carbon dioxide (CO_2) and other greenhouse gases (GHG), as well as other air pollutants, such as NOx, SOx and soot (IPCC, 2013). Since the advent of the industrial revolution around 1750, when energy consumption began rapidly increasing, the atmospheric concentrations of GHG in the atmosphere have increased (IPCC, 2013). The radiative forcing of the gases has led to an uptake of energy by the climate system, which along with feedback loops and the storage of energy by the climate system, influences the rate and magnitude of global climate change (IPCC, 2014). Critically summarising and analysing existing research conducted by the scientific community, the Intergovernmental Panel on Climate Change (IPCC), has concluded that the warming is "unequivocal" (IPCC, 2013), and that human activity, especially the burning of fossil fuels, is the main driver of these changes. Such increases in temperature are likely to have environmentally detrimental consequences such as sea level rise, flooding, ecosystem degradation, and land use change, as well as lead to loss of human lives due to an increase in frequency and severity of natural disasters, such as hurricanes and floods (IPCC, 2013). The risk of such disastrous events unfolding have led to a decision among the governments of the various states to work towards keeping the temperature rise in global average temperatures below 2°C compared to pre-industrial levels to avoid 'dangerous climate change' (Hansen et al., 2013). However, due to economic growth and increasing demand for many goods, annual GHG emissions keep rising, and grew on average by 1.0 gigatonne carbon dioxide equivalent ($GtCO_2e$) (2.2 %) per year from 2000 to 2010, faster than in any of the last three decades of the 20th century, where emissions grew on average 0.4 $GtCO_2e$ (1.3 %) per year (IPCC, 2014). Projections show that without additional effort, current emission patterns will result in global mean surface temperature increases in 2100 from 3.7-4.8 °C, well above the 'dangerous' threshold.

Energy demand from buildings and residential areas contribute a large part of the total demand for energy and electricity, and thus a significant part of global anthropogenic GHG emissions. In 2010, buildings accounted for 32% of global final energy consumption and 51% of global electricity consumption (IPCC, 2014), and in the European Union (EU), direct energy use in households accounted for 26.2% of energy use in 2012 (Eurostat, 2014). GHG emissions from the building sector reached 9.18 $GtCO_2e$ in 2010, equal to 19% of all global emissions (IPCC, 2014), and more than a third of this (3.5 $GtCO_2e$ in 2010) can be directly attributed to electricity use in residential buildings (IPCC, 2014). Between 1990 and 2005, final electricity consumption in the EU increased by 1.7 % a year on average, and The International Energy Agency (IEA) (2010) projects electricity demand to grow more strongly than any other final form of energy. The IPCC expects electricity consumption to grow between 110 and 260% to 2050 (Barker et al., 2007, p. 48), driven by economic growth and technological changes, such as the advent of electric cars (Verbong et al., 2013).

1.1.2 Climate change mitigation and energy efficiency policy

To mitigate climate change, the EU and its Member States have introduced numerous policy efforts to reduce GHG emissions – with the residential sector and increased energy efficiency playing a key role. In the EU, binding targets for a 20% reduction in GHG emissions, a 20% share of renewable energy use, and a 20% increase in energy efficiency[1] (EE) by 2020, has been implement as part of the 2009 climate action and renewable energy package (Directive 2009/72/EC)[2]. If the targets are met, the expenditure on energy could be reduced by more than EUR 100 billion annually by 2020, while avoiding the emissions of ~0.78 $GtCO_2e$ per year (DG Energy, 2007).

Within the energy efficiency context, large cost-effective savings potentials have been estimated for the EU residential sector, partly due to its large share of total energy consumption (DG Energy, 2007). Reducing GHG emissions in the residential sector through energy efficiency improvements can be done in basically two ways: 1) by reducing use of energy through energy conservation, i.e. curtailing the use of products and service, such as switching off appliances, and 2) by increasing EE, i.e. decreasing the energy use needed to meet energy service demands and/or deliver goods and services consumed by households (Abrahamse et al., 2005)[3]. Wall and roof insulation, along with a switch from incandescent to LED light bulbs and greater appliance efficiency, offer large potentials to save energy (DG Energy, 2007; McKinsey & Co., 2010). The full energy savings potential towards 2020 is estimated to be around 27% of total energy use by the sector. If this can be achieved, the EU's total energy consumption would be reduced by ~11% (DG Energy, 2007).

The high energy-use, and large potentials for energy efficiency gains and reduction of consumption, makes the household sector an important target for policies aiming to reduce GHG emissions (e.g. Benders et al., 2006; Dietz et al., 2009; Vandenberg et al., 2010, Attari et al., 2011). Reductions in GHG emissions and increases in EE by the household sector are expected to be key factors in determining whether or not the EU meets its policy targets. The EU considers EE to be one of the most cost-effective ways of reducing GHG emissions (EC, 2011a, p. 2) relative to other abatement opportunities, such as increased penetration of renewable energy or retrofitting older power plants (McKinsey & Co., 2010)[4].

To tap these EE potentials in the most cost-effective way, the EU and its Member States have deployed a great variety of specific policy instruments[5], including regulatory instruments,

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[1] Energy efficiency (EE) is defined by the EU as "the ratio of output of performance, service, goods or energy to the input of energy" (EC Directive 2012/27/EU article 2(4)). As such, increasing energy efficiency means getting the same service or performance (e.g. heating, cooling) or good while using less energy. However, there are various degrees of EE for any good or service; that which is theoretically possible (i.e. limited only by physics); that which is technically possible (given only technological constraints); that which is cost-effective in a market setting, and finally; that which is actually achieved (Mundaca, 2008).

[2] Negotiations towards the updated targets for 2030 are on-going, with new preliminary targets of a 40% reduction in GHG emissions and a 27% share of renewable energy consumption, while no specific target has been set for EE at this point (European Council, 2014).

[3] Studies reviewed in this paper were aimed at both efficiency and/or curtailment behaviors, with the latter somewhat overrepresented. This is striking, because the energy-saving potential of efficiency behaviors is considered greater than that of curtailment behaviors (see e.g. Gardner & Stern, 2008).

[4] Murphy and Jaccard (2011) question this assumption and finds that EE policies show "a more modest potential to reduce GHG emissions at a given marginal cost", and a smaller contribution "relative to other abatement opportunities" (p. 7146). Without going into much detail on this discussion, this thesis takes the position that while EE measures are important, they should not be seen as a panacea for climate change mitigation.

[5] Policy instruments can be understood as the operational forms of interventions by which public authorities seek to change behaviour and achieve the policy objectives set out (Bemelmans-Videc et al., 1998). In literature, two ways of chategorising policy instruments can be identified (Mundaca, 2008). The common definition, as given by Vedung (1998, p. 30) are: (i)

market-based instruments (MBI), and voluntary standards (VS) or informative policy instruments (Carter, 2007; Mundaca, 2008; Stavins, 2001), with the objective of addressing the unsustainable consumption of energy in the residential sector. Regulatory instruments, sometimes labelled 'command-and-control,' are the most widely used policy instruments in environmental policy, and imply setting standards, such as ambient, emission or design standards, in order to control the release of pollutants entering the environment (Carter, 2007). Critique of this approach has led to a greater use of MBIs, the aim of which is to prevent market failure by internalising the external costs of pollution (Carter, 2007). MBIs include environmental taxes, such as effluent charges, deposit-refund schemes, and tradable permits (Stavins, 2001), such as the EU Emissions Trading Scheme (Carter, 2007)[6]. VS aim to encourage actions to protect the environment by individuals or organisations, but these "are neither required by law nor encouraged by financial incentive" (Carter, 2007, p. 329), unlike the first two instruments. In the context of residential energy use, typical examples are information campaigns, e.g. providing information on the (environmental and/or financial) benefits of energy saving; awareness-raising activities, such as alerting citizens to the impact of climate change; or eco-labelling, where consumers are informed of the energy use of a given product (Carter, 2007).

Information generally has public-good attributes and tends to be underprovided by the market (Jaffe & Stavins, 1994a), meaning that individuals bear the cost (temporal, cognitive, and/or monetary) of obtaining the information. This means that consumers lack information or face asymmetric information, which, in the context of energy use, leads to lower uptake of EE measures and less energy reduction than predicted by economic theory; a market failure. The rationale behind informative policy instruments is to correct this market failure by providing information, effectively reducing the transaction costs and uncertainties inherent to many energy-related decisions (Mundaca, 2008; Mundaca et al., 2013). The theoretical assumption is that this information asymmetry is preventing consumers from exercising rational choice and maximising their personal utility (Micklitz et al., 2011) by undertaking these EE measures.

Historically, European consumers have inferred knowledge about their electricity demand through billing estimates and infrequent meter readings, which display the consumption in kilowatt-hours (kWh) as a cumulative total. This means that consumers have not had information on the impact of their energy-related actions, as the total figure obscures the impact of various daily energy use habits (van Elburg, 2009).

1.1.3 'Smart Meters' and European Union energy policy

In order to strengthen the mix of the informative policy instruments and address the lack of information that users have about their electricity use, the rollout of electronic electricity meters, so-called Smart Meters, is essential (Giordano et al., 2011; Christensen et al., 2013a). The deployment of Smart Meters is critical to the development of Smart Grids[7], as the meters

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regulatory measures (e.g. mandating use of certain technologies), (ii) economic instruments (e.g. subsidies for energy-efficient goods), or (iii) informative instruments (e.g. energy-use labels). The approach more common in environmental policy-making literature includes a distinction between regulatory instruments, market-based instruments (MBI), and voluntary standards (VS) (Carter, 2007; Mundaca, 2008; Stavins, 2001).

[6] However, it should be noted that Stavins (2001, p. 3) classifies MBIs as belonging to one of four major categories: pollution charges; tradable permits; market friction reductions; and government subsidy reductions.

[7] To stave off impending challenges to the electricity grid, such as increasing fluctuations to the supply caused by renewables with intermittent production capacity (Christensen et al., 2013a), and increasing demand due to the electricification of society (e.g. electric vehicles) (Verbong et al., 2013), the EU is in the process of developing a smart electricity grid. Even though there is some agreement as to what constitute a smart grid (Christensen et al., 2013a), the term, owing to its novelty, is rather vaguely defined and the terminology is still developing[7] (Darby, 2010). It conveys a future scenario where

provide the technological prerequisite for communication between end-users and suppliers (Christensen et al., 2013a). Smart Meter functionalities vary from model to model, but generally include measuring and displaying electricity consumption in quantity (kWh) and over time and the cost of this, communication capabilities, storage and transfer of data, supporting dynamic tariffing and payment systems, communication with and remote disablement and enablement of electricity and individual devices within the home, and information transfer to a display or other equipment, such as a smart phone or tablet (after Owen & Ward, 2006; Hoenkamp et al., 2011)[8].

In the EU, the development accelerated when the Energy Services Directive (ESD) (Directive 2006/32/EC) required energy suppliers to provide consumers with competitively priced, accurate, individual meters that provide information on time-of-use (art. 13, sub1) and accurate billing based on actual consumption (art. 13, sub 2), prompting the first installation of Smart Meters in some EU countries. The Third Energy Package (Directive 2009/72/EC) created common rules for an internal market in electricity and laid the groundwork for an efficiently managed electricity network. The directive encouraged smart grids and prescribed that EU Member States (MS) should replace at least 80% of traditional electricity meters with Smart Meters by 2020[9], where this was deemed a net benefit as assessed through cost-benefit analysis (CBA) (applying neoclassical economic analysis), a goal which was reiterated in the updated EE Directive (2012/27/EU). MS were free to decide on their own implementation strategies (DG IPOL, 2012), which, consequently, have led to MS taking different routes in terms of timing and technology regulations (Schleich et al., 2013). A 50% rollout target is set for 2015 (Covrig et al., 2014) (Figure 1-1).

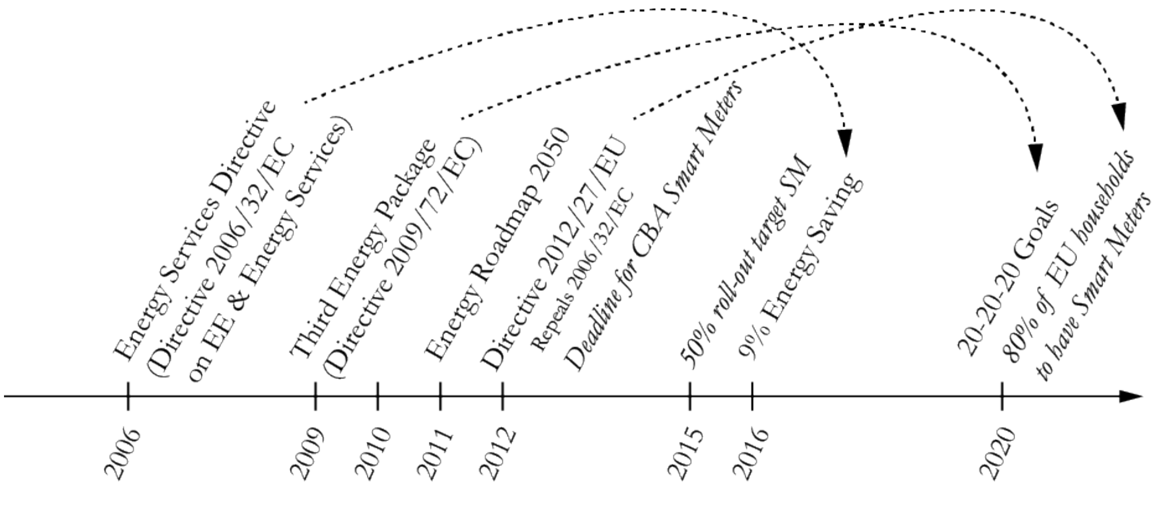

Figure 1-1 – EU policies relevant to the Smart Meter deployment (Author, partly after Flath et al., 2012).

The EU envisions several benefits to result from the introduction of Smart Meters, which, by and large, include reduced operating costs, improved functioning of market mechanisms,

the main energy providers, i.e. the central power plants and the network of decentralised power generation, e.g. wind and solar, communicate with end-users to balance supply and demand.

8 Using Darby's (2010) words, Smart Meters are primarily 'non-dumb', i.e. they communicate electronically. As such, it is "not always necessary to replace a meter in order to achieve smartness: a 'dumb' meter can be 'smarted' by retrofitting it with communications capability" (p. 445). It is important to add that electronic consumption displays (also known as "In-home Displays" (IHD) and widely used in the UK), are not Smart Meters, but merely add-ons to Smart Meters, although they are often referred to as such (Darby, 2010).

9 Directive 2009/72/EC (Annex I): "Where roll-out of Smart Meters is assessed positively, at least 80 % of consumers shall be equipped with intelligent metering systems by 2020."

increased security of supply, and expected energy savings (DG IPOL, 2012). At the grid level, they can help generate GHG emissions reductions and improve supply management, leading to fewer blackouts. To the utility, they are intended to reduce transmission costs and improve customer relations, among other things. At the user level, the meters can generate better and more frequent feedback to households, which should lead to demand reductions and cost savings, and induce consumers to shift the time of consumption to fit generation capacity (Christensen et al., 2013b; Darby, 2010; Martiskainen & Coburn, 2011; Verbong et al., 2013, Covrig et al., 2014). Hoenkamp et al. (2011) identifies five interested parties in the Smart Meter roll out case: the metering industry, the DSOs, the electricity suppliers, the EU, and the electricity consumers (the public).

However, and despite numerous policy expectations and arguments, at present, only Sweden, Finland and Italy have implemented rollout of Smart Meters on a larger scale. A total of 16 MS will proceed with large-scale rollout of Smart Meters by 2020 or earlier, three MS have opted for selective rollouts to some customers, and four MS had negative or inconclusive CBAs leading to no plan for a rollout (EC, 2014)[10] (Figure 1-2). Based on these assessments, MS have committed to rolling out close to 200 million Smart Meters, and it is expected that almost 72% of European consumers will have a Smart Meter for electricity by 2020 at a total investment cost of €35 billion (Covrig et al., 2014). The average cost of installing a Smart Meter is assumed to be €223±€143, while the expected average benefit per metering point is €309±€170 (Covrig et al., 2014; EC, 2014). The lifetime of the meter ranges from 8 to 20 years with an average of 15±4 years (EC, 2014, p. 5).

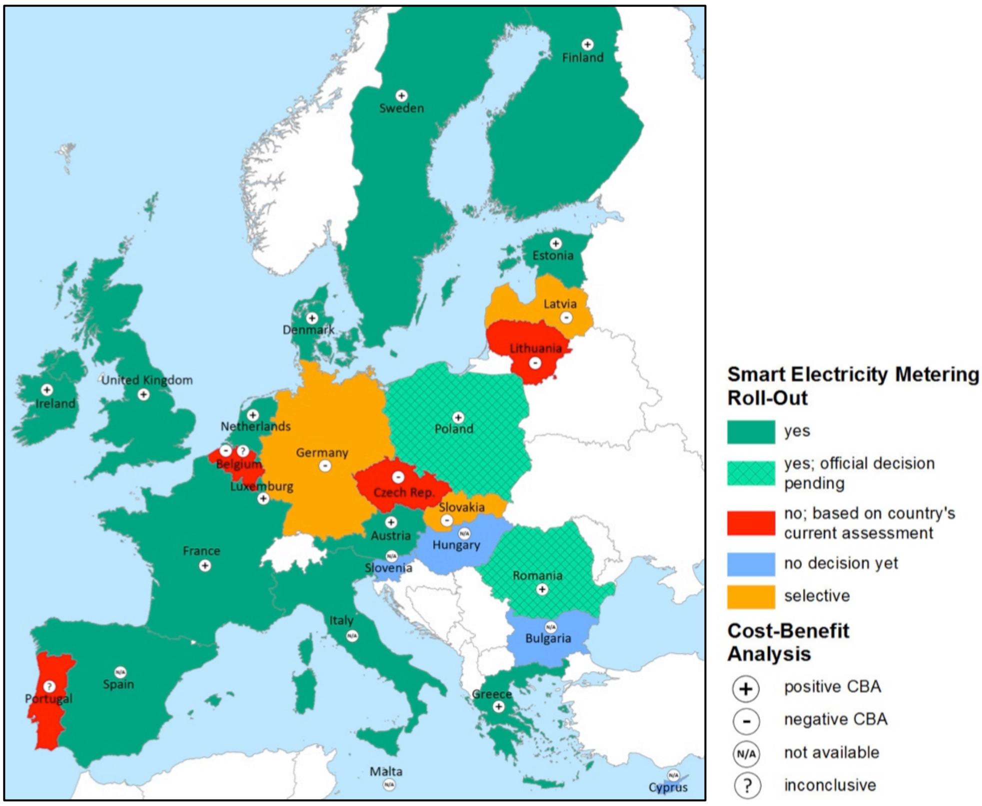

Figure 1-2 – Smart Meter rollout in the European Union (Author, after Covrig et al., 2014).

[10] Full roll-out by 2020: Austria, Denmark, Estonia, Finland, France, Greece, Ireland, Italy, Luxemburg, Malta, Netherlands, Poland, Romania, Spain, Sweden and the UK. Particular groups: Germany, Latvia and Slovakia. No meters: Belgium, the Czech Republic, Lithuania, and Portugal. Finally, four Member States (Bulgaria, Cyprus, Hungary and Slovenia) had not conducted a CBA when JRC evaluated the national proposals (July 2013) (Covrig et al, 2014, p. 13).

The European Commission and most EU Member States find that the perceived overall benefits to society of installing Smart Meters exceed the costs (Giordano et al., 2011), but as neither consumers nor suppliers are able to capture all these benefits (Owen & Ward, 2006), regulatory intervention has been needed to ensure the rollout of Smart Meters. In fact, some critical voices (e.g. Klopfert & Wallenborn, 2011; Ernst & Young, 2013) question whether the rollout will be an overall benefit to society, and argue that especially customers might not be able to capture all of the benefits envisioned. The EU have identified six distinct consumer benefits from the installation of Smart Meters (Borchardt, 2014): (i) Generate energy savings by helping consumers to reduce their consumption; (ii) Increasing energy efficiency by helping consumers master their consumption and realise potentials for energy efficiency; (iii) Provide innovative services by enabling customers to obtain innovative smart home and home automation services; (iv) Fostering consumer empowerment by improving competition in retail markets, (v) Protecting the environment, as less energy consumption and higher energy efficiency lead to lower GHG emissions; and (vi) Increased distribution system efficiency and lower distribution costs. Hoenkamp et al. (2011), in line with most research on the subject (see e.g. Joachain & Klopfert, 2013) argue that reductions in energy consumption is the main consumer benefit expected to arise from the rollout of Smart Meters, though it can be argued that accurate billing is also an important feature (e.g. this was the main rationale behind the rollout in Sweden) (Jennings, 2013).

The core assumption is that providing feedback to customers will lead to more efficient electricity use and reduce overall demand through improved energy management (e.g. during peak loads). That information should lead to change can be viewed as an 'information-deficit' model, where the theoretical assumption is that more information leads to increased awareness and knowledge, which leads to changes in energy-use behaviour and a resulting efficient use of energy. An example of such a model can be found in several studies (e.g. Wilhite & Ling, 1995; Matsukawa, 2004; Abrahamse et al., 2005). Much European consumer policy, including the energy and environmental fields, is based on the information-deficit model and the assumption of the rational consumer (Micklitz et al., 2011; Gowdy, 2008): Verbong et al. (2013) conducted 37 interviews with known expert in the energy sector and found that the dominant perspective among the experts was to describe the individual as 'homo economicus'[11] (Verbong et al., 2013, p. 121).

The Smart Meter policies implemented by the EU in recent years generally follow the same line of thought. The central assumption behind the mandatory disclosure of information is that provision of information enables consumers to regulate their demand[12]. The implicit assumption is that it is only asymmetric or lack of information that prevents people from making rational choices, and that if the right combination of regulations and economic policies are supported by informative policies delivering precise information to customers, their behaviour will change accordingly. Reviewing the current EU legislation (Directives

[11] Homo economicus is understood to be an entity which acts rationally according to self-interest in order maximise personal utility (Frank, 1997; Camerer, 1999).

[12] This was first mentioned in the preamble to ESD (Directive 2006/32/EC): "In order to enable final consumers to make better-informed decisions as regards their individual energy consumption, they should be provided with a reasonable amount of information thereon," (sub 29). Article 13 (sub 2) went further and stated that: "Billing on the basis of actual consumption shall be performed frequently enough to enable customers to regulate their own energy consumption," which was deemed to be one month. The updated energy efficiency directive (2012/27/EU), which repealed the ESD, went further and prescribed that information on historical consumption shall include cumulative data for three years, as well as time of use for any day, week, month and year for the last 24 months (art. 10, sub 2 a, b). The directive stated that the provisions given in the ESD had not "led to customers receiving up-to-date information about their energy consumption, or billing based on actual consumption at a frequency which studies show is needed to enable customers to regulate their energy use" (Directive 2012/27/EU, preamble, sub 32), though no clear indication was given as to what studies that showed exactly what frequency was the optimal.

2006/32/EC, 2009/72/EC, 2012/27/EU), reports (e.g. Giordano et al., 2011; Covrig et al., 2014) and communications (EC, 2011a), it becomes clear that improving feedback via Smart Meters is a key policy means towards meeting the 20-20-20 targets, under the expectation that regulation on the frequency and timing of feedback will raise consumer awareness, improve knowledge, change behaviour, and help overcome any information-related market barriers in order to reduce energy consumption: "…being able to follow their actual electricity consumption in real time gives consumers strong incentives to save energy and money" (EC, 2011b). The EU estimates that Smart Meters should reduce "annual household energy consumption by 10%" (EC, 2011b) as a result of feedback on consumption[13]. This assumption is also present in national CBA assessments of the Smart Meter rollout (Giordano et al., 2011). In their analysis of the CBA's conducted by MS, the EU Joint Research Centre (Covrig et al., 2014) found that "most of the EU Member States addressed the energy savings, in terms of electricity consumption, as one of the main benefits associated with Smart Metering deployment."

1.2 Problem definition

The popularity of the information-deficit model in both academic and policy circles is due to the simple policy recommendation: correct market and behavioural failures by providing consumers with better or more (technical) information, e.g. through Smart Meters. Despite its popularity in policy circles, the information-deficit model has been widely criticised in the academic literature, both on epistemic grounds (e.g. what is "the fact"?) (Owens & Driffill, 2008), and by researchers emphasising that the policy builds on an understanding of the consumer as a rational being, perfectly able to act on the information provided. Findings from other academic areas, such as psychology (e.g. Bell et al., 1996; Stern, 2000a; b; 2011; Gifford, 2011) and sociology (e.g. Bourdieu, 1977; Hargreaves, 2011), suggest that matters are more complicated than correcting market and behavioural failures through the provision of information. The authors have highlighted the importance of aspects such as values, beliefs, and attitudes, as well as the impact of social norms shared by distinct groups of people.

As the expectation of household reduction of electricity consumption features prominently in the EU policy on Smart Meter deployment in Member States, whether this reduction materialises is of importance. To this end, studies focusing on how the provision of feedback by Smart Meters can potentially lead to reductions in electricity consumption or changes in energy-related investment decisions that could, in turn, lower energy consumption, are an important strand of current research (Joachain & Klopfert, 2013). Until recently, little was known about the effects of providing feedback[14] on energy behaviour using Smart Meters, but

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[13] The expectation that provision of information will lead to reduced consumption is pervasive in EU writings on the subject. They feature in reports by the Joint Research Centre (Covrig et al., 2014, p. 96): "Effective deployment and use of the Smart Metering systems will add additional value to the consumers and society in general, leading to reduced amount of CO_2 emissions. This can be achieved as a result of energy savings and more efficient use of electric energy and higher electricity network operational efficiency. Smart Metering systems also help […] make the consumers aware of the CO_2 associated to the electricity they consume"); in communications from Directorate Generals (DG): "With Smart Meters, consumers will benefit from enhanced knowledge of their energy consumption. Moreover, given the right conditions in place, it is expected that a number of improved customer services will allow individual households to make energy savings and financial savings" (DG IPOL, 2012, p. 8). Smart Meters "will provide consumers with the incentive to shift and possibly also cut their consumption" (DG IPOL, 2012, p. 55); and on EU websites: "Following energy consumption in real time allow consumers to control their energy bills better" (DG Energy, 2014).

[14] Providing feedback can be defined as "actions taken by (an) external agent(s) to provide information regarding some aspect(s) of one's task performance" (after Kluger & DeNisi, 1996, p. 255). From a psychological point of view, "feedback is effective when it activates a discrepancy between behaviour and normative beliefs" (Schultz, 1998, p. 33). The discrepancy can be eliminated by raising performance to the desired level, adjusting the normative belief, or rejecting the feedback message (Schultz 1998 after Kluger & DeNisi, 1996), suggesting that feedback will not necessarily lead to "improved" behaviour.

trials in the UK and Netherlands (Kinzig, 2014; AECOM, 2011), as well as newer academic studies (Drozdowski & Vandamme, 2013; Gans et al., 2013; Grønhøj & Thøgersen, 2011; Pyrko, 2011; Schleich et al., 2013) are making up for this lack of research. Kluger and DeNisi (1996) argue that feedback researchers have mostly disregarded the research that suggests that the effect of feedback on performance is "variable", which has led to a widely shared assumption that feedback consistently improves performance. They argue instead that feedback "have highly variable effects on performance, such that in some conditions [feedback] improve performance, in other conditions [it has] no apparent effects on performance, and in yet others [it] debilitate performance." Over the years, several electricity feedback studies have been conducted using various means of communication (summary studies include Abrahamse et al., 2005; Darby, 2006; Fischer, 2008; Faruqui, 2010b). Many of these studies have been based on rational choice theories with the implicit notion that information about energy consumption and its cost will raise awareness and thereby induce behaviour change (this problem is noted by e.g. Hargreaves et al., 2010 and Martiskainen & Coburn, 2011).

Modern research on human behaviour in response to energy use information is generally grounded in two main shifts away from the information-deficit model and the understanding of the consumer as a fully rational agent: *a practice theoretical approach*[15] focusing on the power of social norms and practices (Hargreaves, 2010; 2011; Gram-Hanssen, 2013) and *a behavioural economics approach* proposing the limited rationality of humans and the influence of automatic judgments as explanations of why humans do not make energy-saving decisions to the degree predicted by neoclassical economic theory (Baddeley, 2011; Newell & Siikamäki, 2013; Gilbert & Zivin, 2014; Kallbekken et al., 2013). BE relies on empirical studies to infer the actual behaviour of individuals, rather than derive axiomatic assumptions from theory. The central tenant of behavioural economics (BE) is that cognitive, emotional and social factors influences how information is understood and limits the possibility to display purely rational behaviour, which affect human (economic) decision-making (Kolstad et al., 2014)[16].

[15] In *practice theory*, the focus is not on the behaviour of the individual human being, but rather on the social and societal organization of practices that humans engage in; how they form, reproduce, are maintained, stabilized, challenged or discontinued (Hargreaves, 2011). The theory draws heavily on Pierre Bourdieu's concept of habitus (Bourdieu, 1977), i.e. the values, norms and behaviour of a given social group that is obtained through the activities and experiences performed by the social group as part of daily life (Scott & Marshall, 2009). Practices are to be understood as the "broad cultural entities that shape individuals' perceptions, interpretations and actions within the world" (Hargreaves, 2011, p. 79). In this way, practice theory opposes the understanding of human action as a consequence of rational and informed choices (Christensen et al., 2013b, p. 2287), leaving little space for the rational individual found in neoclassic economic theory. From a practice theoretical approach, humans do not "consume electricity as such, but rather perform practices through which electricity is consumed" (Christensen et al., 2013a, p. 336), and the theory thus takes a fundamentally sociological view of behaviour as shaped by society.

[16] BE has its origins in the relationship between (social) psychology and economics (Etzioni, 2011), and generally, can be said to be the study of the interaction between cognitive psychology and economics, focusing on individual decision-making, or, to use "psychology to inform economics, while maintaining the emphases on mathematical structure and explanation of field data that distinguish economics from other social sciences" (Camerer, 1999), but it is not straightforward to define, and no one single definition exist. The Palgrave Dictionary of Economics (Simon, 1987) defines BE thus: "Behavioural economics is concerned with the empirical validity of these neoclassical assumptions about human behaviour and, where they prove invalid, with discovering the empirical laws that describe behaviour correctly and as accurately as possible. As a second item on its agenda, behavioural economics is concerned with drawing out the implications, for the operation of the economic system and its institutions and for the public policy, of departures of actual behaviour from the neoclassical assumptions. A third item on its agenda is to supply empirical evidence about the shape and content of the utility function (or of whatever construct will replace it in a empirically valid behavioural theory) so as to strengthen the predictions that can be made about human economic behaviour. Thus, behavioural economics is best characterized not as a single specific theory but as a commitment to empirical testing of the neoclassical assumptions of human behaviour and to modifying economic theory on the basis of what is found in the testing process" (Simon, 1987). Lunn (2014, p. 20) goes further and argues that BE can be defined as "the application of the inductive scientific method to the study of economic activity."

Taking insights from BE as a starting point, it is argued that the way information is presented to households has an impact on how the data is perceived and acted on. Research on BE argues that the (social) context in which information is presented, understood as the choice architecture, along with heuristics (rules-of-thumb), biases and salience influence how humans respond to information and make decisions (Sunstein, 2013; Kahneman, 2011). As such, while consumers facing energy-related decisions often lack information or face a cost to obtain it, they more importantly lack expertise in and mental capacity to translate this information into appropriate action (Sanstad & Howarth, 1994; Kahneman, 2003). The reduction in electricity use that is expected to materialise as a result of feedback from Smart Meters, will likely have limited effect if the right type of information and feedback mechanisms does not accompany the rollout. There needs to be an understanding of how consumers behave with regards to electricity decisions to provide this information in a way that has the largest impact. In that light, the introduction of Smart Meters and the opportunities for provision of detailed feedback about energy consumption is interesting (Steg, 2008).

However, there is a lack of knowledge on if and how findings from behavioural economics can inform the provision of feedback to consumers. In a stakeholder interview process, Martiskainen and Coburn (2011, p. 216) found that most agreed that it "is not yet clear *what* information should be displayed to consumers, *how* it should be displayed, and where the display device should be situated to encourage the greatest change in behaviours" (my italics). Because Smart Meter technology allows feedback to be tailored, modified, or in other ways adapted to the individual or household, knowing how to tailor feedback could increase the effect of the meters, helping to meet EU policy goals. The contention in this thesis is not that information provision does not work, but rather that due to inherent behavioural biases, it is not the merely the presence of information (the quantity), but also the quality, form, framing, and presentation of this information that affects how human behaviour with regards to energy and electricity changes as a result of this information.

1.3 Objective and Research question

Historically, research in BE has consisted of two components: (i) Identifying ways in which human behaviour differs from the neoclassical model, and (ii) demonstrating the implications of this behaviour in an economic context (Mullainathan & Thaler, 2000). Recently, BE has come into fashion in both academic (e.g. Epstein, 2006; Gowdy, 2008; Bubb & Pildes, 2013; Amir & Lobel, 2008) and policy-making circles, especially in the US (e.g. Sunstein, 2013) and the UK (UK BIT, 2011, 2012), and some supranational organisations have even embraced the concept (e.g. Lissowska, 2011; van Bavel et al., 2013; Centre d'analyse stratégique, 2011)[17]. BE has gained ground due to mounting evidence that ideas rooted in neoclassical economics are insufficient in describing human economic behaviour as observed in real-life settings in a number of different fields (e.g. Danziger et al., 2011; Hanks et al., 2012; Shogren et al., 2010).

Based on insights from experimental and behavioural economics (e.g. Kahneman, 2003; Kahneman & Tversky, 1979; 1984; Samuelson & Zeckhauser, 1988; Tversky & Kahneman, 1974; 1992; Camerer, 1999), and acknowledging the critique of the information-deficit model, as suggested by other academic fields (e.g. Owens & Driffill, 2008; Stern, 2000; Hargreaves, 2011), this thesis takes the starting point that there is a need to think beyond the assumption that correcting a market failure through information provision *per se* can change consumer behaviour and lead to efficient use of electricity. In that regard, the installation of Smart

[17] The recent surge in behaviourally informed policy (Galley et al., 2013; UK Cabinet Office, 2010) is interesting, all the more that research in these areas have been on-going since the mid-20th century (e.g. Simon, 1959; 1982; Kahneman & Tversky, 1979; Tversky & Kahneman, 1974), and can perhaps even be traced to Vilfredo Pareto reformulation of choice theory at the beginning of the 20th century (Bruni & Sugden, 2007).

Meters offers an interesting research opportunity to better understand the role of BE to support energy efficiency policies and on-going efforts to reduce GHG emissions.

The objective of this thesis is to explore how theoretically grounded interventions from BE work in a real-life setting. Taking a starting point in the current knowledge on human behaviour as understood by BE, it is studied whether known biases, such as *default setting*, *above-average bias*, *information overload*, *salience*, and *loss aversion*, affect behaviour, when consumers are provided with information on electricity consumption or faced with energy-related decisions. By conducting a number of preference-choice exercises and experiments, and subsequently analysing data, an effort is made to determine what effect employing different types of biases has on electricity consumption and energy-related decisions.

In particular, it is explored which biases are applicable to Smart Meter feedback, and what the expected effect on electricity consumption of applying these could be, as this can help determine the role of BE for increasing the effectiveness of Smart Meters. Therefore, the thesis at hand analyses if information provision through Smart Meters can be expected to correct information asymmetries and lead to reduced residential (household and individual) electricity consumption as anticipated by EU and national policy-makers, and whether applying behavioural insights can increase the effect of this information.

Using the installation of Smart Meters in Denmark as a case study, the aim of the thesis is to point at the importance of carefully considering how feedback on electricity is designed taking into account applicable behavioural biases. In turn, the thesis aspires to contribute to improving energy efficiency policies, primarily in the EU, by informing policymakers of the need to look beyond the simple information-deficit model when designing policies, which can potentially contribute to a reduction in electricity consumption and a subsequent reduction in GHG emissions, and help realise policy goals.

The *research questions* that this thesis sets out to answer are:

- Which behavioural biases, as suggested by behavioural economics, are applicable when consumers are faced with energy-related decisions or provided with information on electricity consumption?
- Using insights from behavioural economics, what may be the expected energy efficiency improvements on electricity use as a result of Smart Meter deployment, particularly in the field of controlled customer feedback?
- To what extent can research findings support and be utilized in public policy design?

As such, the aim is not to provide a final answer as to the effectiveness of the Danish and/or European Smart Meter policy, but rather to generate knowledge and provide a better understanding of the interplay between Smart Meters, economic decision-making, and efficient use of electricity in the residential sector. To determine the effectiveness of such interventions, a number of experiments are conducted and supported by an extensive literature review.

1.4 Scope and (de)limitations

The research carried out for this thesis took place over the course of the summer 2014 in Copenhagen, Denmark. The data accessed and the participants involved in experiments all originate in this area, which means that to the extent that results are statistically representative, it will be only to this area. The study relies on only a limited amount of consumption data from Smart Meters, all of which concerns household in the study region. The data all comes from one company, although it was originally planned to have data from several companies, but the reluctance from the utility industry in sharing data complicated matters. This means that the dataset is de-limited both temporally and spatially, and thus most likely not representative of all of Denmark, nor the EU.

It was originally planned to conduct an econometric analysis, but due to the lack of conclusive statistical power caused by the small sample size, alternative analyses were conducted.

The Smart Meter experiment conducted is based on a web-based solution where information is accessible to participants online. Energy monitors (In-Home Displays) were not used, and are only discussed briefly, where deemed relevant, as only a very limited number of European consumers will receive these monitors as part of the Smart Meter rollout.

The literature analysis deals with the information available in scientific journals, consultancy reports, and government briefings to provide an overview of current findings. The analysis that follows is extensive, but it is not possible to provide a complete overview of the potential applications of behavioural economics to economic decisions regarding energy behaviour. Furthermore, it is important to note that this paper only focuses on individual and household electricity consumption, and that BE-based interventions applicable in this field might be different from those of another field (e.g. transportation).

It must be acknowledged that most of the research that this paper builds upon, takes a starting point in high-income countries and the citizens of these countries, and that the findings of this paper thus might not be applicable in other cultural settings (Henrich et al., 2010). It should also be noted that the experiments involved subjects living in and around Copenhagen. Environmental awareness is fairly high in Denmark (EC, 2011d), and also tend to be higher among well-educated citizens (Kollmuss & Agyeman, 2002) who are assumed to be overrepresented in the Copenhagen-region, which might limit generalizability.

Emissions of GHGs from the energy system are affected by technological development, which can change consumer preferences and production systems. Although this thesis does acknowledge the importance of the structure of the energy system and the need for research with a systemic analytical view, the focus of the work at hand is on the demand side of the energy system, and as such, the impact of systems change will not be discussed further.

As Smart Meter data on electricity consumption is collected from households and individuals, there is a need to consider the privacy aspects of this data, i.e. public access and availability to the data, as well as security concerns, i.e. hacking into, stealing, or unlawful distribution of the collected and stored data (Darby, 2012; Brown, 2014). The discussion of these issues, which no doubt deserves careful deliberation and is worthy of several studies and Ph.D.-projects alone, is not considered in this thesis. For an introduction to this topic, see e.g. Brown (2014), Efthymiou & Kalogridis (2010), European Data Protection Supervisor (2012).

Finally, the ethics of using behavioural interventions, i.e. interventions designed to trigger certain behavioural responses or achieve a certain outcome are also not thoroughly considered here. Already a number of papers (e.g. Thaler & Sunstein, 2001; John et al., 2009; Goodwin, 2012) and books (Kahneman, 2011; Sunstein, 2014) have been published on the topic, but there is no doubt that as the influence and ubiquity of behavioural interventions in public and private areas grow, there is a need to consider the practical, legal, and ethical aspects of this. Such deliberation is not found in this thesis.

1.5 Ethical considerations

The data collected from Smart Meters are sensitive data, as is the information that subjects provide as part of the various experiments. This data should necessarily be treated carefully and kept anonymous, as data collected from Smart Meters can potentially be used for commercial or other purposes, while real-time data might be used to gain knowledge of which households are currently uninhabited (Darby, 2010; Gram-Hanssen, 2013), which raises security and civil liberty issues.

The consent to use Smart Meter data was obtained from participants in the Smart Meter experiment (section 3.1.3), who were alerted to the experiment, and explicitly had to express their willingness to participate in the experiment. For ethical reasons, this was necessary, but it had the very unfortunate outcome that the sample size was significantly reduced. With one notable exception, the participants taking part in the experiments conducted as part of this study have been fully informed of the experimental setting and the goal of the study; the participants taking part in the Smart Meter study test group (loss aversion) were not alerted to the fact that they were being exposed to a psychological mechanism (loss framing), but only that they took part in an experiment, as it was assumed that them knowing the presence of the bias would influence the result. The researcher only knew which of the households that had been assigned what bias after the experiment had taken place, as this was assigned randomly.

Participants for the questionnaire-based experiments were selected based on their age, as it was an explicit goal to get people paying the electricity bill in the household. The study location was also chosen to specifically represent a larger proportion of the population. All participants were asked to participate and were free to say no. Participants received no remuneration for participating.

While complete objectivity can never be ensured, experiments were to the widest extent tested beforehand, and all findings, regardless of the impact on the theory under question, were subjected to the same statistical tests and methodological considerations. The results obtained are as accurately represented as possible, and all the material collected is available per request or in the extensive appendix, to ensure that other researchers can replicate the tests done.

Shifting from a focus on the conduct of research to behavioural economics in general, one can eye potential ethical considerations. As BE relies on insights from psychology, it uses findings from this field to 'improve' or alter decision-making. That a decision can be improved is a normative statement that some would probably find offensive. Strategies such as 'libertarian paternalism' or 'nudging' (e.g. Sunstein & Thaler, 2003; Thaler & Sunstein, 2009) rely on knowledge of human behavioural patterns to achieve certain outcomes (e.g. choose X rather than Y). The ethical implications of this are potentially severe, as it comes dangerously close to restraining the free will of human beings through policy or experimental design. So far, this topic has not been sufficiently debated in the literature, though potential implications for policy design have been discussed in some academic circles. These articles provide the starting point for a brief discussion of this towards the end of this thesis. While this is sufficient for a piece of work this size, if one were to implement behavioural interventions on a larger scale, e.g. in large-scale trials, a much more careful deliberation of this would be needed. A thorough discussion of this topic would require a Ph.D. project in itself, and is thus beyond the scope of this paper.

1.6 Audience

This research is primarily intended for policy makers at all levels, specifically those dealing with energy use at household and individual level, and will be especially important for those policy makers seeking to explore options that lie beyond traditional policy means (Bemelmans-Videc et al., 1998; Carter, 2007). On the one hand, the research at hand can hopefully help generate new policies based on behavioural insights (*ex-ante* utilization). On the other hand, the findings in here can help explain why some electricity and energy-related policies worked and others did not (*ex-post* utilization). Since the research builds on research conducted in American and European settings, it will most likely be of greater use to policymakers in these countries.

However, the research might also be important to two other groups of people: academics and people working for (private/public) utility companies or other energy providers. To the first group because the research highlights potential knowledge gaps in our use of conventional economics, as well as behavioural economics, to reduce the negative externalities related to energy consumption. The research also outlines suggestions for further research within energy feedback to customers specifically and the effect of Smart Meters in general, as well as potential areas of interest in relation to energy efficiency and consumer behaviour. To the second group because it can help utility companies and DSOs get an understanding of why and how consumers use energy, as well as how information should be provided to customers to have the largest possible effect, which can potentially help reduce peak demand, cut costs, improve customer relations, and increase competitiveness. Finally, anyone with an interest in mitigating climate change, specifically by reducing energy consumption, through personal or group actions, might find the information contained here useful.

1.7 Disposition

Chapter 1 presented the reader to the relevant EU energy policies and the need to include behavioural considerations in policy making. The research questions were outlined, and the research limitations and considerations were mentioned. In Chapter 2, the conceptual analytical framework is presented and the theoretical assumptions and differences of relevant economic theories that are employed in this thesis are discussed. In Chapter 3, the research methodology is described and the choice exercises, experiments, data collection, and data processing conducted as part of this study are presented. In Chapter 4, the results of the exercises and experiments are presented. Chapter 5 discusses these findings in relation to the theoretical framework, the current knowledge, and the research questions, and provides policy and research recommendations for future studies. Finally, Chapter 6 summarises the main findings and lessons learned in the course of this research, highlights main research contributions and provides suggestions for further research.

2 Conceptual Analytical Framework

The aim of this chapter is to provide a variety of conceptual considerations related to the provision of information on electricity and energy to consumers. The aspects analysed in this thesis build upon findings from different schools of economics, including neoclassical, behavioural, institutional, resource and energy economics to draw insights on how the provision of information affects consumer behaviour with regards to energy and electricity.

2.1 Expected Utility

Microeconomics, the study of individual economic decision-making and markets, has historically been theoretically dominated by neoclassical economic theory, in which market participants are assumed to be self-interested, fully rational, and act independently based on perfect information, which leads to Pareto-efficient allocation of resources and perfect competition (Frank, 1997; Endres & Radke, 2012). Environmental problems are understood as market failures, meaning that the problem lies with the market setup and the institutions (including lack of information), but not the way market participants actually make their decisions (Endres & Radke, 2012; Baddeley, 2011). The basic economic model for analysing individual decision-making is known as the theory of *rational consumer choice* (Frank, 1997).

The rational choice theory, or expected utility theory, has enjoyed widespread popularity, partly due to the influence of the Chicago School of Economics, partly due to its elegant, mathematical structure. The theory is based on the idea that decision-makers weigh the expected costs and benefits of the range of options available before deciding on the one that maximises their utility (Frank, 1997; Endres & Radke, 2012; Jackson, 2005). The model assumes that preferences are well defined, stable and consistent (Frank, 1997). In energy research, it has been widely applied, for example to obtain consumer preferences for energy efficient appliances (e.g. Houston, 1983; Sathaye & Murtishaw, 2004; Lopes et al., 2012). Expected utility theory (EUT) can be attributed to the work of von Neumann & Morgenstern (1944) and is based on a set of axioms that are claimed to have normative rather than descriptive validity in the sense that they describe how individuals ideally *should* behave (normative) rather than how they *actually* behave (descriptive). There are four axioms, which can be formulated thusly (von Neumann & Morgenstern 1944; Kahneman & Tversky, 1984):

- *Transitivity*: if A is preferred to B and B is preferred to C, then A is preferred to C.
- *Substitution*: if A is preferred to B, then an even chance to get A or C is preferred to an even chance to get B or C.
- *Dominance*: if A is at least as good as B in every respect and better than B in at least one respect, then A should be preferred to B.
- *Invariance*: if A is preferred to B, then this preference should not depend on the way in which A and B are described.

In the experimental field research conducted for this thesis, it is tested whether framing of energy-related decisions leads to systematic violation of one or more of these axioms. If this is the case, this has implications for the way energy use information is presented (or to use the BE term, framed) to customers using Smart Meters, as it can potentially affect the decisions made, and as such, the effectiveness, of such information.

Based on these axioms, one can (theoretically) determine an individual's subjective probability and utility function by observing their true preference in structured choice situations (Frank, 1997; von Neumann & Morgenstern 1944). As such, the (neo-)classical economic understanding of choice posits that individuals assess unknown situations by weighing the individual benefit or loss (the utility) of an outcome (*Xi*) by its probability (*Pi*)[18]:

$$v(P) = \sum iPiU(Xi)$$

where *u* is the function that measures the value of the outcome (Camerer, 1999, p. 10575).

The model has been discussed extensively and challenged by economists, sociologists and psychologists alike (e.g. Frank, 1997; Henrich et al., 2001; Thaler, 2000; Hargreaves, 2011), but still enjoys some popularity and remain the basis for construing decision problems. It has been widely applied to assess how market participants *should* behave when faced with e.g. energy-related decision, such as curtailment decisions or procurement of energy-efficient devices. Its normative nature ensures that it is widely used to recommend policy options that are expected to maximize utility for individual decision makers. In the context of this thesis, however, there is extensive research on numerous market failures and other aspects that, contrary to theoretical assumptions, prevent the dissemination of efficient technologies, and thus the materialisation of energy efficiency potentials and the reduction of GHG emissions.

2.2 The 'Energy Efficiency Gap'

The term 'Energy Efficiency Gap' is often used to describe the slow diffusion of profitable energy-efficient technologies that fail to achieve market success. As such, the EE gap does not concern the gap between what is theoretically or technically possible and actually achieved, but rather the gap between what should be cost-effective in a market setting and what is actually achieved; despite the very real economic and environmental benefits of procuring energy-efficient technologies (Mundaca, 2008), people forgo EE investments, which net present value (NPV) calculations show to be cost-effective, such as procuring CFL's or efficient fridges (Jaffe & Stavins 1994b; Howarth & Sanstad, 1995). A number of market barriers and failures have been suggested as explanations for this EE gap, e.g. lack of or asymmetric information and other transaction costs, high (implicit) discount rates, hidden costs, bounded rationality, principal-agent problem, negative externalities not reflected in energy prices, lack of sufficient capital, and uncertainty about risks, costs, and benefits (c.f. Mundaca, 2008; 2010; Sathaye et al., 2004; Sanstad and Howarth, 1994; Lucon et al., 2014)[19]. A major energy policy focus thus has been to reduce or overcome these barriers to encourage end-users (i.e. consumers) to undertake EE measures (Baddeley, 2011)

The following sections present an overview of two important aspects, transaction cost and discounting, that have been proposed as causes or drivers for the existence of the EE gap, and which are worth exploring in detail. The first, because it relates to the provision of information and economic decision-making in the context of such information or lack thereof, the second, because it concerns how individual preferences for energy efficient goods depend on the valuation of current and future costs.

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[18] According to EUT, decisions are evaluated in terms of total wealth, e.g. an offer to bet €10 on a coin toss is represented as a choice between an individual's current wealth (W) and an even chance (0.5) to move to W + €10 or to W - €10 (Kahneman & Tversky, 1984).

[19] Another explanation of the EE gap is that some cost-effectiveness calculations are based on the economic situation in the average household, which means that there are household where installing a given technology will not be cost-effective. This is the explanation that some European nations use for not rolling out Smart Meters to households; they assume that Smart Meters will only be cost-effective for those with high consumption. Whether this assumption is correct is not known with certainty, but Schleich et al. (2013) find evidence that it does not hold. This question is not further explored in this thesis, as the data available was insufficient to explore this and it is beyond the scope of this work, but the question no doubt deserves further attention.

2.2.1 Transaction costs and information asymmetry

The analysis of transaction costs is a fundamental component of New Institutional Economics, the focus of which is on "how transactions made by market agents are frequently based on imperfect and asymmetric information and how institutional frameworks influence the behaviour of these agents" (Mundaca et al., 2013, p. 4). Transaction costs, or as they are sometimes labelled, 'the hassle factor' (Fox-Penner, 2010, p. 143) can be understood as the costs that arise from transaction activities, but which are not included in the direct price of the good or service in question (Mundaca et al., 2013). For instance, transaction costs could be the costs of searching for and evaluating information on EE technologies or the costs associated with negotiating a deal (Mundaca et al., 2013). The approach is that transactions in markets are made by individuals that act on imperfect information (Mundaca et al. (2013), contrary to the assumption underpinning EUT that decision-makers are fully informed. Viewed from this theory, potential energy savings and energy efficiency investments fail to happen as a result of market failures, such as lack of capital, lack of information/information asymmetries, principal-agent problems, and split-incentives (Sanstad & Howarth, 1994; Baddeley, 2011). As such, TCs can slow or even hinder the diffusion and commercialization of EE technologies, which in turn can undermine the potential for GHG emissions reductions. Though TC's come in many forms (Mundaca et al., 2013), only one will be discussed in detail here, namely information search costs.

It is well known that imperfect or asymmetric information can lead to outcomes that deviate from Pareto optimal allocation (Endres & Radke, 2012; Faure & Skogh, 2003), and several researchers (e.g. Sanstad and Howarth, 1994; Ruderman et al., 1987) argue that this does in fact contribute to the EE gap. As an example, the cost of adoption of a new technology (e.g. information acquisition) is not included in calculations of cost-effectiveness, and as consumers are generally "poorly informed concerning the energy choices they face" (Howarth & Sanstad, 1995, p. 106) they face a cost of obtaining this information, leading to lower than expected EE diffusion. For instance, Attari et al. (2010, p. 16055) in a survey found that although EE technologies are often more energy saving than curtailment, "only 11.7% of participants mentioned efficiency improvements, whereas 55.2% mentioned curtailment as a strategy for conserving energy." Smart Meters should theoretically overcome some of these barriers stemming from asymmetric information, as consumers can be informed about the effect of various actions. The effect of information provision on consumer decisions is tested as part of the research for this thesis. In the same manner, sellers of goods that increase EE face costs in conveying this information to the consumers, especially if the EE relevant characteristics are not salient in market transactions (Howarth & Sanstad, 1995). The energy labels mandated by the EU are trying to make up for this by providing information on energy consumption for various goods, such as fridges. How the design of these affects consumption patterns is explored in an experiment for this thesis, as it is assumed that this can inform decision-makers on the way information should be presented to consumers using Smart Meters.

If an economic analysis of the diffusion of EE technology does not take TCs into account, it will arrive at a higher diffusion rate than is feasible in real life, and thus overestimate EE potential and underestimate costs (Mundaca et al., 2013). For policy purposes, the important issue is therefore whether any interventions can reduce TCs when they occur (Sanstad & Howarth, 1994). As Coase (1960) pointed out, market failures will persist when transaction costs, perceived or real, exceed the benefits of undertaking the intervention[20]. The EU Smart Meter policy can in this regard be seen as a way of overcoming these transaction costs.

[20] The Coase theorem (1960) state that, in the absence of transaction costs (TCs), bargaining will lead to an efficient allocation of resources, regardless of the initial allocation of property rights (Faure & Skogh, 2003, p. 151)

However, Sathaye & Murtishaw (2004) found that it was difficult to explain the gap between cost-effective potential and current penetration rates for EE technologies, even accounting for TCs. They suggested that "cognitive limitations on gathering and processing information may account for much of this gap" (Sathaye & Murtishaw, 2004, p. 4), which suggests information provision in itself is not sufficient to close the EE gap. The research conducted as part of this thesis explores whether the way in which this information is framed facilities or hinders the ability of humans to act on it, and in turn, narrow the EE gap.

2.2.2 Implicit discounting rates

The literature about the (non-)adoption of EE technologies reviewed for this thesis yields compelling evidence that households implicitly apply high discount rates (e.g. sometimes in the order of 100% or more) when evaluating EE technologies, which is effectively hindering the adoption of such technologies (see e.g. Hausman, 1979; Gately, 1980; Train, 1985; Ruderman et al., 1987; Jaffe & Stavins, 1994a, 1994b; Hasset & Metcalf, 1993; Howarth & Sanstad, 1995). In the context of the research conducted here, various explanations for the use of high implicit discount rates can be found: a lack of information about costs and benefits of efficiency improvements; a lack of knowledge about how to utilize the information available; uncertainties about technical performance of EE investments; income level/access to capital; high transaction costs (perceived or real) involved in obtaining useful information, and; risks associated with such investments (e.g. Ruderman et al., 1987; Train, 1985; Sutherland, 1991; Gates, 1983; Hasset & Metcalf, 1993).

As an individual's discount rate is not known, it must be inferred from the behaviour in the market displayed by that individual (Ruderman et al., 1987). If it is assumed that observed behaviour is consistent with cost minimization, as is the case in neoclassical economic theory, the discount rate required to make the individual's behaviour rational can be calculated, since "implicit discount rates will equate with the rate-of-return available on alternative investments of comparable risk, revealing information concerning the marginal time preference of decision makers" (Howarth & Sanstad, 1995, p. 102). Theoretically, non-credit constrained consumers would be expected to have discount rates equal to the real market interest rate plus depreciation rate, i.e. in the order of 5-15%[21] (Dubin & McFadden, 1984).

Using an econometric model, Hausman (1979) estimated the implicit discount rate used by buyers of air conditioners and found an implicit discount rate that averaged 25%, but varied with income (higher income yielded lower discount rates). A similar estimate by Gately (1980) found implicit discount rates ranging from 45-300%. Train (1985) reports on three other studies on implicit discount rates, all of which yield discount rates significantly above real market interest rates. If the high implicit discount rates do in fact correspond to the true discount rates of the individual, there is nothing wrong (in an economic sense) with this, and no EE gap can thus be said to exist. For instance, Sutherland (1991) argue that high discount rates may be appropriate as EE investments are often highly uncertain and often irreversible. In markets, investors demand higher rates of return on risky assets, and high discount rates could thus imply that consumers see EE investments as particularly risky (Howarth & Sanstad, 1995)[22]. Gately (1980) points out that the high implicit discount rate raises questions about

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[21] Dubin and McFadden (1984) finds the value to be in the range of 0.10-0.15, but as the interest rate is currently historically low, it could be argued that this figure could be lowered to 0.05-0.15.

[22] In a similar fashion, Hasset and Metcalf (1993, p. 710) argue that "the apparently high discount rates attributed to investors making energy conservation investments are not irrational or the result of some market failure. Rather they may result from an investor recognizing that many conservation investments entail substantial sunk costs. In the presence of these costs and uncertainty over future conservation savings, consumers should use a higher hurdle rate for investment than if there were no uncertainty." In a response to this claim, Howarth and Sanstad (1995, p. 105) argue that even when higher hurdle rates are taken into account, this still fail to account for the discount rates found in the literature.

consumer behaviour, arguing that "one would be hard put to defend the purchase of a low efficiency unit as an intelligent choice" (p. 374). It is suggested that the irrational choice is made "because the calculations were difficult or impossible because of ignorance of the monthly operating costs," (p. 374) which suggests that humans do not fail to buy the efficient units because of high discount costs, but because we fail to take non-salient costs into account. This assumption is tested in a number of preference choice exercises conducted as part of this thesis. Train (1985) speculates that discount rates for consumer appliances, such as freezers, are higher than for cars, say, because the energy usage these appliances are less known to consumers (Train, 1985). This observation fits recent research (Kallbekken et al. 2013; Newell & Siikamäki, 2013), which show that consumers purchase decisions change when the operating costs are made salient[23]. This implies that the *implicit* discount rate observed in the market is not the *true* discount rate. For Smart Meters, this has the implication that simply providing information might not be enough to change behaviour, as consumers can display varying discount rates depending on how information is presented. Whether this is indeed the case will be tested empirically as part of this research[24].

2.3 Behavioural Economics

2.3.1 Bounded Rationality

The theory of bounded rationality is based on research by Simon (1959; 1982; 1986), who found that people do not have unlimited information processing capacity, and thus fail to make consistently rational choices. Rather, they have inherent behavioural biases that lead to predictable outcomes, as explored by the psychologists Daniel Kahneman and Amos Tversky, and others (Tversky & Kahneman, 1974; 1992; Kahnemann et al., 1982; 1991; Kahneman & Tversky, 1979; 1984; Thaler, 1980; Slovic et al., 2002; 2007; Camerer, 1999). Bounded rationality implies that humans' reason to some extent; our decisions are more or less good, but seldom optimal in the economic understanding of the term. Humans do not employ decision calculus when making a decision (Pasche, 2014), nor do they evaluate every available option (John et al., 2013), but instead apply certain *cognitive heuristics* (mental shortcuts and 'rules of thumb') (Tversky & Kahneman, 1974; Shogren & Taylor, 2008). Bounded rationality should not be confused with irrationality; humans are generally goal-oriented, and specify a reason for what they do (John et al., 2013), but decision-making processes are often characterised by procedure rather than results (Pasche, 2014).

An important aspect of the bounded rationality of humans is the theory known as Prospect Theory (PT) developed by Tversky & Kahneman (1979), a purely descriptive theory of how people make choices under uncertainty, which was further refined in Cumulative Prospect Theory (CPT) (Tversky & Kahneman, 1992). A prospect can be defined as an opportunity or

[23] Newell and Siikamäki (2013) found that labels with simple information on the economic value of saving energy had a substantial impact on purchasing behaviour, leading to a choice of appliances with higher energy efficiency. Kallbekken et al. (2013) also found evidence of this, noting that consumer purchase decisions were on average 5% more efficient when the operating cost was made salient on the energy label.

[24] Experiements have found other behavioural inconsistencies with regards to discounting. For instance, consumer behaviour, using both models and experiments, has been shown to fit a hyperbolic discount function, which is a time-inconsistent model of discounting, "characterized by a relatively high discount rate over short horizons and a relatively low discount rate over long horizons" (Laibson, 1997, p. 445). This is inconsistent with rational choice theory, which assumes an exponential function, where discount rates are constant over time (Frederick et al., 2002). Congdon (2013, p. 473) speculates that hyperbolic discounting might "depress investments in energy-saving technologies because of the way in which the costs of such actions are front-loaded, while the benefits are realized only in the future" (Congdon, 2013, p. 473). Other inconsistencies in discounting behaviour include discounting gains more than losses, and discounting small outcomes more than large ones (Frederick et al., 2002). As these inconsistencies do not directly apply to the research conducted her, this will not be further elaborated upon. For a comprehensive overview of discounting over time and time preferences, see Frederick et al. (2002).

contingency (a 'gamble') (Read, 2002, p. 469); a set of outcomes (e.g. A and B) with a probability (*P(A)* and *P(B)*). In contrast to EUT, prospect theory evaluates decisions in terms of changes from a reference point, usually, but not always, the status quo, i.e. the gamble from above becomes a choice between (a) nothing (0) (no gamble), or (b) a 0.5 chance winning €10 or losing €10 (gamble) (Read, 2002).

Kahneman and Tversky (1979) found that humans display several pervasive effects when choosing among risky decisions (gambles) that are inconsistent with the basic axioms of EUT. In CPT, value is assigned to relative gains and losses rather than to total wealth, and probabilities are replaced by decision weights, which are generally lower than the corresponding probabilities, except in the range of low probabilities. EUT assumes that the decision weight put on an option is equivalent to its probability, but Tversky & Kahneman (1979; 1992) found that decision weights are an increasing, but non-linear function of probability, as opposed to the linear probability function in EUT (Figure 2-1). In other words, very unlikely events are overweighed, while likely events are underweighted: A change from impossibility to possibility (from 0 to 0+x) or from possibility to certainty (1-x to 1) has a bigger impact than a comparable change in the middle of the scale (from 0.5 to 0.5+x)[25] (Kahneman & Tversky, 1984). This 'certainty effect' is captured by the probability weight function, which has a discontinuity before the endpoints (0 and 1), making events that are certain to happen (or not) far more impactful than those that occur at 0.9 or 0.1, respectively (Kahneman & Tversky, 1984; Weber, 2013). This has implications for how humans decide among events with an uncertain outcome, a feature characterising many energy-related decisions. As part of this research, a preference choice exercise on human decision making for an uncertain outcome is conducted to test how the effect influences behaviour.

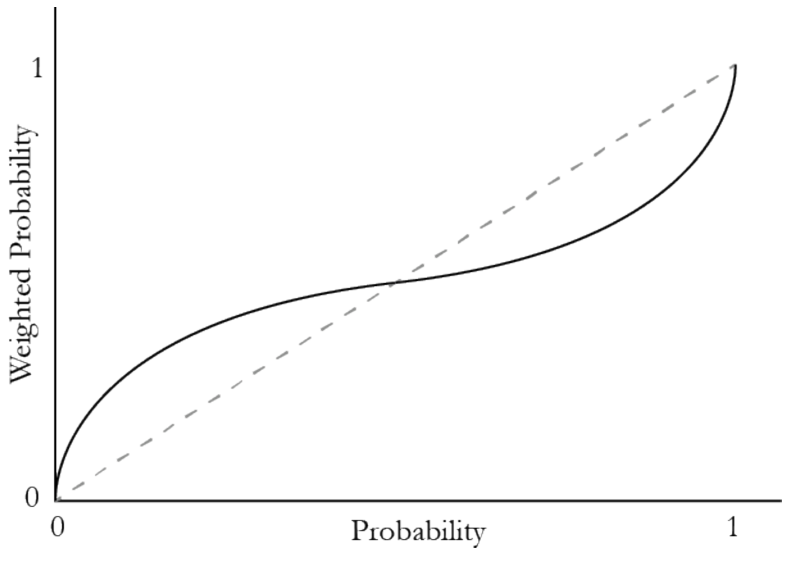

Figure 2-1 – Stylistic representation of the weighted probability function in CPT (solid line) and that of EUT (dashed line) (Author, after Tversky & Kahneman, 1992, p. 310)

In their seminal paper on "Judgment under Uncertainty," Tversky and Kahneman (1974) found that humans rely on heuristics to guide their decision-making, e.g. substituting probability (difficult to estimate) with representativeness (easy to estimate), and that these heuristics systematically depart from basic principles of probability. They found three types of heuristics: *'representativeness'*, *'availability'*, and *'adjustment and anchoring.'* In evaluating probabilities

[25] Intuitively, this makes sense. The difference between no risk of dying in an accident and a risk of 0.01 feels huge and very important, while a difference between a risk of dying of 0.5 and 0.51 seems trivial (Read, 2002).

using *representativeness*, humans have been found to assess the likelihood that A belongs to B by "the degree to which A is representative of B, i.e. by the degree to which A resembles B" (Tversky & Kahneman, 1974, p. 1124). For instance, when consumers are asked to assess the energy use of appliances, they tend to rely on the representative heuristic: that energy use is related to the size of appliances. The larger the appliance, the higher perceived energy use (Steg, 2008). If this holds in practice, it has the implication that Smart Meters should display electricity information by appliance, and not just as a cumulative total, in order to help correct for this bias, as consumers would otherwise target the largest appliances first, and not (necessarily) those that used the most electricity. The presence of this bias was not tested as part of the research conducted here. *Availability* bias occurs when people assess an event by the ease of which a similar instance can be brought to mind, instead of using statistical inference. Salience affects the retrievability of instances, and thus leads to an overestimation of those factors that can easily be brought to mind (Tversky & Kahneman, 1974). This means that presenting a cost on its own makes it more salient than when presented as part of a larger cost, and thus more available, enabling humans to act on it. For electricity, this means that providing information on the cost of standby electricity in itself ("stand-by costs you 500 DKK per year) is more effective than when seen as part of a whole ("you can reduce your bill from DKK2500 to DKK2000 by turning off stand-by electricity"). It is theorised that aggregation of smaller costs into one should also make these more salient, and thus easier for humans to act on. In terms of stand-by electricity, this means that a cost of DKK500 per year appear larger than 1.37 DKK per day, although the total yearly cost is the same. EUT states that whether a cost is presented alone or as part of a whole should not make a difference to human behaviour, but heuristics would say that it does. Some of the experiments conducted for this thesis tests whether these assumptions about salience do in fact impact observed behaviour. Due to *adjustment and anchoring biases*, people make numerical estimates or predictions by starting from an initial, often completely arbitrary value, which is then adjusted, most often in the right direction, but to an insufficient degree, to yield the final answer (Tversky & Kahneman, 1974). This effect has been demonstrated in numerous experiments since then (e.g. Etzioni, 2011, Kahneman, 2011; Ariely, 2008), e.g. Attari et al. (2010) found that using a relatively low anchoring point (100W light bulb used for 1 hour) when evaluating energy use caused participants to underestimate energy consumption and savings. This has the implication that if consumers are presented with comparative figures in order to understand the information provided by Smart Meters (e.g. CO_2 emission from an activity presented with equivalent "km driven by car"), the comparative figure used (in this case, "km driven by car") would serve as an anchor. The choice of anchor can thus affect how effective the comparative information is. Although this potentially impacts behaviour, it was not possible to test this bias in the research conducted for this thesis.

2.3.2 Loss Aversion

Another central element to the research at hand that distinguishes CPT from EUT is the non-linear value function, or the tendency for people to put substantially greater weight on relative losses than on gains of the same magnitude (Weber, 2013), when evaluating choices and trades (Kahneman et al., 1990). There are three important features of the individual value function in prospect theory, as seen in Figure 2-2, which will be briefly discussed, as these can help guide how feedback on electricity consumption should be designed. Firstly, the function concerns relative changes to wealth as evaluated from a reference point, rather than absolute wealth, as in EUT[26] (c.f. footnote 18). Secondly, the loss function is steeper than the gain function, i.e. a

[26]"The influence of the reference state on people's valuations appears to offer a far more general and parsimonious explanation of observed instances of losses being valued more than otherwise commensurate gains, than reliance on incentives recognized in standard theory alone. Further, the valuation disparity seems to be a pervasive though perhaps not universal characteristic of their preferences" (Knetsch and Wong, 2009, p. 413)

change in satisfaction is larger in response to a relative loss (-A) than a relative gain (A) in wealth, which is also in opposition to the value function of EUT. This difference in steepness is the notion of loss aversion, and suggests that behaviour can be influenced depending on framing (Weber, 2013). For electricity consumption, this has the implication that information on how to save electricity should be framed as preventing a loss, rather than achieving a gain. As part of this research, the effect of such a framing is tested in a real-life Smart Meter experiment, where participants will receive feedback on their electricity framed as a loss, which should incentivise them to avoid this loss. Thirdly, the function shows diminishing sensitivity to gains and losses (Mullainathan & Thaler, 2000), i.e. the value function is concave for gains and convex for losses. This has the implication that individuals show risk averse behaviour with respect to sure gains and unlikely losses, but risk seeking behaviour with respect to sure losses and unlikely gains (Kahneman & Tversky, 1984; Samuelson & Zeckhauser, 1988). If risk preferences depend on the framing of reference point, this effect violates the invariance axiom of EUT (c.f. Kahneman & Tversky, 1984; Samuelson & Zeckhauser, 1988). Tversky and Kahneman (1981, 1986) found preference reversal (i.e. violation of invariance axiom) in choices concerning monetary gains and losses, both hypothetical and real, and in questions of loss or saving of human lives, while Kahneman et al. (1990) found that the effect persisted even under market settings. As part of this thesis, an experiment was conducted test whether preference reversal depending on framing also holds for energy efficiency investments, traditionally viewed as uncertain, as this has implications for how information on the EE investments should be presented to consumers.

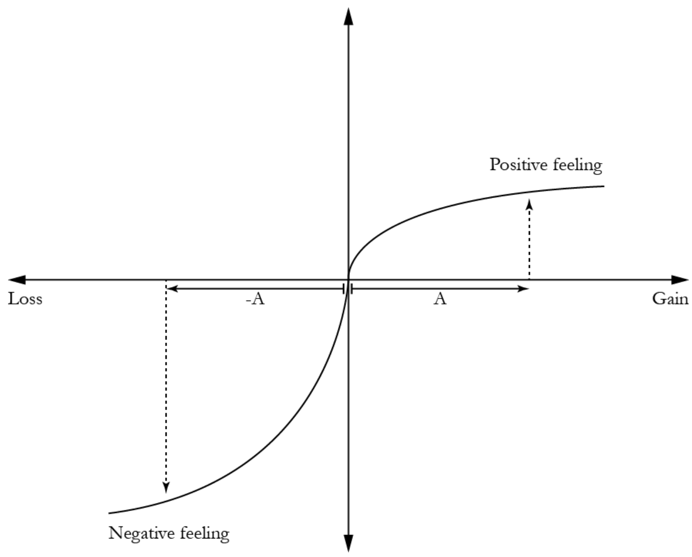

Figure 2-2 – Loss aversion. A change in satisfaction is larger in response to a relative loss of wealth than a relative gain of wealth (Author, partly after Kahneman, 2011).

2.3.3 Endowment effect

EUT assumes that an individual's preference for good A is not affected by ownership and that, when income effects are small and transaction costs negligible, an individual's willingness-to-pay (WTP) for good A should, in theory, equal the willingness-to-accept (WTA) the loss of good A (van Dijk & van Knippenberg, 1996). This prediction contrasts with empirical observations; individuals place a higher value on something they have than on identical goods that they do not possess[27]: good A might be preferred to good B when A is the

[27] Gowdy (2010) rightly points out that this feature partly explains the oft-observed discrepancy between WTP and WTA in measures of environmental change.Venkatachalam (2008) also touches upon this subject.

endowed good, while the reverse can be true if good B is the endowed good[28] (Kahneman et al., 1990) This effect was first suggested by Thaler (1980) who labelled it "the endowment effect," and has been demonstrated in numerous experiments since (see Etzioni, 2011; Kahneman, 2011, Ariely, 2008; Kahneman et al. 1990; van Dijk & van Knippenberg, 1996). This effect has been suggested as a reason why people are reluctant to trade or switch position, although doing so would entail economic benefits; Faruqui et al. (2010a) suggest that this can possibly explain consumer resistance towards electricity plans with variable (dynamic) tariffs. As part of the research for this thesis, an experiment was set up to test the whether the effect of changing the default settings, i.e. automatically enrolling consumers to either a dynamic or a conventional plan, would have an effect on electricity plan selection. Following EUT, an individual would choose the option that maximised utility, regardless of whether or not this option was the default option[29] or not. Humans, to the contrary, tend to choose the default option (Samuelson & Zeckhauser, 1988; Johnson et al., 2012), even when "an alternative option is markedly better and switching appears easy" (Allcott & Mullainathan, 2010)[30]. Theoretically, this has the implication that changing the default can influence the choices made by economic actors, contrary to what is assumed in EUT[31]. McKenzie et al. (2006) found that individuals uncertain about their preference are more likely to be influenced by defaults. This fits the finding from neuroscience that humans are more likely to stick with the default when decisions are complex and/or difficult (Fleming et al., 2010), a statement which would characterize many energy-related decisions.

2.3.4 Limited self-interest

Limited self-interest captures the notion that people are other-regarding and concerned about the opinion and welfare of others, and include behavioural traits such as fairness, altruism, and reciprocity (Shogren & Taylor, 2008). Several of these traits are described in Gifford (2011) and Gsottbauer & Bergh (2011). These aspects are important for the research because they demonstrate that behaviour takes place within a (social) context, which affects both how individuals respond to information and the decisions taken by these individuals.

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[28] It is important to realise that the theory does not postualate that this is *always* the case, but simply that humans show inconsistency in preferences which is affected by initial endowment (Kahneman et al., 1990, p. 1344). This violates the axioms of rational choice theory (c.f. Von Neumann and Morgenstern, 1947).

[29] Defaults can be defined as "settings that apply, or outcomes that stick, when individuals do not take active steps to change them" (Sunstein & Reisch, 2013, p. 401). Johnson and Goldstein (2003) suggest three possible answers as to why the default effect exists: (1) loss aversion; as the default is seen as the status quo, a change might feel like a loss; (2) Changing the default requires an effort, leading to a bias towards maintaining status quo; and (3) the choice of default signals a recommended course of action (McKenzie et al., 2006). Whether any of the three possible explanations for the default effect is more valid than the others will not be further discussed in this thesis. It is important to note that defaults are ubiquitous and thus has an impact on outcomes, even if the choice architecture (the framing of the problem) has not been subject to careful consideration (Thaler et al., 2010).

[30] When deciding among options, the classical view is that each option is assigned a subjective value, or utility, and the option with the highest utility is then selected. Contrary to this, behavioural research found that people often have a hard time deciding among options and that more options can complicate the decision, effectively worsening the decision (Barr et al., 2013, p. 441). In a rational choice model, the assumption is that more options are always better, but some behavioural research suggests that limiting the number of options would entail better decisions (Iyengar & Lepper, 2000; Schwartz, 2004).

[31] Using EUT, one could argue that defaults could have an effect on decision outcome, if these were seen as a type of market failure. If the cost of selecting the preferred option is larger than the benefit gained from that preference, then defaults would be selected even when they would be rejected if transaction costs were zero. A transaction cost prevents equilibrium from being reached because the cost of reaching equilibrium is higher than the benefit gained (Johnson & Goldstein, 2013, p. 420). However, the problem is that understanding defaults in such a way would make the transaction costs involved enormous (in the order of several thousand euros in some examples), leading one to suspect that most individuals do not perform a rational calculation of whether the transaction costs exceed the benefits.

Societies are based on values and norms, which often vary from place to place, that govern what is (and what is not) socially acceptable behaviour (Lundgren, 1999). Humans compare their belief and attitudes with those of others, deriving subjective and descriptive norms from their observations, to learn what constitutes socially acceptable behaviour (Gifford, 2011) or the "social norm." Cialdini et al. (1990) distinguish between descriptive social norms, i.e. beliefs about behaviours people actually engage in, and injunctive social norms, i.e. beliefs about what most people believe is the right course of action. Because of perceived status or to maintain a self-image, humans are more likely to contribute when their actions are visible to others. Reflecting this, human behaviour has been found to change when others can observe it (Bell et al., 1996; Schultz, 1998; Nolan et al. 2008). Along those lines, and in the context of this thesis, it can be argued that a preference for green energy displayed by an individual arise not because of a careful deliberation that the perceived (social) environmental benefits outweigh the private costs, but rather to express the values that this choice connotes (Sunstein & Reisch, 2013).

Altruism means helping others while making sacrifices of your own. In a behavioural economics understanding of the word, altruism can be defined as being "costly acts that confer economic benefits on other individuals" (Fehr & Fischbacher, 2003, p. 785). Without external incentives, a utility-maximising individual would not contribute to goods that benefited others or a group, but would 'free-ride,' i.e. live off of the contributions made by others. Although free-riding is found in many settings where incentives or rewards are not clear, Kahan (2002) found that in collective action settings, utility 'calculations' took on a more social form; when individuals perceive that others behave cooperatively, they are moved to contribute to public goods. In contrast, when they find that others 'free-ride' or in other way evades contributing to a public good, they retaliate, even at a cost to themselves (i.e. reducing individual utility) (Boyd et al., 2010). These responses are known as altruistic punishment and altruistic rewarding. Interestingly, Fehr and Fischbacher (2003, p. 785) found that "a minority of altruists can force a majority of selfish individuals to cooperate or, conversely, a few egoists can induce a large number of altruists to defect." Along these lines, Reiss and White (2008) found a surprisingly large reduction as a result of public appeal. Absent any pecuniary incentive to do so, energy use declined by 7% over a six-month period. This confirms that humans respond altruistically when this seems to be the norm: "Issuing public appeals like these is like soliciting anonymous contributions to a public good: respondents incur private costs individually; yet achieve tangible benefits only if aggregate participation is high" (Reiss & White, 2008). This suggests that using Smart Meters to subject people to statements of positive peer behaviour, e.g. installation rate of green technology, can increase installation of EE technologies.

2.4 Feedback and Energy Use

According to neoclassical economic theory, electricity is a commodity and consumers will adapt their usage in response to price signals. How consumers respond should depend on the price elasticity of demand for electricity, but, ceteris paribus, one should expect financial incentives to have some impact on electricity behaviour. Cook et al. (2012) find that income influences price elasticity, with low-income consumers showing a relatively elastic demand (around -1), while high-income consumers show relatively inelastic demand, but effects are unknown as previous estimates very widely (Platchkov & Pollitt, 2011). Nonetheless, electricity is considered the most inelastically demanded form of energy (Reiss & White, 2008). Whether this is due to lack of information or actual low elasticity has important implications for information provision on electricity use, especially with regards to a future with variable prices. Jossoe and Rapson (2013) found that "information feedback about electricity usage increases the price elasticity of demand" (p. 18)[32], which suggests that provision of feedback can lead to reduction in consumption.

Electricity feedback can come in various forms, either verbal or written, online or offline, and through various devices (e.g. separate displays (IHD), smart phones, TV's, and web-based). The information on electricity consumption provided to customers can be presented in many forms, but has traditionally been shown as kWh or alternatively using local currency (€, £, $). As part of this thesis, an experiment was conducted to test how much consumers know about these units relative to each other. A natural way to present this information would be to present it in the form of environmental impact (e.g. in CO_2e), as the principal purpose of reducing energy consumption (at least from an EU policy point of view) is to reduce GHG emissions. This presents the problem that people are generally unable to act on this information, not knowing what 1 kg of CO_2e signifies, meaning that comparative data would be needed (Karjalainen, 2011). This being said, presenting factually correct information "may be insufficient to induce consumers to make substantively rational decisions" owing to cognitive limitations. The interpretation and use of the information presented needs to be taken into account, as this will affect the behavioural response, in this case, the reduction in electricity or adoption of EE technologies (Sanstad & Howarth, 1994; Kahneman, 2003). As part of this research, it is explored whether increasing the salience of one part of two factually similar pieces of information changes consumer preference.

Consumers can get two types of feedback about their energy consumption: indirect feedback provided after consumption, or direct feedback provided in real-time (Ehrhardt-Martinez et al., 2010)[33]. Here, the focus is on feedback from Smart Meters delivered through some form of connected device, such as a phone, IHD, or computer. Typically, feedback with regards to electricity consumption tries to influence one of two types of behaviour: electricity reduction or load shifting (Ehrhardt-Martinez et al., 2010). Load shifting is typically induced through variable prices, where electricity prices vary over the course of the day or the year. Various pricing schemes exist, such as time-of-use rates, real-time pricing, critical peak pricing, or peak time rebate[34].

The effect on overall electricity consumption of providing feedback has been studied by several researchers (e.g. Midden et al., 1983; Wilhite et al., 1999; Abrahamse et al., 2007; Allen et al., 2006, Hargreaves et al., 2010; Gleerup et al., 2010; Petersen et al., 2007) and summarised in several review studies (e.g. Abrahamse et al., 2005; Darby, 2006; Fischer, 2008; Faruqui et al., 2010b; Vine et al. 2013;). The general conclusion is that the frequency of the feedback, whether it is direct or indirect, and the way it is presented (the context), has an impact on the effect (Ehrhardt-Martinez et al., 2010, p. 39). Early studies generally found quite large effects (e.g. Midden et al., 1983 found savings of 18.8%), while newer studies have been more cautious, generally reporting savings in the range of 0-5%). This is in line with the expected reductions of Smart Meter feedback, as reported by EU Member States in their CBA's of Smart Meter rollout, but below the expectations by the EC. Two widely cited studies by Darby

[32] The authors provide the very interesting insight that, should consumers be rational and change their behaviour, "the direction of social benefits may be setting-specific", meaning that although information makes consumers more price elastic in their case, "in other settings consumers may realize that they consume too little or are too price responsive. If there are externalities in these markets, then this response will make private decisions more efficient, but may increase social costs" (Jossoe & Rapson, 2013, p. 19).

[33] This paper will not elaborate on the classification of feedback, but a thorough discussion of this can be found in Darby (2006) or Ehrhardt-Martinez et al. (2010).

[34] The nature of these and the impact on consumption of enacting the various pricing schemes will not be discussed in detail here. For more information, the reader is referred to Faruqui et al. (2010a).

(2006) and Fischer (2008) find potential savings from feedback of 5-15% and 5-12%, respectively, while a recent review by Ehrhardt-Martinez et al. (2010) find savings of 4-12%. However, it is less clear whether feedback provided by Smart Meters lead to these reductions, as e.g. Darby (2006) do no discuss in detail the effect of providing feedback through various media. It is generally not known for how long any of these reductions persist, but Staats et al. (2004) suggest that there is some evidence that the effect diminishes over time, and might even completely disappear once the feedback is gone. Fischer (2008, p. 101) suggest that the most effective form of feedback is based on actual consumption, given frequently, involves interaction and appliance-specific breakdown, is given over a longer period, may involve historical or normative comparisons, and is presented in an understandable and appealing way. The effect of feedback on reducing peak demand has been studied less than the effect of reducing overall consumption, but a general finding is that programmes with this focus are somewhat "successful in shifting energy use from peak periods to off-peak periods, [but] much less successful in generating energy savings" (Ehrhardt-Martinez et al., 2010, p. v). The research conducted here focus solely on overall electricity consumption, and this question will not be discussed further here.

A separate strand of literature has focused on the effect of normative feedback, i.e. providing information on consumption relative to social norms. Although people generally believe that they are not influenced by the actions of others (Wood & Newborough, 2007; Nolan et al., 2008), their actions prove otherwise, and effects have been found in behaviours ranging from recycling (Schultz, 1998) to towel reuse (Goldstein et al., 2008) to electricity consumption (Schultz et al., 2007). For instance, Schultz et al. (2007) demonstrated that when informed of the amount of energy that the average peer used, homeowners tended to decrease consumption when they were above the norm, but, importantly, increase consumption if they were below the norm. However, the invisibility of electricity consumption prevents people from not only assessing their own, but also the consumption behaviour of others, making normative comparison impossible (Ehrhardt-Martinez et al., 2010). If this finding is consistent across various populations, it follows that information on electricity consumption should include descriptive normative information.

2.4.1 The 'Rebound effect'

The 'rebound effect' theorises that increased energy efficiency in goods (e.g. a car) lead to increasing level of energy services (e.g. more driving) and thus more energy consumed (e.g. gasoline), and has been heavily discussed in the literature (Khazzoom, 1980; Nässén & Holmberg, 2009; Greening et al., 2000)[35]. In relation to EE, Khazzoom (1980) pointed out that energy savings from mandated efficiency standards was most likely not as significant as expected ex ante, as increased efficiency will reduce the effective cost of energy services (e.g. cost per hour of light) which, *ceteris paribus*, should increase demand for the service, thus diminishing the energy reduction expected (or even increasing demand)[36].

The rebound effect can be expected to take four different forms in response to an increase in energy efficiency: (1) direct effects; (2) indirect effects; (3) economy-wide effects; and (4) transformational effects (Greening et al., 2000, p. 390). Only the first two will be discussed, as the latter two are less important for end-users, who are the foci of this thesis.

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[35] For an outline of the history of the academic discussion and estimates of the size of the rebound effect, see e.g. Nässén & Holmberg (2009) and Greening et al. (2000).

[36] "We may expect the reduction that increased efficiency entails to exert an upward pressure on the demand for energy. This pressure will partly offset, and may more than offset, the energy saving that results from improved appliance efficiency" (Khazzoom, 1980, p. 22).

The direct rebound effect essentially reflects the argument provided by Khazzoom (1980). If one assumes that energy consumption drops to a third if efficiency is increased three-fold, this would imply that the "'own' elasticity of energy demand with respect to appliance efficiency is -1," which would imply that the "elasticity of energy demand with respect to energy price is 0," (Khazzoom, 1980, p. 22) which would be unreasonable[37]. As long as the average individual's price elasticity of demand for appliances is not zero, the lower energy price, implicit in the higher efficiency, will exert an upward pressure on the demand for the service delivered by the appliance (Khazzoom, 1987, p. 86). Academics disagree about is the size of this effect, which can be either insignificant (e.g. a few percent increase in demand for the service) or massive (e.g. result in higher energy consumption). Research (Greening et al., 2000; Nässén & Holmberg, 2009) indicates that the magnitude of the direct rebound effect is less than postulated by Khazzoom (1980). Nässén and Holmberg (2009, p. 221) find "rebound effects in the order of 10–20%," while the IPCC (Lucon et al., 2014) assumes effects to be in the range of 0-30%. Indirect effect results from the reduced cost of energy services, which increases the disposable income available to procure other goods and services (Nässén & Holmberg, 2009). As these goods also require energy, this increases demand, and leads to economic growth with the associated environmental impact of this growth. The size of these indirect effects depends on the share of the consumer's income spent on energy services (e.g. driving, electricity) (Greening et al., 2000, p. 391). Greening et al. (2000, p. 399) give an overview of over 75 estimates of the rebound effect in the literature with estimates derived from both econometric studies and direct measurements, and finds that "available measurements of the rebound for residential end-uses suggest a range of responses of 0-50% for a 100% increase in energy efficiency." They arrive at the conclusion that "the rebound is not high enough to mitigate the importance of energy efficiency as a way of reducing carbon emissions" (p. 399). For Smart Meters, especially the size of the indirect rebound effect becomes important; assuming that people reduce their electricity bill as a result of installing the meter, this will increase their disposable income. If they then spend this money on energy intensive goods, such as air travel, this has the implication that the overall reduction in GHG emissions as a result of the policy will be limited.

[37] The mathematics behind this is explained in a fairly straightforward manner in Khazzoom (1987, p. 87), and in slightly more complicated terms in Khazzoom (1980). While some of Khazzoom's (1980; 1987) conclusions have since been rebutted, the price elasticity argument still hold true, at least to this author's knowledge.

3 Research Methodology

This chapter elaborates on the methodology used during this thesis. The research methodology was framed by behavioural economics, which is defined as an inductive science, relying primarily on experiments and observations to establish theories on how humans behave. This highlights the legacy owed to experimental psychology, a predominantly inductive science, and is in stark contrast to the deductive method used in neoclassical economics, where theory is deduced from axiomatic assumptions and then subjected to empirical tests. However, inductive experiments can, and sometimes do, confirm theories suggested by neoclassical economics[38] (Lunn, 2014). Following the presentation of the exercises and experiments conducted as part of this work, the different methods of data collection and analysis used to conduct this research are summarized. Data was collected across various sources to increase objectivity. Experiments, interviews, questionnaires and raw data collection were part of the research, and the collected material was analysed using both qualitative and quantitative methods. An extensive literature review from related or applicable research was also carried out.

3.1 Experiments

The experiments conducted as a part of this thesis aim to test the effect of a number of behavioural biases on consumer behaviour with regards to electricity use and energy-related decisions. This knowledge is used as starting point to determine which biases could be applicable when providing consumers with information using Smart Meters. However, it must be noted that this thesis does not provide an exhaustive overview of how BE-based interventions can potentially be applied to increase Smart Meter effectiveness, but rather explores human susceptibility to a select number of these. All of the biases explored here have been found in other experiments or real-life settings and are reported in research on BE. In order to answer research question 1, the experiments explore questions such as:

- What is the effect of framing feedback as avoiding a loss rather than obtaining a gain?
- What is the effect of changing the amount and salience of electricity information?
- Does changing the default choice/value have an effect on consumer decisions?
- What is the effect of salience on consumer discount rates?
- What is the effect of loss aversion on energy-related investment decisions?

All of the experiments have been conducted in the greater Copenhagen region, Denmark, which constitutes the case area for interventions. Results for statistical representativeness are thus for Denmark or Copenhagen, unless anything else is reported.

3.1.1 Energy-use awareness

From studies in psychology (e.g. Dunning et al., 2004; Kruger, 1999), it is known that people consider themselves to perform above average for a given task, e.g. when asked to rank their own behaviour, and that of others, people often rank their own behaviour consistently above the behaviour of others. To test how people perceive their actions on electricity relative to those of others, an experiment was conducted at a science fair in collaboration with researchers from a consultancy working on behavioural design in public spaces. The goal was to test whether 'above-average bias' could be found for electricity consumption, specifically whether participants, all of whom lived in the Copenhagen region, believed themselves to be

[38] Leaving aside here the discussion initiated by scholars of scientific theory of whether or not a finding can really be 'confirmed' or whether only falsification is possible (c.f. the work of Karl Popper (1973) and others).

more aware of their energy consumption than the average Dane. Participants were asked two ranking questions and told to provide an answer on a scale from 1-10:

1. How aware are you of your own energy consumption?
2. How aware do you think the Danes are of their own energy consumption?

The rationale behind the experiment is to test whether 'above average bias' exists for energy consumption. This could provide valuable insight into the utilisation of Smart Meters, because if this bias can be confirmed, it constitutes an argument for providing people with information about other peoples' actual behaviour. The information conveyed by the Smart Meter would enable participants to act on a descriptive social norm (c.f. Cialdini et al., 1990). In other words, if people think they are more aware of their energy use (i.e. use less electricity) than Danes in general, but the information from the Smart Meter conveys that they are actually below, i.e. use more electricity than the average person, this constitutes a strong incentive to change behaviour to obey to the descriptive social norm, i.e. reduce their electricity consumption to a level that aligns with the norm.

3.1.2 Exercises on preference choices in energy-use decisions

While insights from CPT (Tversky & Kahneman, 1979; 1992), such as loss aversion or default setting, appear theoretically promising, no practical evidence of successful utilisation of this for Smart Meter feedback was found in the literature. The following exercises did not directly address Smart Meter use. Instead they were intended to test four specific biases; information overload, salience, loss aversion, and defaults, over seven experiments. This was done in order to understand whether these biases could be expected to occur when humans are provided with information on energy use or faced with energy-related decisions through a Smart Meter. This knowledge is crucial, as it expands our understanding of how feedback should be provided using Smart Meters to overcome, work with or avoid these biases, rather than be prone to them. The exercises all build on previous evidence or experiments found in literature, all of which will be presented for each exercise. *Exercise 1* tests whether the presence of unnecessary information (information overload) impedes optimal (rational) choice, *exercise 2* tests whether salience of information changes energy-related decisions, *exercise 3* assesses participant knowledge of electricity consumption data, *exercise 4 and 5* explores how the salience of information changes discounting preferences, *exercise 6* assesses whether loss aversion changes willingness to undertake EE investments (c.f. CPT value function), and finally, *exercise 7* looks at the effect of default setting on electricity plan selection. The order of the exercises is random, and does not signify anything special (e.g. exercise 1 is not more important that exercise 7), but refers to the order in which the participants were asked these questions.

To test whether these biases were present in relation to information on electricity consumption, two versions of the seven exercises were created, one with the theoretical findings in question, and one without. About half of the subjects received version 1 of the questionnaire (Q1) and half received version 2 (Q2). All seven exercises took the form of a question that had to be answered. For each exercise, subjects were asked to select one of two or three options available, and all questions had to be answered. Besides the questions related to electricity consumption, subjects had to indicate gender and age, in order to make it possible to test whether these variables had an influence on the biases in question. The full version of the two forms of the seven exercises questions can be seen in Appendix 6.1.

Exercise 1: Information-overload and choice invariance

Rational choice theory predicts that humans should select their most preferred option, regardless of ranking and the presence of inferior options (c.f. section 2.1; von Neumann &

Morgenstern, 1944; Samuelson & Zeckhauser, 1988). To test whether this was the case, participants were asked to select between two ways of receiving and paying for Smart Meter feedback, one with online-only feedback (relatively cheap) (option A), and one with online feedback as well as detailed consumption reports mailed to the customer (relatively expensive) (option B). The assumption behind this type of question is that the developments in technology will lead to various data services being made available to consumers at an added cost. If preference for these can be influenced by unnecessary information, this calls for standardised ways of offering these services to consumers. In version 1 (Q1), only the two described options were available (A & B), while an inferior version of option B (B-) was added in version 2 (Q2). Based on an experiment conducted by Ariely (2008), where preference for newspaper subscriptions was found to change based on the presence of an inferior option, the assumption is that a larger proportion select option B in Q2 than in Q1, as the presence of B- makes B appear more beneficial.

Exercise 2: Salience and preference for energy-efficient goods

This experiment was intended to test the effect of the salience of information on the preference for energy-efficient goods. It has implication for feedback if salience changes decisions, as it implicitly follows that not just providing information on consumption, but also how consumption is displayed, can affect decisions. The aim was to explore whether making the energy cost part of the total life-cycle cost (c.f. section 2.2.2) explicit (salient) would change procurement decision. If this is the case, this bias could lead to procurement of more energy efficient models and thus help close the EE gap. The inspiration for this experiment comes from Kallbekken et al. (2013) and Newell & Siikamäki (2013) who conducted similar trials. In the experiment, participants were asked to choose between two fridges, a relatively efficient and a relatively inefficient model. Participants were given information on procurement cost, size, and electricity consumption (kWh/year) of both fridges. In version 2 (Q2), however, the cost of electricity over the lifetime of the refrigerator was stated explicitly as part of the information provide to participants, in order to increase the salience. The lifetime was assumed to be 12 years, but the payback period for the relatively expensive, but efficient model was only about 6.5 years. The assumption was that in version 2, where the electricity cost was explicitly stated, a larger proportion would opt for the efficient fridge.

Exercise 3: Assessing participant knowledge of electricity prices

This experiment had two goals: Firstly, to assess what level of knowledge on electricity and electricity prices consumers can be expected to have. If consumers generally know very little about electricity and electricity prices, this could signify that comparative information is needed. Secondly, to assess how consumers understand the information on electricity and electricity prices that they are provided with, depending on how this information is presented. In other words, does the way information is presented affect the knowledge-level one can infer from consumer behaviour? Participants were asked to correctly identify the largest yearly cost out of two possible options: the electricity (in kWh) or currency (in DKK) option, with the alternative option to choose "I do not know." The way the total cost was presented differed in the two versions. In version 1 (Q1), both options were labelled as a total per year (4,000 DKK and 4,000kWh), while in version 2 (Q2), the electricity was per given per month (330 kWh/month), while the monetary cost was per year (4,000 DKK/year). CPT (c.f. section 2.3.1) (Tversky & Kahneman, 1974) predicts that knowledge is not an absolute constant, and that the different framing in the two versions of the experiment would lead to differing levels of inferred knowledge. The electricity cost stated in kWh is more than twice as large (in monetary terms) as the price stated in DKK, so to anyone with knowledge of electricity prices, determining the largest cost, even in version 2, should mathematically prove a relatively easy task. It was expected that participants given version 1 would perform better than those given version 2, as getting the answer right in version 1 only involved having a rough knowledge of the cost of electricity (more or less than 1 DKK per kWh), while in version 2, the participants needed to know the price *and* calculate what the monthly use translated to in yearly consumption in order to arrive at the correct option.

Exercise 4 and 5: The effect of information salience on implicit discount rates

As presented in section 2.2.2 on discounting, some researchers (e.g. Sutherland, 1991) argue that the low uptake of EE measures is not a market failure, but are rather due to high consumer discount rates caused by the inherent uncertainty of these. These two experiments had three objectives in combination: Firstly, to gauge the implicit discount rates that consumers employ when faced with energy decisions. Secondly, to test whether the implicit discount rate changes if the question used to assess this is framed in more difficult language (i.e. reducing the salience). Thirdly, to test whether participants are consistent in their application of discount rates. If consumers do have high implicit discount rates and apply these consistently, this would provide an argument that no EE actually exist, as Sutherland (1991) argued. Contrary, if consumer rates are inconsistent and can be affected by how information is presented, this means that an EE gap exists, and that the size of this gap depends on how consumers are provided with information. It then follows that the framing of the EE information that Smart Meters can technically provide, e.g. benefit of switching to compact fluorescent light bulbs or buying an efficient fridge, can affect whether consumers in fact decide to undertake the EE measure. If the framing of knowledge can lead to more EE measures being undertaken, this can help close the EE gap and increase the social surplus of Smart Meter deployment.

The purpose of the first discount exercise (#4) was to derive a rough estimate of consumer discount rates, by asking participants whether they would be willing to undertake either or both of two explicit EE measures. These had payback periods of four and six years (implying discount rates of 25% and 16.6%), respectively. However, the payback period was not stated explicitly, but the cost and the benefit of the respective measures were given. To test whether smaller sums were discounted more than large sums, which have been shown in other areas (c.f. Frederick et al., 2002), the cost and benefits of the EE measures stated in version 2 (Q2) were ten times higher than those in version 1 (Q1). If consumers do discount smaller amounts more than large, it would provide an argument for providing EE information as aggregate amounts, rather than in separate smaller parts, as this would lower discount rates and help close the EE gap.

To test whether discount rates were subject to the salience of EE-related information provided, i.e. whether an inconsistency in consumer discount rates could be found depending on the formulation of the information given to participants, the discount question was stated in more difficult language in experiment 5. The experiment builds on a similar experiment conducted by Houston (1983) who tried to assess implicit discount rates by asking consumer about their preferred return on an investment, rather than ask about willingness to undertake an EE measure, or willingness to purchase an efficient good, as is usually done (c.f. Hausman, 1979; Gately, 1980). The implicit discount rate was implied by asking participants to indicate the minimum return on an investment of 500 DKK (€~70) required in order to undertake an EE measure. Bounded rationality and CPT (c.f. heuristics) predict that consumers would show higher rates when the language was difficult, as more mental capacity would be required, and as such, the implicit discount rates derived from exercise 5 are assumed to be higher than those derived from exercise 4.

Exercise 6: Loss framing and the willingness to undertake risky EE investments

When explaining the EE gap, some researchers (e.g. Hasset & Metcalf, 1993) have argued that the uncertainty involved in EE measures makes it a risky investment, which justifies the high discount rates. If the perceived riskiness of an EE measures leads to higher discount rates, reducing the risk should lead to a higher uptake of EE measures. However, according to CPT, riskiness is a relative concept that depends on framing, meaning that the willingness to run a risk (in essence, the willingness to gamble) depends on the framing. This experiment was designed to test whether the willingness to undertake an EE investment could be changed depending on whether the outcome was framed as a gain or loss relative to the status quo. The idea for this experiment comes from an experiment conducted by Kahneman & Tversky (1984, p. 343), who showed that preference for a risky medical treatment changes depending on framing. If this can be found for energy-related decisions, it has the implication that decisions on whether or not to undertake EE measures involving a degree of uncertainty can be changed by changing the framing. This implies that information should be framed so as to reduce the perceived risk, which should increase the willingness of participants to undertake risky EE investments.

Participants were asked to decide between a certain outcome and a more risky outcome when deciding on procurement of an EE good. The questions participants were asked in the two versions of the experiment are indistinguishable from each other in real terms, meaning that they are mathematically identical. However, the impact of installing the EE measure is framed as obtaining a benefit in version 1 (Q1), and as avoiding a cost in version 2 (Q2). According to the value function in CPT (c.f. section 2.3.2), participants given Q2 are expected to show a risk seeking preference for the gamble (gambling to avoid a loss of 600 DKK) (option B) over the sure loss of 400 DKK (option A). Contrary to this, participants given Q1 are expected to show risk aversion (taking a sure gain of 200 DKK) (option A) over the risky prospect (gambling to gain 600 DKK) (option B).

Exercise 7: The effect of Default setting on electricity plan selection

Adoption of dynamic pricing by consumers could potentially lead to savings in energy (Faruqui et al., 2010a). However, Faruqui et al. (2010a) speculate that loss aversion could influence consumer willingness to try these new plans, as consumers, rather than focusing on potential savings, would focus on the risk that costs might increase, leading to the incumbent being favoured. Previous experiments (Samuelson & Zeckhauser, 1988; Pyrko & Darby, 2009) had found that current type of plan was the most important predictor of future plan selection. Along the same lines, in an experiment, Pichert & Katsikopoulos (2008) asked participants to choose between two different types of electricity: conventional and "green" (renewable). When conventional was the default, 31 of 75 participants (41%) chose the green utility, whereas 52 of 77 participants (68%) chose the green utility when this was the default. Smart Meters could potentially be used to automatically determine which plan would fit consumers (e.g. dynamic or static pricing), but if the incumbent plan influences preference for future plans, this would affect the degree to which Smart Meters can be used to switch consumers to a new (more appropriate) plan. To test whether the type of incumbent plan (the default) had an effect, an experiment was set up. In version 1 (Q1) of the experiment, the conventional (static) tariff was the incumbent, so participants would have to take action to get the dynamic tariff plan. Contrary to this, in version 2 (Q2) participants were told to imagine that they had been moved to the dynamic price tariff, meaning that participants would have to take action to get the conventional (static) plan. Participants were told that the assumption was that dynamic tariffs could lead to savings of 5%, but that this could not be guaranteed. Based on the results from previous experiments (e.g. Pyrko & Darby, 2009), the assumption was that the majority of the participants would keep the default plan, meaning they would select the conventional plan in Q1 and the dynamic pricing plan in Q2.

3.1.3 Smart Meter experiments

In Denmark, the rollout of Smart Meters has begun and an increasing number of customers have Smart Meters installed with more or less advanced features. To assess the effectiveness of a Smart Meter where no behavioural intervention was conducted, data from 92 Smart Meters installed in households in Copenhagen was collected. Customers with such Smart Meters were provided with near-real time feedback, as their consumption was reported and made available in 15-minute intervals. The data was analysed to assess whether any effects greater than those expected from natural yearly fluctuations could be discerned. The Smart Meters used in this experiment are so-called add-ons, i.e. extra meters added to a 'dumb' meter to make them 'smart,' meaning that they are able to transmit consumption data. The customers have access to a portal where they can check their consumption in kWh and DKK on an hourly, daily, weekly, monthly or yearly basis, but unless they access this portal they receive no other information than what a "normal" meter can provide (Figure 3-1). The rationale behind the analysis of the Smart Meter data is to test whether the EC prediction of a reduction in energy consumption of 10% from installation of Smart Meters in Europe is in any way reflected in consumption profiles of the users who have already had a meter installed.

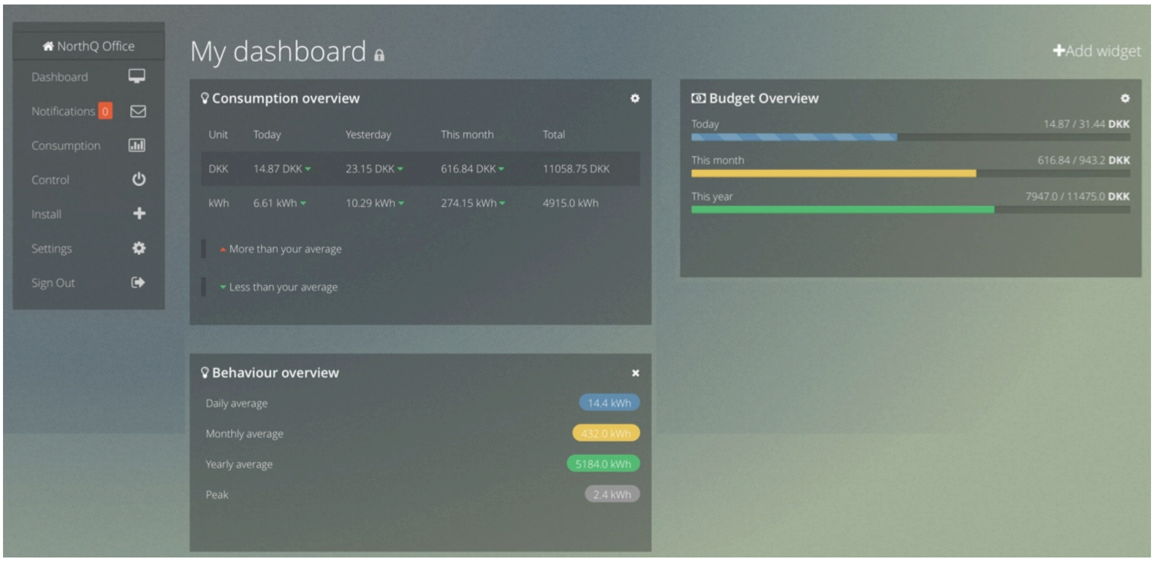

Figure 3-1 – Snapshot of consumption information available to Smart Meter customers online. ©NorthQ (used with permission).

Given CPT, it is assumed that framing a cost as avoiding a loss rather than obtaining a gain should have an effect on behaviour (see e.g. Kahneman, 2011; Weber, 2013) (see also section 2.3.2). It is also known that the salience of the information upon which humans act can systematically change behaviour, as shown by e.g. Gilbert and Zivin (2014). Employing these insight to Smart Meter feedback can hep determine whether these biases also exists for electricity consumption and how large the effects are, which can assist in answering RQ#2.

In order to test these assumptions, a second Smart Meter experiment was set up. The rationale behind the Smart Meter experiment was thus two-fold: Firstly, to assess whether framing the total daily electricity consumption as a loss can trigger *loss aversion*, meaning that any reduction in consumption will be seen as reducing a loss, which theoretically (c.f. the value function in CPT) should induce a more significant change in behaviour than if electricity consumption reduction is seen as a gain. Secondly, to test whether the *salience* of the information presented makes a difference to final electricity consumption. This was tested by presenting the nightly consumption (00-06) as a cumulative figure per year, rather than in kWh and DKK per day, as is usually the case, as it was assumed that the cumulative figure would be more salient to the consumer than the daily figure[39]. If salience does have an impact, this means that not only *whether* information is provided, but also *how* it is provided, can impact consumption. This would entail that simply correcting the information asymmetry is not enough, and it should be carefully considered how the information is framed.

The participating households were divided in two groups: a test group and a reference group. The reference group received information on household electricity consumption in kilowatt-hours (kWh), and information on how much their consumption aligned with a pre-defined budget (in DKK per year), which had been set by the household. The test group received the same information, along with information on the running cost of electricity consumption and the estimated weekly cost (framed as a loss), and the cost of passive and stand-by electricity consumption per day and per year (framed as a loss and made salient), as described. The widget in the software interface read: "Money lost from electricity consumption" and then stated the number (see Figure 3-2). The widget displayed the amount spent per day as a running total, which was updated every few seconds and reset every day, meaning that it looked like the money was "flowing" out of the pocket. The estimated weekly cost was updated every 15 minutes. The standby consumption data was updated once every day to reflect the standby consumption of the previous night.

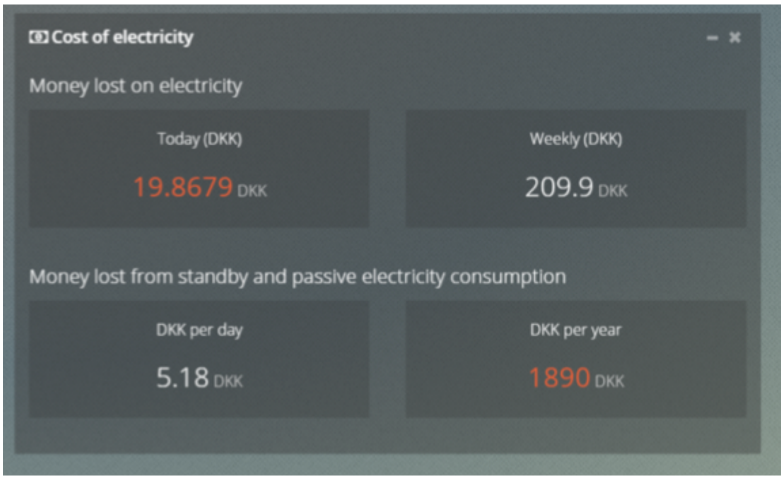

Figure 3-2 – Loss Aversion widget as seen by participants in Smart Meter experiment. ©Bager & NorthQ.

3.2 Methods for data collection and processing

The literature review conducted for this thesis had several aims: Firstly, to provide a comprehensive and up-to-date overview of human behaviour as understood by the economic theories discussed in this thesis; mainly neoclassical (Frank, 1997; von Neumann & Morgenstern, 1944), new institutional (Sathaye & Murtishaw, 2004; Mundaca et al., 2013), and behavioural (Kahneman & Tversky, 1979; 1992; Tversky & Kahneman, 1974; 1986; Thaler,

[39] It was assumed that the nightly consumption primarily consisted of stand-by and passive consumption (e.g. freezers, refridgerators), and thus would be representative of the standby consumption for the household, absent any daily activities, such as cooking, cleaning, etc. In the functionality requirements for Smart Meters, the EC states that information on energy consumption should be "provided in a fashion that does not require any numerical computation or energy literacy to understand, examples include display of cost rather than kWh" (EC requirements report, p. 21). As the electricity consumption in this experiment is shown in DKK rather than kWh, this is in line with EC recommendations.

1980). Secondly, the literature was scorched for research on the effect of feedback on energy and electricity consumption in order to be able to compare the effect of the research conducted here against previous research (most notably Abrahamse et al., 2005; Darby, 2006; Fischer, 2008; Ehrhardt-Martinez et al., 2010). This also included newer research into the effect of using Smart Meters for feedback provision (e.g. Joachain & Klopfert, 2013; AECOM, 2011; Gans et al., 2013; Schleich et al., 2011; 2013). Thirdly, the experiments conducted here are either inspired by or take a point of departure in research conducted by experimental economist or psychologists (e.g. Pichert & Katsikopoulos, 2008; Kahneman & Tversky, 1984; Houston, 1983; Kallbekken et al., 2013; Ariely, 2008).

In order to expand on the knowledge gathered in the literature review, a number of interviews with relevant stakeholders were conducted. For the purpose of understanding Smart Meters and the technical details behind these, Mr. Christian von Scholten and Mr. Andrei Cimpoeru of NorthQ were interviewed. They played an important role for this research, as the Smart Meter experiment was conducted from data collected by their meters. The loss aversion widget was designed by the author in collaboration with Mr. Cimpoeru. To gain a deeper understanding of the electricity market and the benefits to companies of installing Smart Meters, Mr. Lars Elmegaard of Danish utility company SEAS-NVE was interviewed.

Sample data was subjected to statistical tests to learn the significance of the results. The most common test applied was chi-squared test (see Appendix 6.2) (McGrew & Monroe, 2000), which was used to test whether a significant difference between the answers to the two version of each of the exercises could be found, in order to determine whether the intervention in question could be said to have a statistically significant effect.

3.2.1 Data collection for energy-use awareness experiment

The sample collected for the test of energy-use awareness consisted of 64 answers for question 1 (n_{q1} = 64) and 67 answers for question 2 (n_{q2} = 67), as not all participants answered both questions. The data was collected using an iPad, where people filled in their answer to the two questions and then submitted these. No background information on the participants was collected. Given that there are roughly 3 million adults in Denmark (Statistics Denmark, 2012), and taking into account a confidence level of 95% and a margin of error of 5%, the sample should have been 385 to be representative. This means that results cannot be said to be representative of the case area using standard statistical uncertainty. To determine whether a significant difference between the answers to the two questions could be found, the results were subjected to a *t*-test.

3.2.2 Data collection for Smart Meter experiments

The data collected from the Smart Meters without loss aversion intervention is sampled from 92 meters (n_{SM}=92). The observation from each meter is of varying time span and covers a period from the fall of 2012 to early August 2014. The number of observations is much higher in the final part of the period, due to a higher number of Smart Meters being installed at that point. Before analysis, data from weeks with less than 7 observations in one week, i.e. weeks with data missing for any days, were discarded, as was weeks that returned a total consumption of "0" (zero), as this indicated something had gone wrong when transmitting the data. Finally, meters with observations spanning less than 3 weeks in total were excluded. This yielded at total sample of 51 meters. Furthermore, two meters with extremely high readings were also excluded based on an assumption that this data was incorrect. This yielded a final sample of 49 meters ($n_{SMfinal}$ =49). Taking into account that there are 2.6 million households in Denmark (Statistics Denmark, 2014), and using a confidence level of 95%, results are representative when the margin of error is 14%. With standard margin of error (5%), sample should have been 385 to be representative.

Data for the Smart Meter experiment on loss aversion was collected over a 5-week period in July and August 2014. 85 households located in Copenhagen were invited to participate in the experiment, but only 63 chose to do by providing their written consent. Even though the experiment was postponed two weeks to increase the sample size, out of the 63 households that accepted the invitation, only 16 installed the meter in time to be part of the experiment, meaning that the two group were reduced to a test group of 11 households (n_{test} = 11) and a reference group of 5 households (n_{ref} = 5). The sample was contains information on daily consumption (kWh/day), weekly consumption (kWh/week), nightly consumption (passive and stand-by) (kWh/night (23-06)), as well as average daily consumption (kWh) and average weekly consumption (kWh).

The participating households have similar building characteristics, as all houses are semi-detached houses, constructed around the same time, all connected to the district-heating grid, none of them using electric heating, and with sizes varying from 103-130 m^2. The households had the same type of Smart Meter installed as those meters from which the long-term data is collected, along with software to monitor the consumption of electricity.

Supplementary socio-economic data on the target group was collected through a questionnaire-based survey in order to ensure that any difference in electricity consumption could be attributed to the framing of consumption, and not structural differences. The dependent variables were selected based on evidence from previous research (Gram-Hanssen, 2013; 2014; Mills & Schleich, 2012; Gans et al., 2013; Kavousian et al., 2013). Mills and Schleich (2012) in a study of 5,000 households in 10 EU countries and Norway found that family age-composition (variable #2 and #3) had "a distinct impact on household energy use behaviour" (p. 616), as did education (not included) and income (#5) (Gram-Hanssen, 2003)[40]. Gram-Hanssen (2003; 2013) and Kavousian et al. (2013) makes the case that the total number of appliances influences total household electricity consumption (#6), while Gram-Hanssen (2014) argues that environmental awareness (#8) also has an impact. Kavousian et al. (2013) find that the size of the house (#4) has an impact, while "number of hours spent at home" (#7) was included as it was hypothesized that this could possibly have an effect.
The data was collected in June, July and August 2014, prior to and during the experiment. Data on eight dependent variables was collected (questionnaire can be seen in Appendix 6.3):

1. Previous yearly consumption (2011, 2012, 2013) (in kWh)
2. Number of occupants (#)
3. Age of occupants (year)
4. Size of house (m^2)
5. Yearly income (four brackets, do not want to disclose option)
6. Number of electric or electronic appliances (five brackets)
7. Number of hours spent at home (07-15, 15-23, 23-07)
8. Environmental awareness (yes/no).

The household data gathered was entered into a spreadsheet, which is available per request, while the consumption data (in *.csv-form) was collected from the server of the utility company. This is also available per request.

[40] It should be noted that Kavousian et al. (2013) observed "no significant correlation between electricity consumption and income level" (p. 184). They furthermore found no correlation between electricity consumption and home ownership nor building age, and as these were deemed difficult to obtain information about, they were excluded.

3.2.3 Data collection for preference choice exercises

The sample had a size of 278 participants (n_{total}=278) divided between two versions of the questionnaire (n_{Q1}=131, n_{Q2}=147). The data was collected by hand at a hardware store in a suburb in Copenhagen, Denmark, during a summer weekend in early August 2014. Subjects were given no reward for participating. Thoroughly incomplete data sets were discarded (n=2), while datasets with answers to gender and age, as well as some of the seven exercises were kept, as questions were deemed to be independent of each other. This yielded a total of 276 questionnaires, but a different number of observations for each of the seven exercises (see Table 3-1). Taking into account that there are 2.6 million households in DK (Statistics Denmark, 2014), and using a confidence level of 95%, results are representative when the margin of error is 6%. With standard margin of error (5%), sample should have been 385 to be representative. Of those 276 questionnaires, men answered 184 questionnaires, while women answered 92, which mean that men make up two-thirds of the sample. The average age of the participants is 47.9 years (*SD* = 13.4 years), with the oldest participant being 81 years old and the youngest participant being 21 years old (spread = 60 years).

Preference choice exercise	Version 1 (Q1)	Version 2 (Q2)
Exercise 1: Information plan	128	138
Exercise 2: Fridge	131	145
Exercise 3: Electricity knowledge	130	144
Exercise 4a: Discounting, 25%	131	145
Exercise 4b: Discounting, 16.6%	124	134
Exercise 5: Discounting, unknown rate	198 (same question in both Q1 and Q2)	
Exercise 6: Risk profile	128	139
Exercise 7: Default plan	131	142

Table 3-1 – Sample sizes from questionnaire experiment

4 Results

The following section presents the findings from the various analyses, choice exercises and experiments conducted for this thesis. First, the results from the eight choice exercises are presented in order to answer RQ#1. Secondly, the results from the Smart Meter data analysis are presented. Then the findings from the experiment on Smart Meters with loss aversion framing are offered, in order to answer RQ#2. This is followed by the results from literature-based analysis of the effect of feedback provision, conducted in order to have something to compare the results of the Smart Meter experiments against.

Where applicable, statistical tests of significance have been conducted. Unless anything else is stated, *significant* means significant at a 95%-confidence level (p-value <0.05).

4.1 Behavioural biases and energy-related behaviour

The following section presents the results of the various choice preference exercises conducted to test the effect of behavioural biases. The section first presents the exercise intended to assess the knowledge-level displayed by participants. Next, the results determining the effect of information provision and the salience of this information are presented. This is followed by the results from the default-effect and energy-use awareness exercises, and finally the results from the exercises with loss framing of information are presented.

4.1.1 Consumer Knowledge of Electricity prices (Exercise 3)

As mentioned, this exercise had two objectives: To test the level of knowledge present in the sample, and to test whether the way information was presented affected this. The results show that generally, only about half of the participants (54%) know enough about electricity prices to correctly identify the kWh-option as the right option. Older people seem to have a higher knowledge of electricity than young people, but a chi-squared test determined that the difference is not significant (p-value: 0.418) (Table 4-1).

The different framing of the options in the two versions of the exercise reveal that the salience of the information, i.e. the ease at which the kWh and DKK options can be compared, had an impact on perceived knowledge. Overall, a slightly higher percentage of the participants were able to identify the right option in version 1 (Q1) than in version 2 (Q2), but a chi-squared test determined that the difference is not significant (at 95%). Women do not perform significantly different in the two versions (at 95%), though there seems to be a tendency that more women select the "I do not know"-option, when direct comparison is made more difficult. Men perform significantly better (at 95% level) in version 1 than in version 2, dropping from well above average (72%) to average (54%). Interestingly, the main difference between the genders seem to be that women are willing to admit that they do not know the answer, while men are not, and as a result guess wrong when direct comparison is difficult (c.f. men selecting the DKK option increase from 9% to 24%). All of the chi-squared tests of significance can be seen in Appendix 6.4.

	n_{DKK} (percentage)	n_{kWh} (percentage)	$n_{Do\ not\ know}$ (percentage)	Total
Overall	43 (16%)	147 (54%)	84 (31%)	274
Age <40	14 (17%)	39 (48%)	29 (35%)	82
Age 40+	29 (15%)	106 (56%)	54 (29%)	189
Q1 all	16 (12%)	78 (60%)	36 (28%)	130
Q2 all	27 (19%)	69 (48%)	48 (33%)	144
Q1 men	7 (9%)	57 (72%)	15 (19%)	79

Q2 men	24 (24%)	55 (54%)	23 (23%)	102
Q1 women	9 (18%)	21 (41%)	21 (41%)	51
Q2 women	3 (7%)	14 (34%)	24 (59%)	41

Table 4-1 – Breakdown of results from experiment 3 by age and gender.

4.1.2 The effect of multiple options on choice selection (Exercise 1)

This choice exercise did not confirm the bias proposed by Ariely (2008) that the presence of a clearly inferior option would lead to increased preference for a similar, but better option. Participants selected option A to the same degree in both versions of the experiment, while only option B seemed to be affected by the presence of a clearly inferior option (B-) (Table 4-2) One would expect none to select option B- (Ariely, 2008) as it is clearly inferior. From a neoclassical economic perspective, this is suboptimal behaviour, as it violates the dominance axiom of EUT.

	Option A	Option B-	Option B	Total
Version 1 (Q1)	77 (60%)	(N/A)	51 (40%)	128
Version 2 (Q2)	85 (62%)	16 (12%)	37 (27%)	138

Table 4-2 – Breakdown of results from experiment 1.

Within the context of this experiment, note that information overload and the effect on consumer behaviour have received some attention in the academic literature, but experimental results are inconclusive (e.g. Jacoby, 1984; Malhotra, 1984; Hwang & Lin, 1999). Honing in on choice selection, psychologists have discussed the observation that multiple options or the presence of inferior options can lead to suboptimal decisions visibly in violation of EUT (e.g. Iyengar & Lepper, 2000; Schwartz, 2004). If decisions can be affected by the presence of multiple or irrelevant options, this would suggest that the information presented to consumers should be limited to ease choice. The results from this exercise do seem to align with the suggestion that increasing the amount of options leads to suboptimal decisions, though it must be noted that the amount of options presented here much is lower than in the original experiment (c.f. Schwartz, 2004; Iyengar & Lepper, 2000).

4.1.3 The effect of electricity cost salience on consumer purchase decisions (Exercise 2)

The following choice preference exercise was intended to test whether the way information was presented (i.e. the salience of information) would make a difference to consumer choice. In both versions of the exercise, the participants were asked to choose between two fridges, a relatively efficient model (A) and a relatively inefficient model (B). Both questionnaires contained information on purchase price and yearly electricity consumption (in kWh). However, in version 2 (Q2) the kWh was also translated into cost of electricity over the lifetime of the fridge (set to be 12 years). A perfectly rational, utility maximising actor with perfect information would choose the same model in both experiments, as s/he would calculate the electricity price over the lifetime of the fridge and relate that to his personal discount rate, selecting the fridge that provided the highest utility (Frank, 1997).

In version 1, where the electricity cost was not made salient, 85% of the participants chose the efficient fridge. When the electricity cost was made salient (version 2), this was the case for 95% of the participants (Table 4-3). As such, making the information salient had a significant (at 99%) effect on purchase decision. As in exercise 3, men showed larger changes from version 1 to version 2 than women did. The percentage of men selecting the efficient model increased from 83% to 96% (significant difference at 95%), while the percentage of women selecting the efficient model increased from 90% to 93% (this is not a significant difference, though it must be noted that small sample size for women can bias this result). That making information salient has an effect on preference is in line with other research on the topic (Newell & Siikamäki, 2013; Kallbekken et al., 2013). Kallbekken et al. (2013) found that highlighting the lifetime electricity cost led to consumers buying fridges that were 5% more efficient on average. In this experiment, the selection between the two fridges led to the fridges being selected having an average electricity consumption per year of 168 kWh/year in version 1, while version 2 led to an average electricity consumption per year of 156 kWh/year, which translates into a 7% drop in yearly energy consumption, in line with the results found by Kallbekken et al. (2013)[41]. Results from statistical tests can be seen in Appendix 6.5.

	Fridge A (Efficient fridge)	Fridge B (Non-efficient fridge)
No cost salience (version 1) – all	112 (85.5%)	19 (14.5%)
Cost salience (version 2) – all	138 (95%)	7 (5%)
No cost salience (version 1) – men	66 (82.5%)	14 (17.5%)
Cost salience (version 2) – men	98 (96%)	4 (4%)
No cost salience (version 1) – women	46 (90%)	5 (10%)
Cost salience (version 2) – women	38 (93%)	3 (7%)

Table 4-3 – Breakdown of results from experiment 2

4.1.4 The effect of information salience on implicit discount rates (Exercises 4 & 5)

As elaborated on in section 2.2.2, implicit consumer discount rates have been discussed extensively in academic literature, especially in relation to EE (e.g Hausman, 1979; Gately, 1980; Train, 1985; Ruderman et al., 1987; Jaffe & Stavins, 1994a, 1994b; Hasset & Metcalf, 1993; Howarth & Sanstad, 1995). However, whether the accessibility or salience of EE information affects the implicit discount rate has only received scant attention in literature (Houston, 1983; Train, 1985). The following two exercises intended to test whether information does affect decisions by subjecting participants to a number of imagined EE investment decisions, and deriving implicit discount rates from their answers.

The first question was framed in a relatively simple manner, asking participants to indicate their willingness to undertake an EE investment with known costs and benefits. The first observation from this exercise is that the implicit consumer discount rate appears to indeed be high: A little less than half of the participants provide answers that indicate that they are not willing to undertake investments with a payback period of 6 years, which translates into a discount rate >16%, while around 10% are not willing to undertake an investment with a payback period of 4 years, which implies a discount rate >25%. Overall, as slightly over half of the participants are willing to undertake both these measures, this translates into a discount rate for the group somewhere above 16%, possibly in the range of 16-20% (Table 4-4).

To test for the notion that small sums are discounted higher than large, as theorised by e.g. Frederick et al. (2002), the values indicated in the two versions of the experiment differ by a

[41] Calculation for electricity use: Average electricity consumption = (electricity usage per year fridge A * percentage selecting fridge A) + (electricity usage per year fridge B * percentage selecting fridge B). Version 1: (150kWh/year*0.855) + (274kWh/year*0.145) = 168 kWh/year. Version 2: (150kWh/year*0.952) + (274kWh/year*0.048) = 156 kWh/year.
Drop in consumption: (average electricity use version 1 – average electricity use version 2 / average electricity use version 1) = (168-156)/168 = 0.0714 = 7.14%.

factor of 10 between version 1 (Q1) (small values) and version 2 (Q2) (large values). Although it would seem that large values lead to lower discount rates, there is no significant difference between the answers in the two versions (p-value: 0.41), indicating that people are fairly consistent in applying discount rates even if the total sum changes (Table 4-4).

	Discount rate ≤ 16%	**Discount rate 16-25%**	**Discount rate > 25%**
Both versions (Q1 + Q2)	149 (57%)	84 (32%)	28 (11%)
Version 1 (Q1)	67 (56%)	36 (30%)	16 (13%)
Version 2 (Q2)	82 (58%)	48 (34%)	12 (8%)

Table 4-4 – Breakdown of results from experiment 4.

The following exercise (#5) tested whether the difficulty of the language with which the question was asked had an impact on the implicit discount rate derived. The participants were asked to state how large a yearly saving they would need in order to be willing to install an energy saving device that cost 500DKK. This question is, if understood in economic terms, indistinguishable from the question asked in choice exercise 4, as it can be used to derive the implicit discount rate of participants. Almost a third of the participants (29%) found this to be such a difficult task that they either gave no answer (14.5% of participants) or gave answers indicating very large discount rates (upwards of 200%) (14.5% of participants). These values are similar to those found in other studies (e.g. Hausman, 1979), and also reflects a finding from an experiment by Houston (1983) from which this experiment (#5) is derived, namely that framing a question on discounting in difficult language leads to a significantly larger amount of "no data" or "do not know"-answers than putting the question in simpler terms (as in exercise #4). Those of the participants that did state a reasonable return (defined here to be ≤500 DKK) wanted on average a return of DKK164 per year, equal to an implicit discount rate of 33%, higher than in the exercise above (#4), where discount rates were found to be around 16 to 20%.

The two exercises were also intended to test whether participants showed inconsistencies in discounting preferences with the aim assess if salience systematically influenced discount rates. In line with previous experiments on discounting (Train, 1985; Houston, 1983), participants were found to apply discount rates inconsistenly depending on framing. 5% of the participants said no to the short payback period (high discount rate) in exercise 4, but yes to the long payback period (low discount rate). More than a third (38%) of the participants gave inconsistent, none-overlapping discount estimates in the two examples, e.g. stating an implicit discount rate under 16% (yes to both questions in experiment 4), but above 25% in question 5 (stating a payback of 200, say). It should be noted that participants conducted exercise 5 immediately after exercise 4, and as such, should have their answers in recent memory, but the answers suggest that participants did not link the answers provided in the two exercises to each other.

Reviewing the answers from exercise 2 that asked participants to select between two models of a fridge can also yield implicit discount rates (Table 4-5). Given current electricity prices, the payback period on the expensive, but energy efficient fridge is just over 6 years, meaning that the implicit discount rate is 15% or less for those buying the efficient fridge. As 85% of the participants select the efficient fridge, these 85% should also say yes to both questions in experiment 4, which would indicate a discount rate ≤16%. However, only 57% does so (Table 4-4). Furthermore, the amount of participants that selected the efficient fridge increased when the electricity price was highlighted, which indicates that the discount rate is not a static figure, but changes depending on how a question is framed, as the other experiments also indicate.

	Fridge, version 1	**Fridge, version 2**
Cost of fridge (DKK)	5,599	3,805
Yearly electricity cost (DKK)	330	603
Purchase cost difference	1,795 DKK	
Payback period (expensive fridge)	6 years 7 months	
Implicit discount rate	≤0.1519 (≤15.2%)	

Table 4-5 – Implicit discount rate derived from consumer purchase decisions

4.1.5 The effect of default setting on electricity plan selection (Exercise 7)

The effect of default setting on consumer decision making is well established in the literature (e.g. Johnson & Goldstein, 2003; Pichert & Katsikopoulos, 2008; Carroll et al., 2009; Dinner et al., 2011; Brown et al., 2013). To test whether the default setting influenced preference for electricity plan, consumers were asked to state whether they wanted to keep the default plan or take action to get the non-default plan. In version 1 the static tariff (conventional) plan was the default, and in version 2 the dynamic tariff (new) plan was the default. Provided that the default is expected to have an effect on choice, the results are somewhat unexpected. In both versions, slightly less than 60% of the test subjects opted for the variable plan (Table 4-6). A chi-squared test was conducted, and no significant difference in choice of plan was found between the two versions (p-value: 0.59). This is contrary to what was expected, as previous research (Pyrko & Darby, 2009) found that 70% of customers wanted their old conventional tariff back when the dynamic plan was the default.

	Conventional plan	Dynamic tariff plan	Total
All participants	115 (42%)	158 (58%)	273
Participants (version 1) – Conventional plan default	53 (40%)	78 (60%)	131
Participants (version 2) – Dynamic tariff plan default	62 (44%)	80 (56%)	142

Table 4-6 – Breakdown of results from experiment 7

4.1.6 Assessing the potential to use normative feedback (Energy-use awareness)

The results from the test on above-average bias for energy-use awareness show that participants generally believe that they perform above average, meaning that they tend to believe that they are more aware of their own energy use, than the average Dane is of his/her own energy use. Results for own behaviour (m=5.83±2.02, n=64, M=6) are higher than results for other peoples' behaviour (m=5.05±1.80, n=67, M=5). An *f*-test was performed to determine variance within the two samples (p-value: 0.351) indicating equal variance (homoscedasticity). A two-tailed *t*-test for equal variance samples was performed, which indicated a significant difference between the two answers (p-value: 0.0287). This indicates that the bias found was statistically significant, meaning that "own behaviour" was rated significantly above "other peoples behaviour." However, it must be noted that only the sample for "Danes" was normally distributed, while the answers for "Me" had a slightly bimodal frequency distribution, limiting the conclusive power of a *t*-test, since this test requires samples to be normally distributed (Figure 4-2). Participant answers, as well as results from statistical tests can be seen in Appendix 6.6.

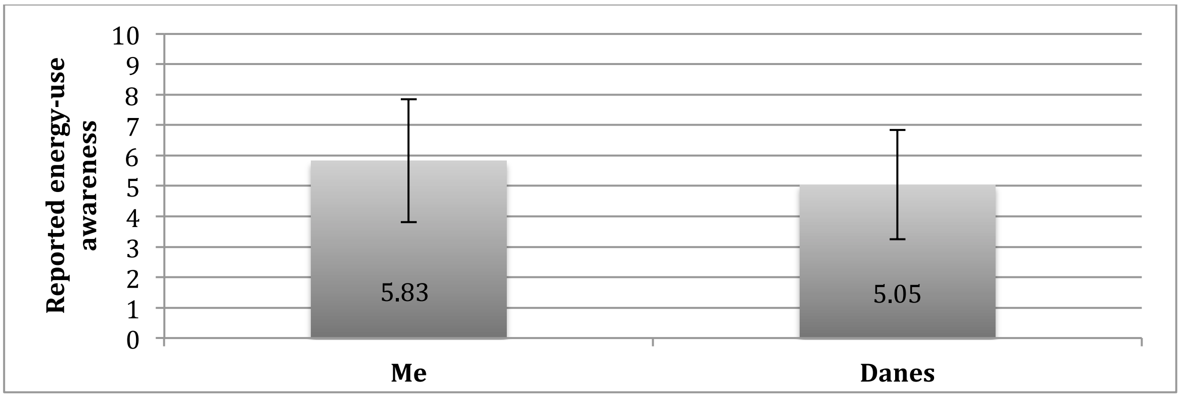

Figure 4-1 – Average energy-use awareness

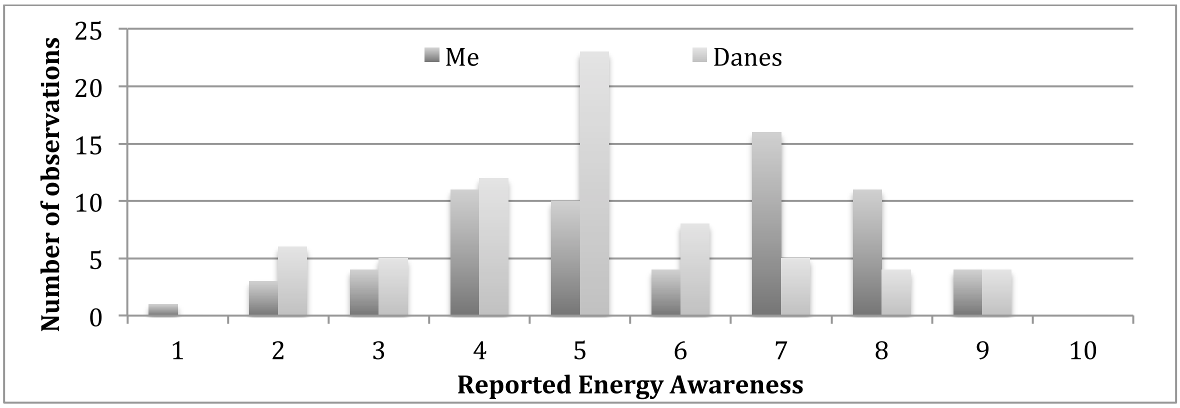

Figure 4-2 – Frequency distribution for energy-use awareness, "Me" and "Danes"

4.1.7 The effect of framing on EE decisions and risk (Exercise 6)

That EUT does not fully explain human behaviour with regards to risks has been amply discussed in economic research (e.g. Kahneman & Tversky, 1984; Samuelson & Zeckhauser, 1988; Rabin & Thaler, 2001). In experiments (e.g. Kahneman & Tversky, 1984; Tversky & Kahneman, 1981, 1986; 1992), it has been shown that changing the framing of a question changes the outcome of the decision. The following experiment was intended to test whether this effect could be replicated for participants faced with a choice of buying either of two appliances, one with a guaranteed saving and one with a larger, but uncertain saving. When this was phrased with a gain framing (in version 1 (Q1) of the question), 89% of the participants were risk averse and only 11% were risk seeking. When the framing was changed to avoidance of loss, the percentage of participants showing risk averse behaviour had dropped to 72%, and the percentage of those showing risk seeking behaviour had increased to 28% (Figure 4-3). A chi-squared test showed that there was a significant difference (at 99%) between the answers in the two versions, as was expected. The results are not as pronounced as in the experiment by Kahneman & Tversky (1984), as a higher percentage of participants in this experiment show loss averse behaviour than was found in the original version. However, participants do behave as predicted by the value function in CPT, as those participants subjected to a loss framing showed higher degrees of risk seeking behaviour, i.e. higher willingness to take the uncertain bet. The increase in risk seeking behaviour with loss framing is significant for both genders, and especially pronounced for women (95% for men and 99% for women). Men show a slightly higher degree of risk seeking behaviour when not subjected to a loss framing (not significant at 95%), but the two genders show similar behaviour when subjected to a loss framing (Table 4-7). All results from statistical tests can be seen in Appendix 6.7.

	$n_{RiskAverse}$ (percentage)	$n_{RiskSeeking}$ (percentage)	Total
Gain framing (version 1) – all	114 (89%)	14 (11%)	128
Loss framing (version 2) – all	100 (72%)	39 (28%)	139
Gain framing (version 1) – men	66 (86%)	11 (14%)	77
Loss framing (version 2) – men	74 (73%)	27 (27%)	101
Gain framing (version 1) – women	48 (94%)	3 (6%)	51
Loss framing (version 2) – women	26 (68%)	12 (32%)	38

Table 4-7 – Breakdown of results from Experiment 6

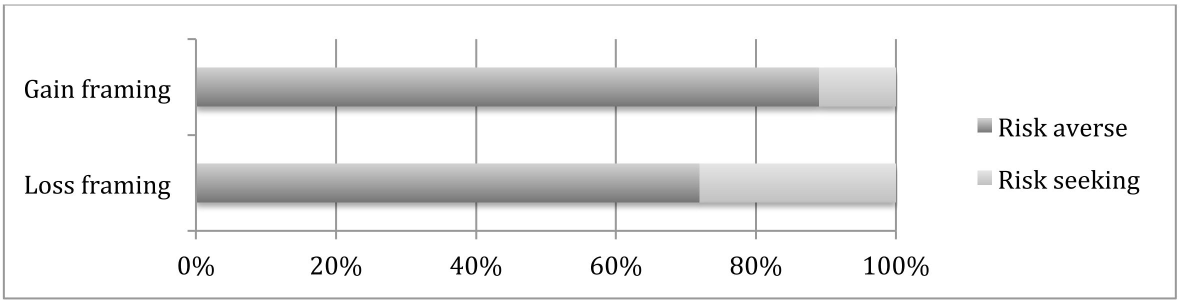

Figure 4-3 – Percentage of participants showing risk averse and risk seeking behaviour, respectively, in the two versions of the experiment

4.2 Smart Meters and electricity use reduction

4.2.1 Smart Meter analysis

As it was not possible to get extensive background information about the households where the Smart Meters were installed, a multiple regression analysis of consumption was not an option. Instead, to assess the effect, the deviation in weekly consumption from expected consumption was compared. Data from 3,000 Danish households was used to create a yearly demand profile for an average Danish household, against which the consumption data from the Smart Meters could be compared (NorthQ, 2013). The data is based on daily readings, but has been converted into weekly values and normalized, displaying the weekly consumption as a percentage of the yearly consumption. The profile can be seen in Figure 4-4.

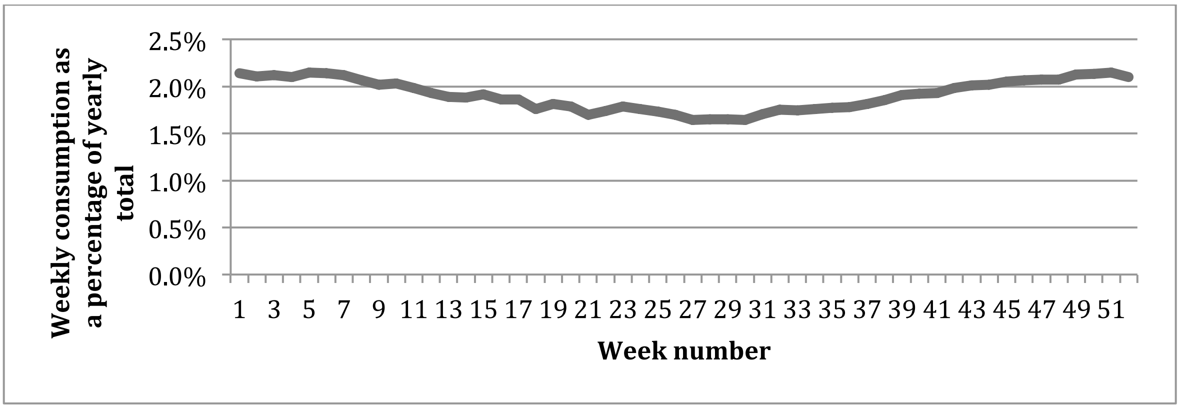

Figure 4-4 – Weekly consumption as a percentage of yearly total (Data from NorthQ, 2013).

To assess the effect of installing the Smart Meters, the consumption from the first week after installation was taken as a starting point, assumed to be the 'normal' consumption from which an effect should be discerned. Based on the yearly consumption profile, the expected weekly consumption was calculated, while taking into account the time of the time of the year the meter was installed (week = 0) (e.g. in week 27 consumption was expected to be 1.644% of total yearly consumption). This means that the starting point varies according to the installation time for the meter ($1 \geq X \leq 52$). The actual consumption in week 0+X was then compared to the expected consumption in week 0+X, and the relative change in consumption from the expected consumption was found.

$$E_{SmartMeter} = \frac{C_{Actual} - C_{Expected}}{C_{Expected}} * 100\%$$

Based on this, the relative effectiveness of the meters, i.e. the deviation in percentage from the expected consumption, was found for the 49 Smart Meters. Due to the applied method (using only week 1 as baseline), relative large deviations (±50%) were found. The deviations are especially large (+200%) for two datasets (no. 217 & 451), as can be seen from Appendix 6.8. Data is quite scant for the weeks before week 43 in 2013 (less than 10 observations), due to a lack of installed meters in the early period. For this reason, the early results are not included; neither are the two 'abnormally' large observations. The final results can be seen in Figure 4-5. Due to lack of space, the legend is excluded, but a larger version can be seen in Appendix 6.8.

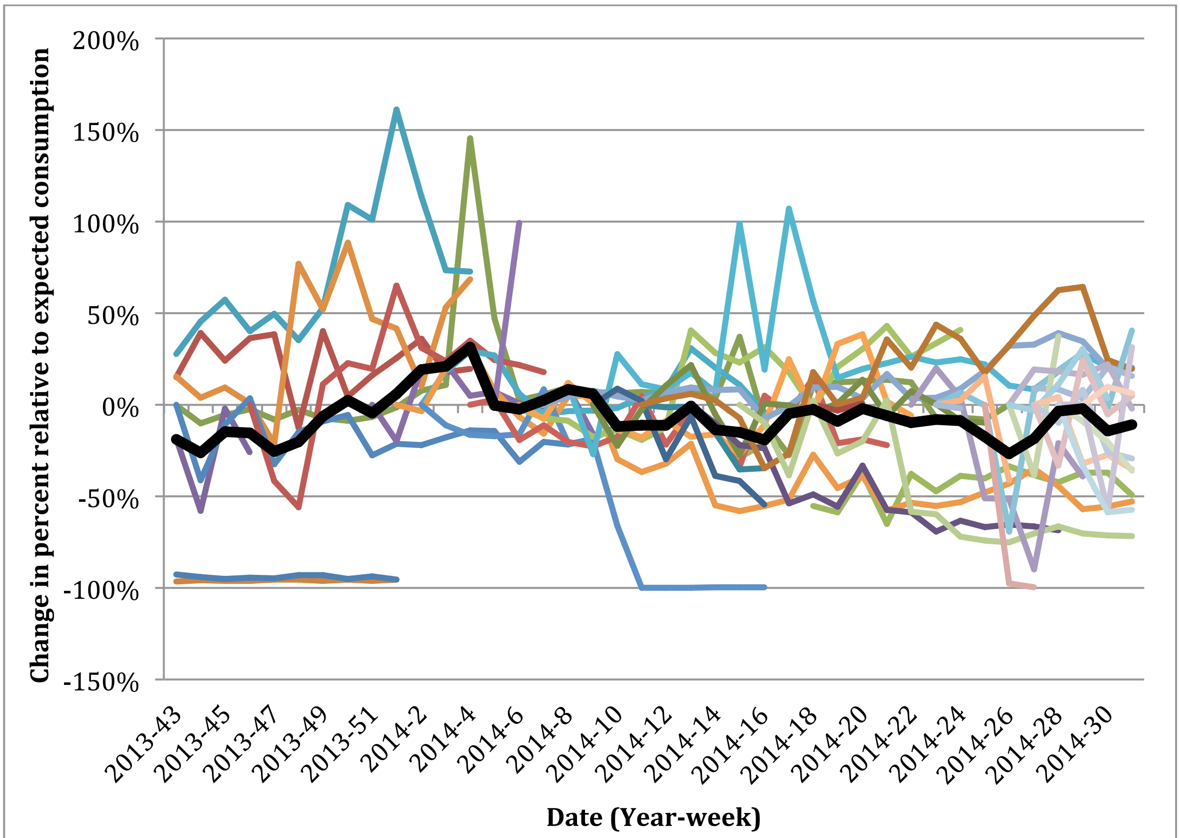

Figure 4-5 – Deviations in electricity consumption from expected values for the Smart Meters analysed.

Although the effect on electricity use reduction is difficult to quantify due to large fluctuations, an assessment was made nonetheless. The average deviations are negative 75% of the time (31/40 weeks) (i.e. consumption is below the expected value). Overall, the average change from the expected consumption is -6.6%. However, the standard deviation is 0.43, or

43% (n=47), meaning that there is a large variation in the effect found. Taking only values from week 43 in 2013 and onwards changes the effect to -6.7%(±41%, n=47). The weekly deviations are negative in 309 instances and positive in 341 instances, indicating that the average negative deviation is slightly larger than the average positive deviation.

4.2.2 Loss aversion and Smart Meter effectiveness

Whether loss aversion can affect electricity use consumption has, to the knowledge of this author, not been previously tested. This experiment was intended to make up for this lack of knowledge. Due to the limited sample size ($n_{final} = 6$, $n_{LAReg} = 3$, $n_{NoReg} = 3$) available for regression analysis, a multiple regression analysis of consumption was finally dismissed after statistically insignificant results were computed.

Due to the low level of responses and thus the statistical power to explain the variability of the dependent variable (energy use) using econometric analysis, a different analysis was performed for all households (n=16) for which Smart Meter data was available. 11 of these households had been subjected to the loss aversion widget ($n_{LA} = 11$), while 5 had not ($n_{No} = 5$). The analyses ignore the fact that there is a difference in the composition of the households (e.g. size, number of householders, income), and is somewhat similar to the analysis conducted for the long-term Smart Meter data in section 4.1.6. However, as the experiment took place over just 5 weeks in the summer months, no climate correction was done[42]. The results for the two analyses and the respective parts (daily and standby consumption) can be seen below.

The effect of loss framing on total daily household electricity consumption

The daily consumption for each day in the time series was plotted for all households. Data is somewhat scattered and fluctuates significantly within and between households (see full data plot in Appendix 6.9). There is a tendency that the average consumption of the two groups drops over time. However, there is an indication that those households subjected to the loss aversion widget reduced their consumption by a larger figure over the course of the intervention period, than those in the reference group (Table 4-8 and Figure 4-6). Incidentally, the same reduction is found for the reference group as for the Smart Meter group as a whole, but this is assumed to be a coincidence and further research is needed to address causality. The larger reduction for the participants subjected to loss aversion suggest that seeing a reduction in electricity as avoiding a loss (as done by the LA group) provides a stronger incentive to reduce this loss than seeing a reduction is electricity as gaining a benefit (as done by the No group). This is in line with the value function of CPT (section 2.3.2) and previous research on loss aversion in other areas (e.g. Genesove & Mayer, 2001; Tom et al., 2007). Though the reductions are highly uncertain, they roughly correspond with the general notion (e.g. Kahneman, 2011) that losses are felt twice as much as gains.

	First week Average (kWh)	Mid-period week Average (kWh)	Last week Average (kWh)	**Change in consumption**
Loss Aversion (n=11)	5.72	4.88	4.68	**-18%**
No intervention (n=5)	5.10	--	4.72	**-7%**

Table 4-8 – Daily average consumption for households in loss aversion experiment

42 Based on the yearly consumption data used to correct the Smart Meter data, consumption is expected to be about 5% higher at the end of the test period than at the beginning, so if anything, not correcting for climate impacts yield answers that might be too low. As so many other variables were also not accounted for, it was assumed that not correcting for climate variability would have little influence.

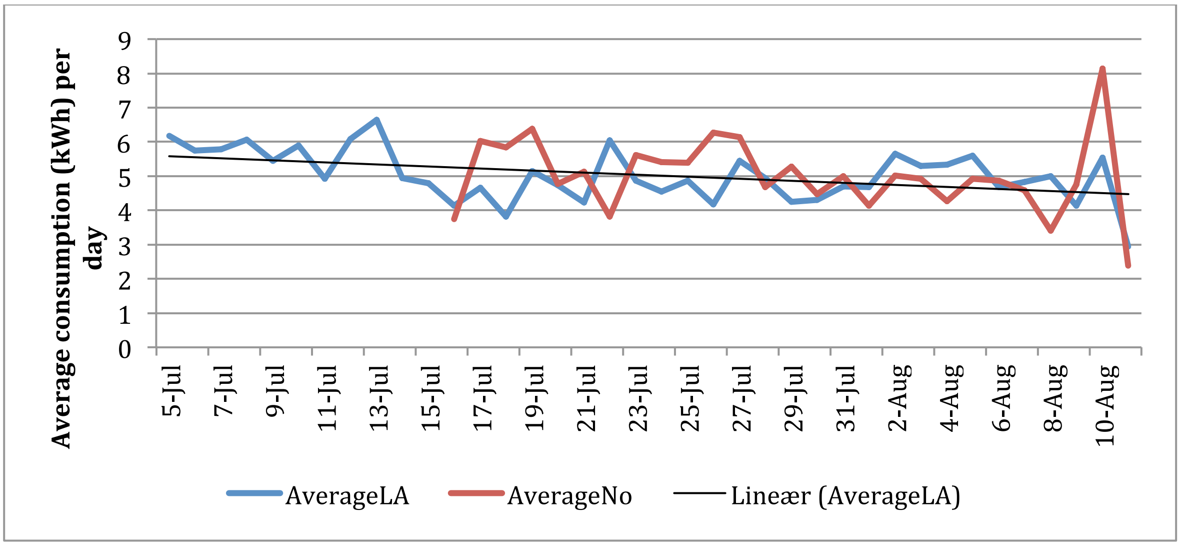

Figure 4-6 – Average electricity consumption per day (kWh) for the test group (blue) and reference group (red) over the course of the experiment

It was also assessed what the effect of the loss framing can be said to be, when the data is analysed using the same methodology as applied in the Smart Meter data analysis (c.f. section 4.2). The data series contains daily data and run over a shorter time period, but the method is almost identical; the first seven days was used as a starting point (reference consumption) while the relative change from this was taken as the effect of the intervention. Analysis reveal that the relative change is -5.2% on average for the loss aversion meters, and 2.2% for the non-loss aversion meters if starting from day 8, and slightly less if all days are included (Table 4-9). However, and with due limitations, the findings are still consistent with the results found with the first method: the loss aversion widget has a larger effect than when no loss framing is applied.

	With loss framing	No loss framing
Change, all days included (also first week)	-4.3%	1.8%
Change, all days after day 7 (not first week)	-5.2%	2.2%

Table 4-9 – Effect of loss aversion framing on daily consumption using a different method for calculation

The effect of loss framing on household standby electricity consumption

The nightly consumption for each calendar day in the time series was plotted for all households under the assumption that nightly electricity consumption could be taken as a proxy for standby electricity consumption[43]. As is the case with the daily data series, the nightly data display fluctuations within and between households, but the internal variation is smaller, indicating that standby consumption is comparatively steady (see full data plot in Appendix 6.9). As above, there is a tendency that those subjected to the loss aversion frame reduced their consumption over the course of the experiment, however in this case the reduction is larger (Table 4-10). Those without the intervention consumed roughly the same in the beginning and the end of the experiment, while those subjected to loss aversion cut their consumption by a quarter on average (Figure 4-7 and Table 4-10). For the nightly values, the difference between the two types of framing is markedly larger than for the daily values. As

[43] It should be noted that the data nightly data is not available for one of the households that are part of the daily data series, which reduces the number of non-intervention households to 4 in this case.

nightly values was labelled standby consumption and aggregated to a yearly figure, this suggests that the salience of the standby cost increased, which would further contribute to the reduction in consumption. This would be in line with other research (e.g. Gilbert & Zivin, 2014) as well as the other experiments conducted for this thesis (e.g. exercise #2), and indicates that highlighting certain aspects can increase the effect of feedback.

	First week Average (kWh)	Mid-period week Average (kWh)	Last week Average (kWh)	Change
Loss Aversion (n=11)	1.04	0.94	0.75	-28%
No intervention (n=4)	0.89	--	0.86	-3%

Table 4-10 – Nightly average consumption for households in loss aversion experiment

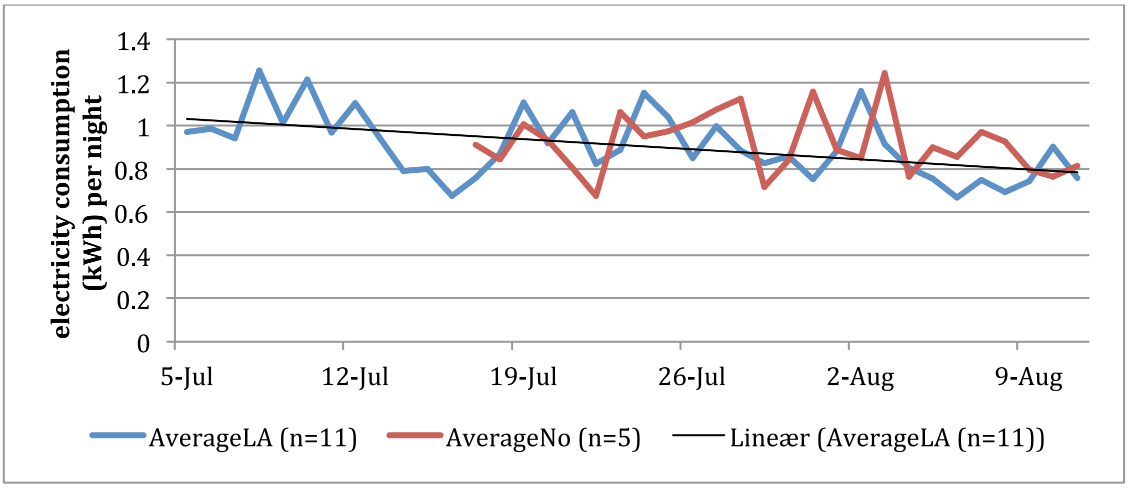

Figure 4-7 – Average electricity consumption per night (kWh) for the test group (blue) and reference group (red) over the course of the experiment

Similar to the daily consumption figures, standby data is also analysed using the same approach as applied in the Smart Meter data analysis (c.f. section 4.2). Analysis reveal that the relative change is -12.8% on average for the loss aversion meters, and 2.4% for the non-loss aversion meters (Table 4-11). The findings are slightly smaller if all days are included, consistent with the findings for daily consumption. The findings are consistent with the results found with the first method in that it also finds the loss aversion widget to have a larger effect on consumption than when no loss framing is applied. Similarly, this method also finds that there is a larger effect on standby consumption than on daily consumption from applying the loss framing.

	With loss framing	No loss framing
Change, all days included (also first week)	-10.5%	2.4%
Change, all days after day 7 (not first week)	-12.8%	3.2%

Table 4-11 – Effect of loss aversion framing on standby consumption using a different method for calculation.

4.2.3 Review of the effect of Individual Feedback

In order to be able to compare the effect found in the Smart Meter analysis and the loss aversion experiment against the 'normal' effect of feedback, a literature-based analysis was conducted[44]. Though some literature reviews exist, they were, with the notable exception of Ehrhardt-Martinez et al. (2010), deemed to contain an insufficient amount of information to conclude on the magnitude of the effect of feedback, as basic statistical tests, as well as comparisons against intervention time or group size, were generally lacking. The feedback was divided into groups depending on how often feedback was provided, as, theoretically, providing feedback more often should increase salience and thus lead to higher reductions.

In general, the studies reviewed indicate that providing feedback results in electricity reductions of 1-13% (m=-6.9±5.8%, M=-6.5%, n=23). The result can be seen in Figure 4-8. This range (1 to 13 percent) is generally in line with the ranges given in recent studies (Abrahamse et al., 2005; Darby, 2006; Fischer, 2008), though in the lower end. The mean and median are almost similar, indicating that there are just as many studies finding no effects as studies finding large effects. The standard deviation is around ±5% (percentage points), which shows that there is a relatively large spread in the effect found in the studies. There is an indication that the studies that provided feedback frequently, i.e. weekly or more often, are more effective than those that provide feedback less often, but the difference is not significant.

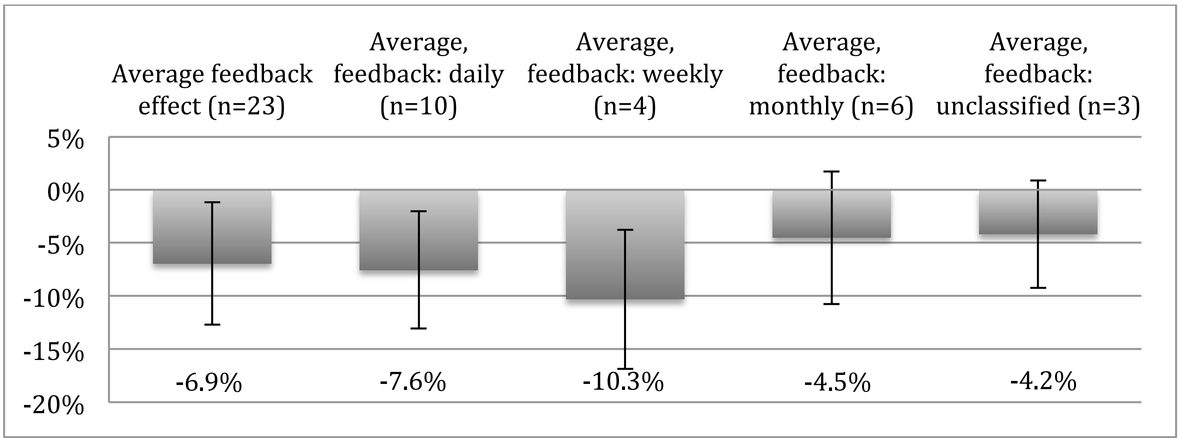

Figure 4-8 – Average change in electricity consumption from feedback intervention (non-normative) with percentage change, as well as one standard deviation.

Similarly, Ehrhardt-Martinez et al. (2010) speculate that the effects found are somewhat dependent on group size and intervention period. Indeed, there seems to be an indication that smaller studies and studies with short intervention periods find larger effects than studies with large groups and long time horizons (Figure 4-9 and Figure 4-10). To assess whether this was the case, an *f*-test was conducted to test whether any of these had a significant influence on the variability in electricity reduction reported (Table 4-12). Applying a 95%-confidence level, none of the two can be said to have a significant influence. However, changing the confidence level to 90% brings the "feedback as function of sample size" within range of the critical value, and changing the confidence level to 85% brings it below. This means that it can be said with an 85%-confidence interval that the sample size has an effect on the size of the feedback. However, applying such a low confidence interval is not the norm, and therefore this thesis does not draw any conclusions from this. However, due to the limited sample size (n=20), an effect cannot be ruled out, especially not for sample size, and further research is warranted.

[44] The criteria for including a study in the review was: (a) the presence of a control/no effect group, (b) a quantitative estimate of the effect of the intervention provided, (c) a test group larger than 10 individuals/households, (d) the feedback could not be normative (social). Where available, the intervention length was also included. The studies included in the review can be seen in Appendix 6.10.

Statistical parameters	Feedback as a function of length of intervention period	Feedback as a function of sample size
n	20	20
r, r^2	-0.165, 0.027	-0.339, 0.115
f-test	0.557	2.597
f-critical (95%, 90%, 85%)	4.351, 2.975, 2.241	4.351, 2.975, 2.241
p-value	0.465	0.123

Table 4-12 – Statistical test results for the f-test

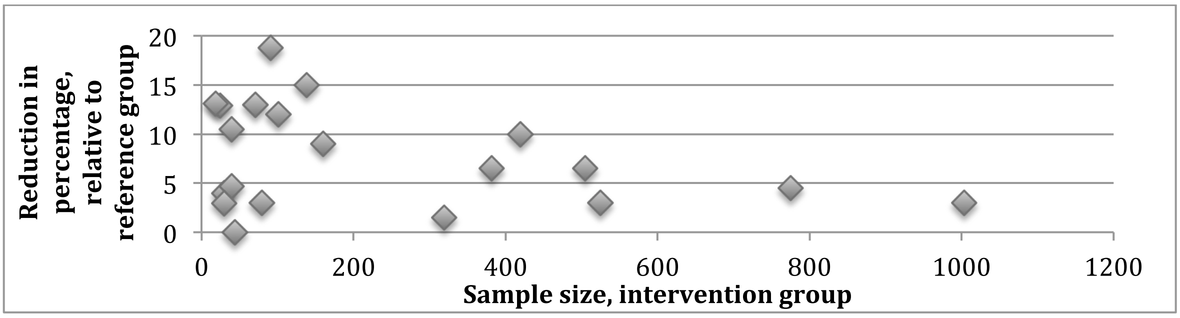

Figure 4-9 – Effect of feedback as a function of intervention group size

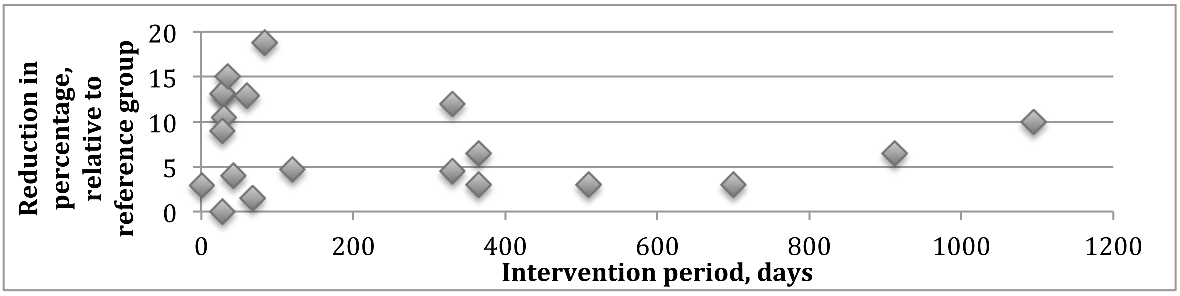

Figure 4-10 – Effect of feedback as a function of intervention length

Only a limited amount of academic studies explicitly testing the effect of comparative feedback could be found (Midden et al., 1983; Schultz et al., 2007; Abrahamse et al., 2007; Nolan et al. 2008), and these all find reductions in consumption. Excluding the oldest study (Midden et al., 1983) yields an effect slightly higher than that found for individual feedback (m=-7.2%±2.4%, n=3). It should be noted that these reductions are notably larger than those found in a large-scale study (n>3,000) conducted by the American utility OPOWER, who found reductions of 2.24%[95%-confidence interval: 1.91%; 2.56%] (Klos, 2009, p. 2) from normative feedback, and a large-scale British trial (AECOM, 2011) who found effects ranging from 1-2% reduction in energy use from comparative feedback. As these trials are larger and of newer date, they probably provide a more accurate view of the reductions, which can realistically be expected from feedback. The effects found in the large-scale trials are about a quarter to a third of effect found in the smaller studies. If the findings from this type of feedback (normative) provide any indication of what can be expected with behavioural feedback, this suggests that feedback using loss aversion should result in reductions of 4-6% in daily consumption and 6-8% reduction in standby consumption[45].

[45] Daily consumption effect: 18%. 18*0.33 = 6%. 18*0.25 = 4.5%. Standby consumption effect: 25%. 25*0.33 = 8.33%. 25*0.25 = 6.25%

5 Discussion

This section opens with a discussion of the results. Firstly, the results from the preference choice exercises are discussed, and suggestions for further research needs are given. This is then followed by a discussion of the results from the Smart Meter analysis and the Smart Meter experiment, in this context and in relation to other feedback studies in general. Finally, the limitations and applicability of the results found in this thesis are discussed. The following section discusses the methodology applied for conducting this research, and the experiments and the conceptual framework are discussed in turn. The final section of this chapter discusses the policy implications of this research before providing considerations for further development of Smart Metering and behavioural interventions.

5.1 Discussion of Results

5.1.1 Behavioural Interventions and energy-use behaviour

Knowledge and the effect of information type and salience

The two stated goals of the exercises on this topic, to test the level of knowledge and to test whether the way information was presented would make a difference to consumer choice, were both assessed successfully. Generally, it is confirmed that a knowledge-gap (information deficit gap) exists, since only about half of the participants were able to identify the right price, even in the relatively easy version. Although the knowledge displayed in the two questionnaires was not statistically significantly different overall, it was interesting to note that there was a different in knowledge between genders and that especially men were influenced by the salience of the information. That participants do not know the price of a kWh indicate that presenting information on kWh-consumption alone would have little effect on consumption. This reflects findings from other studies, e.g. o Karjalainen (2011, p. 466) who found that "many people have problems with understanding scientific units and do not understand the difference between W and kWh."

The exercise on salience of information (exercise #2) confirmed that the salience of information affects consumer choice, as there was a significant difference between the fridges selected in the two versions. If people had perfect knowledge on electricity prices and were perfectly rational and not limited in mental processing capacity, they would be able to calculate the electricity price in version 1, as the electricity consumption is displayed in both versions, and then select the appropriate fridge. However, as exercise 1 showed, people do not know the electricity price, and are thus not able to select the fridge that correspond to their preference. As the only difference is the salience of the electricity cost, this shows that the salience of and the way information is presented can influence behaviour. The implications for EE is that e.g. energy labels should display expected energy costs over the lifetime of the product (and/or per year) rather than the total kWh per year, as this clearly do not have the intended effect. For Smart Meter feedback, it indicates that cost is more salient and easier to interpret than scientific units, and that aggregation (over life time rather than year, or over year rather than month) also make it more salient, and thus easier to understand. This suggests that Smart Meters should provide lifetime benefit of undertaking an EE investment such as procuring a new fridge, rather than simply displaying the amount of saved kWh that an upgrade could result in[46]. The effect of salience is recognised by very few studies, let alone policies, indicating that this observation has not yet translated into common knowledge.

[46] An interesting thought suggested by Baddeley (2011) would be to make salient and aggregate the impact of a certain act, such as washing clothes at a lower temperature, over an entire population, rather than the individual, to increase the

Contrary to the first two exercises presented here, the results from exercise 1 did not obey by the theoretical expectation. The presence of an additional option (B-) did not increase the attractiveness of option B, but rather decreased it. Ariely (2008) theorised that it should increase, as the inferior option (B-) would make option B appear more attractive. One can speculate that perhaps the presence of extra information did nothing more than confuse participants rather than making any option appear more attractive. Research by Iyengar and Lepper (2000) found that increasing the amount of options makes choosing the preferred option more difficult for participants and decreases the percentage making the optimal (rational) decision. The results from this exercise, although the amount of choices are more limited here than in the research by Iyengar and Lepper (2000), yield some support to this. The implication of this insight is that more information is not necessarily better and that consumers should be presented only with information relevant to energy efficiency investments and electricity consumption, nothing more, as this simply complicates the decision.

Discounting preferences and the effect on the EE gap

The exercises (4 and 5) confirmed the expectation that people are inconsistent in applying discount rates, and provided interesting insights into how this can potentially be used when providing consumers with EE information through Smart Meters. When the question was framed as an easy calculation (exp. 4), the implicit discount rates were rather low (around 16-20%), while they increased significantly (to above 30%) when the question was difficult (exp. 5). The discount rate is lowest (<15%) and actually close to the expected market rates (c.f. footnote 21) when participants face a direct comparison between two fairly similar goods (exp. 2). As noted, participants are generally inconsistent in applying discount rates. This, along with the relatively large proportion not able to understand or answer either the more difficult question indicate that asking participants to state an expected saving (and thus their implicit discount rate) is not likely to yield very accurate estimates of actual behaviour. The results show that how information is provided and the context it is placed in affects the discount rate of the participants, exactly as theorised. How information is provided thus has an effect on how people behave, and indirectly affect their total electricity consumption, as their willingness-to-pay (WTP) for energy efficient measures can be greatly influenced depending on how the information is presented.

It is possible that loss aversion also contributes to the relatively higher discount rates in exercise 4 and 5. The question is framed as a cost now and a benefit occurring later in time. This means that if the investment is not made, the upfront cost is seen as avoiding a loss, while the gains are forgone benefits. This could probably be avoided if the question was turned around to indicate that forgoing a gain now could lead to avoiding a loss in the future (the two decisions are mathematically identical, but psychologically different). The impact of this has not been tested here, but Johnson and Goldstein (2013, p. 422) find that this framing significantly changes savings behaviour, which in essence is not much different from investments in EE, in that both entail forgone benefits now (money cannot be spent on other goods), but greater benefits later in time (interests in the case of saving, reduced energy costs in the case of EE).

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perceived effect of this change: "if all UK households were to wash their clothes at 30 degrees centigrade or less, this could save 620,000 tonnes of CO_2 and £170million on energy bills. However, the disaggregated savings per change are generally not large; one household washing clothes in water at 30 degrees or less would save just £12 per year on their energy bill" (Baddeley, 2011).

Since discount rates are inconsistent, the EE gap could be narrowed if Smart Meters were used to provide consumers with simplified information on energy efficiency investment decisions. The results indicate that providing tangible information, such as "by spending €100 on XX you could save €25 on electricity per year" lead to lower discount rates than those that are derived from actual consumer behaviour or less concrete suggestions. Furthermore, due to loss aversion, the effect would probably increase if it was not framed as a gain, but as an avoided loss: "by spending €100 on XX could reduce your electricity cost by €25 per year." Providing this information through Smart Meters is technically possible and can contribute to closing the EE gap, which could increase the overall effect of installing the meters.

The effect of defaults on plan selection

Based on the results from previous research on the effect of defaults (e.g. Johnson & Goldstein, 2003; Pichert & Katsikopoulos, 2008; Dinner et al., 2011; Brown et al., 2013) and the apparent reluctance of consumers to adopt dynamic tariffs (e.g. Pyrko & Darby, 2009), the results of the default choice exercise were somewhat unexpected, as the dynamic pricing plan was chosen by about 60% of the participants in both versions. It is possible that the mentioning of an expected 5% reduction in electricity costs with the dynamic pricing plan had an effect, but it was not possible to test whether this was the case. Furthermore, as the consumers did not actually change their tariff, but merely indicated what they would do in such a situation, there were virtually no TCs, nor any risk, involved in selecting the dynamic pricing plan. However, if the decision made by participants actually had to be carried out in real life, it is likely that the results would have been different, a possibility which is discussed later in relation to the limitations of these exercises.

Individual behaviour and normative statements

Assuming energy-use awareness is normally distributed and non-skewed, naturally about half of us will be less energy-aware than the average person[47]. However, the results from the energy-use awareness experiment show that people generally believe that they are more aware of their energy use than the average Dane is. This shows that people hold beliefs about their actions that are sometimes not in accordance with reality, which has implications for information provision, as it suggests that descriptive normative statements (Cialdini et al., 1990) would induce these people to change behaviour. It then follows that feedback, such as that provided by OPOWER (as described in Klos et al., 2009) would be a cost-effective way (Allcott & Mullainathan, 2010) of correcting this bias through information provision.

Risk aversion and framing

In risk aversion exercise (#6), there was a very significant difference in the option preferred by participants in the two versions, indicating that this frame do indeed affect behaviour. Some researchers (e.g. Hasset & Metcalf, 1993) have argued that the risk inherent in many EE decisions justifies the apparently high discount rates observed. This experiment showed that risk preferences depend on framing, and that a loss framing can induce risk-seeking behaviour. This means that framing an energy efficiency investment decision as avoiding a loss, rather than obtaining a gain, can possibly increase the number of people willing to undertake such investments and thus help close the EE gap. Similarly, as noted by Weber (2013), the willingness to undertake EE investments should also increase if the added up-front costs of most EE investments can be reframed not as losses, but rather as forgone gains (c.f. the value

[47] It must be noted, however, that while the answers on "Danes" are unimodal, the answers on "Me" are slightly bimodal. It is now known why this tendency is found, but if it is replicated in the population as well, one could speculate that people "classify" themselves as belonging to either an "I'm doing okay"-group, or an "I'm doing good"-group. It then follows that feedback would have the most significant impact on those people in the 'good' group, who are actually not performing well. This possibility was not explored further.

function in CPT). Weber (2013) further argues that the certainty effect can explain why humans often fail to capture energy-efficiency gains; sure outcomes (e.g. deciding between an efficient, but more expensive fridge, or a cheaper, but less efficient one) tend to be costly, whereas gains (e.g. savings on energy from the efficient fridge) are delayed in time and uncertain, meaning that the sure, but negative decision carry more weight than the uncertain decision. The findings in this study support this argument.

5.1.2 Behavioural interventions and the potential to use Smart Meters to improve feedback to electricity customers

Smart Meter effectiveness

The amount of large-scale trials testing the effect of installing a Smart Meter is somewhat limited. McKerracher & Torriti (2013) conducted a meta-analysis of the effect of feedback using Smart Meters, and argue that using data from current studies, a realistic, large-scale conservation effect from feedback is in the range of 3-5 %. As few longitudinal studies are available, the long-term effect is difficult to assess. Van Dam et al. (2010, p. 465) find that participants equipped with a Smart Meter achieved average savings after four months of 7.8% (SD = 13.8%, n = 54), but report that the effect had dropped to an average of 1.9% (SD = 11.8%, n = 54) after 15 months. All in all, a total of 19 separate Smart Meter intervention studies testing the effect of feedback were found (these were found in Gans et al., 2013; van Dam et al., 2010; Ersson & Pyrko, 2009; AECOM, 2011; Schleich et al., 2011; 2013; and Grønhøj & Thøgersen, 2011). The average effect was -1.6%(±9.7%, 1st-3rd quartile: -6.15% to 0.05%, M=-2.9%, n=19). If meters with IHD's are excluded, the effect changes to -0.7%(±11.2%, M=-2.4%, n=14). Given the different nature of the studies, the lack of longitudinal studies, and the general context in which these studies were conducted (different countries, different setups, different time of the year), it is very hard to generalise from this[48].

The results of the Smart Meter data analysis are roughly consistent with the reductions found in the literature, as an effect of 6.7%(±41%) falls within most of the studies reviewed. Gans et al. (2013) find reductions ranging from 11% to 17%, somewhat larger than this experiment, while Grønhøj and Thøgersen (2011) found reductions of 8.1% and Van Dam et al. (2010) found reductions of 7.8%, almost exactly the same as this study. Schleich et al. (2013) find reductions of 4.5%, slightly below the reductions found here. The findings from the large-scale trials in the UK also all find reductions below 4.0% (AECOM, 2011). Schleich et al. (2011; 2013) and Gans et al. (2013) all use regression analysis, but find fairly different effects, indicating that other contextual factors probably also matter.

The large standard deviation found in the analysis conducted for this thesis indicates that one probably should not take the results too literal. The small sample size and the large fluctuations mean that one "odd" sample have enormous influence on results, as shown by the effect of removing two observations (changing the overall effect from an increase to a reduction). This means that the results are incredibly sensitive to deviating observations. As no background information on the households included in the sample was available (household size, income, housing type, etc.) it was not possible to test for the effect of these variables. Obviously, this also limits the strength of the results. Using the first week as "background consumption" also introduces an error, as an unusually high or low first week will lead to large deviations later on. In order to have a firm basely from which to estimate a change in

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48 However, the lower median value indicates a larger number of studies found low values (i.e. reductions), and perhaps the presence of a single (or a few) studies (e.g. Ersson and Pyrko, 2009a; 2009b) finding high values (i.e. large increases) distorts the picture.

consumption, a much longer time series pre-installation of the meter is needed. As the climate lead to seasonal fluctuations, correcting the consumption for yearly fluctuations should increase the relative strength of the results.

Loss Aversion and the effect of framing feedback as avoiding a loss

The Smart Meter experiment with loss framing intervention was intended to test whether the reduction in electricity consumption could be affected by framing electricity consumption as a loss, which would mean that a reduction in consumption would be seen as avoiding a loss, rather than a gain, as is the usual frame. A regression analysis was not possible due to the low number of participants that filled out the accompanying questionnaire, and instead simpler analyses were conducted.

In the first analysis, the effect was assessed by comparing average use in the beginning of the period with average use at the end of the intervention period, while in the second analysis, the effect was found by comparing the average deviation from the baseline consumption in a manner similar to that applied for the first Smart Meter analysis. The effect found using the second analysis method is slightly smaller than with the first method, possibly because the first seven days (where the meter is already installed) are taken as a starting point, which means that any reduction made in that period would lead to a lower starting point from which change should then be discerned. However, both analyses found that the loss framing leads to larger reductions in electricity and that this is especially pronounced for standby consumption. As the standby consumption is framed as a loss *and* made more salient by aggregating costs for a year, this supports the hypotheses that increasing the salience and framing reductions as avoiding a loss rather than obtaining a gain, leads to changes in behaviour.

However, it must be noted that this loss framing Smart Meter experiment is also short-term and small-scale, as most studies reviewed, meaning that if other feedback studies provide any indication, the effect will be smaller in the population than in the study sample and possibly diminish over time. It must be noted that it is plausible that people with an interest in electricity conservation are overrepresented in the sample, as all the participants in the loss aversion experiment that did answer the background questions indicated that they considered themselves to be "environmentally aware." However, knowing from the energy-use awareness experiment that people consider themselves more aware of energy use than other people, it is also possible that they suffer from the same "above average" bias as was found in that experiment. This possibility has not been further explored.

As was discussed earlier, the studies reviewed for the effect of feedback were also limited by low statistical explanatory power due to limited sample sizes and lack of background information. This suggests that feedback studies generally are very difficult to conduct and that the work conducted for this thesis, which also was limited by this, might not be the exception. Although the results are not representative of the Danish population, and although it was not determined whether there was a significant difference between the intervention group and the reference group, the experiment nonetheless provide an indication that future research should do well to focus on these aspects when designing feedback studies.

Reviewing the effect of feedback provision

Compared to studies employing meters to provide feedback, there is a relative abundance of studies that have tested the effect of information provision to consumers, and several review studies (Abrahamse et al., 2005; Darby, 2006; Fischer, 2008; Ehrhardt-Martinez et al., 2010; Vine et al., 2013) have assessed the overall effect of these interventions. As noted, these studies, which are similar to the review conducted here, do find an overall reduction of electricity as a result of feedback. The review conducted for this thesis is in the lower range of the scale, but generally consistent with previous estimates. However, some researchers (e.g. Gans et al., 2013) caution against taking the reductions reported too literal, as many of the studies and reviews do not contain any statistical tests of the significance of the results, mostly due to the relative low number of households/participants in the experimental group, as well as the large within-group variation (Osbaldiston & Schott, 2011; Abrahamse et al., 2005). This suggests that it is common to have very low-level (statistical) sample data, meaning that the sample size and statistical power of the experiments conducted for this thesis are the norm rather than the exception. Similarly, almost no studies employ multiple regression analysis to test the influence of other variables, and it is thus difficult to know whether there is really an effect (a driver or signal) or it is merely the influence of another variable ("the noise"), such as housing size, which is picked up as a signal (Silver, 2012). Contrary to other reviews of feedback (e.g. Darby, 2006; Fischer, 2008; Vine et al., 2013), this thesis cautions against concluding that an effect of the magnitude found in a sample will arise in a population, as a number of factors potentially affecting the magnitude of the reduction needs to be further explored. The following paragraphs will elaborate on these.

Longitudinal effects

Reviewing studies against their duration, Ehrhardt-Martinez et al. (2010, p. 53) find that "average energy savings were higher for shorter studies (10.1%) than for longer studies (7.7%)." This is reflected by the finding that in the situations where a follow-up to a short-term study was conducted (e.g. van Dam et al., 2010; AECOM, 2011), the effect had often diminished over time (this is acknowledged in some review studies (e.g. Abrahamse et al., 2005; Owen & Ward, 2006; Ehrhardt-Martinez et al., 2010). However, the analysis conducted for this study showed that the duration of the study did not have a significant effect on the magnitude of the electricity reduction found. The Smart Meter data collected for this experiment also cover relatively short time periods (less than 3 months) for most of the data point in the sample. Although the effect is not significant, the possibility of a diminishing effect over time, this calls for further research to explore the longitudinal effects of feedback, comparative, normative, as well as behavioural.

Effect of sample size

Some studies (e.g. Ehrhardt-Martinez et al., 2010) also speculate that small-sample studies find higher levels of effect than large-scale studies, e.g. Ehrhardt-Martinez et al. (2010) find that "average energy savings across large-sample [>100] studies is roughly 6.6% compared to average savings of 11.6% across small-sample [<100] studies." This report also tested these relationships, and although there is an indication that Ehrhardt-Martinez et al. (2010) are right in assuming that small-scale studies generally find larger effects, the results are not statistically significant. However, the finding is not robust, and the low number of studies evaluated (n=20), calls for further evaluation studies that take these issues into account. If small samples do find larger reductions, it would of course have implications for real-life interventions, as it would suggest that the effect found in a population would be smaller than in the study sample, meaning that the effect of the Smart Meter rollout would be smaller than indicated by trials.

Ehrhardt-Martinez et al. (2010) further caution that only two household-level studies in recent times (post-1995) have found energy savings in excess of 10% as a result of feedback, a finding which indicate that the very large numbers reported in older literature (e.g. 18.8% reduction in Midden et al., 1983) most likely are not a reflection of the reductions that one can expect from Smart Meter interventions. They further speculate that reviews including studies older than 20 years (as is done by e.g. the widely cited study by Darby, 2006) might result in "inflated expectations regarding potential energy savings today" (Ehrhardt-Martinez et al., 2010, p. 74). Furthermore, all reviews studies that this work consulted gave equal weight to studies, meaning that small-scale, short-term studies count as much in the final average given as long-term large-scale studies. The review conducted for this study applied the same methodology. As more than half of the studies reviewed are short term and small sample, this could lead to inflated expectations about possible energy savings if these studies generally report larger electricity reductions. In sum, the studies reviewed for this thesis, as well as the experiments conducted, yield support to the concern voiced by Ehrhardt-Martinez et al. (2010) that the provision of feedback alone is unlikely to lead to reductions above 10%.

The influence of experimental design on the effect of feedback

The variability in the field settings of the studies reviewed complicate comparison of these. The studies include participants with highly different housing types, household composition, financial means, cultural backgrounds, and climatic conditions (van Elburg, 2009), and findings might reflect these or other factors such as variations in equipment used, regulatory regimes, or the cost of electricity in that location (Darby, 2010). In the experiments conducted for this thesis, some of these problems also surfaced; in the analysis of Smart Meter data, the cultural context and climatic conditions of the households included are the same, but the actual composition of the households (e.g. income, house size) is not know, which potentially affects results. Furthermore, many studies were "opt-in" trials, which, based on findings from BE, could have an effect on the outcome, as it must be assumed that those deciding to "opt-in" have a reason to do so, and thus are more willing to change behaviour than the general population, which could lead to higher reductions in the study samples than in the population (Raw et al., 2011).

5.1.3 Limitations and applicability of the results

The types of experiments and studies conducted and analysed for this thesis take place on a spectrum: At one end are lab experiments, where one change can be observed by holding all other things constant. At the other end are real-life situations, such as the loss aversion intervention using Smart Meters conducted for this this thesis, where the behaviour takes place in the actual setting, but the causal link is difficult to establish. The field experiments, such as those on salience and discounting conducted for this thesis, can be seen to be somewhere in between. The two ends of the spectrum yield a trade-off between internal and external validity[49]: "laboratory experiments provide greater internal validity than field data, while field data provide greater ecological validity and […] a lower burden for establishing external validity" (Roe & Just, 2009, p. 1267). An overview of this can be seen in Table 5-1.

	Internal validity	**External validity**	**Replicabability**
Lab experiments	High	Low	High
Field experiments	Medium to high	Medium to High	Medium to Low
Real-life interventions	Low	High	Low to medium

Table 5-1 – Validity (after Roe & Just, 2009).

[49] Validity is the question of whether a particular conclusion represents a good approximation of the true conclusion, i.e. whether the methods of research reflects the truth. Generally, one distinguishes between internal and external validity. Internal validity can be defined as "the ability of a researcher to argue that observed correlations are causal," whereas external validity can be defined as "the ability to generalize the relationships found in a study to other persons, times, and settings" (Roe & Just, 2009). Finally, ecological validity is understood to be the "extent that the context in which subjects cast decisions is similar to the context of interest," i.e. whether the experimental settings reflect the settings where decisions would be made in real life.

Generalizability

It is unclear whether people across the globe in different cultural and social settings would respond uniformly to some of these interventions. Social norms differ, and it seems likely that our response to defaults, feedbacks and framing could differ within and between countries and subsamples of the population (Henrich et al. (2001). Experiments have historically relied on a distinct set of people (university undergraduate students are highly overrepresented), so there is a need to test these interventions on a broader group of people having "participants that are representative of whole countries or cultures" (Fehr & Fischbacher, 2003, p. 790). If a specific finding is inferred on a narrow sub-set of the population (e.g. undergraduate students), the relationship may not exist in more diverse samples. This study does not contribute to filling that particular knowledge-gap, as all participants from a society that Henrich et al. (2010) classify as WEIRD – "Western, Educated, Industrialized, Rich, and Democratic." However, as the research is mainly intended to inform EU and EU Member State policy, countries all belonging to the "WEIRD" group, this probably is less problematic, although it must be noted that there is some difference in the concern over energy-related issues e.g. climate change between EU countries (EC, 2011d), as well as a "great deal of country heterogeneity in household energy-efficient technology adoption, household use of energy conservation practices, and household attitudes towards energy savings" in the EU (Mills & Schleich, 2012, p. 625). This means that findings from this study, which took place in a comparatively very energy-use aware country are not necessarily applicable in another EU country.

It is also likely that different population segments experience different barriers and therefore will respond differently to some of these interventions (Gifford, 2011, p. 298). Romanach et al. (2013) found that only 10% of the energy-saving programmes in Australia involving households were targeted at low-income households, so there is a need to be cautious against assuming that these findings are applicable in any social settings in high-income countries. The extrinsic and intrinsic motivations for (or against) an intervention (e.g. energy use) need to be considered. Romanach et al. (2013) found that "financial savings" was the main reason low-income household participated in energy-use programmes, but this would not necessarily be the case for high-income households (e.g. it might be social norms or other non-monetary reasons) and these issues need to be tested, and then considered when designing these experiments, so that they experiment fits the context. It is not known what income group the participants in the questionnaire-based experiments belong to, but the participants in the Smart Meter loss framing experiment all live in semi-detached houses near Copenhagen, and must be assumed to be middle class or richer in order to afford these houses, meaning that the findings from this study are not necessarily representative of residents in low-income areas.

Scalability

Whether or not the experiments described above can actually improve information provision and lead to reductions in GHG emissions hinges to large extent on their scalability. If an intervention cannot be scaled, the resulting impact will be all the smaller.

The choice preference exercises were carried out in an artificial real life setting (participants' decisions had no influence on their real-life situation), meaning that the external validity of the results is fairly low. As the choice exercises generally tests only one bias, the internal validity is fairly high, meaning that the effect in question is probably what is causing the change in behaviour. The experiments could easily be tested in real-life settings, where decisions had consequences, and the tentative indication of an effect from most experiments calls for further testing.

The Smart Meter experiment on loss aversion took place in a real-life setting where consumers actually used and paid for their electricity. This means that the results have a high external and ecological validity, as the experiment took place in the home of the participants, indicating that this effect is likely to be found even if implemented in real life. The very specific context makes replicating the experiment difficult (low internal validity), which means that the effect found in this case cannot be assumed to be of the same magnitude once scaled to a population. If previous large-scale trials are any indication, effects in a population is assumed to be in the order of 4-6%. Had a complete regression analysis been possible, the internal validity of the loss aversion intervention could have been improved, i.e. there could have been reason to expect that a causal link between loss aversion and a reduction in electricity actually existed. However, as only preliminary statistical tests were conducted, the internal validity is fairly low, as it cannot be determined whether the loss aversion widget did in fact reduce electricity (if there was a signal) or whether another unknown factor (noise) was interpreted as an effect of the widget. In any case, the clear indication of an effect in both instances (daily and standby consumption), and the likelihood of replication in real-life situations, calls for large-scale trials to further test this[50].

Potential biases in the experimental design

There are two reasons why it is worth reflecting on how the design of the various experiments impacted the results obtained. Firstly, this has implications for the conclusions that can be drawn based on the experiments conducted. Secondly, it has implications for future research, as this can help inform and improve any experiment that other researchers might undertake to test the findings of this study.

The 'Hawthorne effect'

There is some evidence that people that are aware of their participation in an experiment modify their behaviour because they are partaking in said experiment; an effect sometimes labelled 'the Hawthorne effect' (Draper, 2013; Olson et al., 1994). In the original study, workers were found to be more satisfied and effective when observed. The theory thus suggests that people are more responsive when observed than when not. It it not confirmed whether this effect in fact exists, but based on the importance of randomised-controlled trials (Haynes, 2012) in other research areas, especially medicinal and pharmaceutical sciences, it seems plausible that behaviour does change when people know they are part of an experiment. If this is the case, it has implications on the conclusions to be drawn based on the experiments conducted for this thesis. For the loss aversion experiment, the possibility of a Hawthorne effect is possible. Both groups know they partake in an experiment, since written consent had to be obtained before the intervention was set in motion. This entails that there is a risk that people want to perform well (reduce consumption) because they know they are being observed; an effect that would not be found under normal circumstances. It seems likely that this could be the case, but due to the limited knowledge on the subject (no double-blind experiments have been performed on electricity feedback to the authors knowledge), no assessment to quantify the effect of this has been carried out. The implications of such an effect is that the experiments conducted for this thesis can serve as guidance for future studies by providing an indication of what intervention work, e.g. salience of information, and this intervention can then be tested in a controlled setting where participants; a) do not know they partake in a study and b) suffer the consequences of their action. This would increase the

[50] In general, as pointed out by Levitt & List (2007), there is a lack of knowledge on how to scale economic behaviour as found in a lab or artificial setting to the market. This calls for further large-scale trials in order to close this knowledge gap.

external validity and provide a more accurate picture of what to expect if these interventions are scaled to an entire population.

Respondent bias

It is a well-established fact that human behaviour changes when others can observe it (Bell et al., 1996; Schultz, 1998; Nolan et al. 2008). This has implications for the choice preferences exercises conducted as part of this research, as the respondents typically filled these out in a public space where other participants could (in principle) watch their results (though the extent to which this happened was actually fairly limited). However, as Nolan et al. (2008) demonstrated, even the feeling of having other people watch your behaviour can lead to changes to behaviour. For instance, the participants asked to select a refrigerator might select the efficient one, because they feel that this is what the experimenter (or other participants, or "society") wants them to do. Along those lines, it can be argued that a preference for a green product displayed by a participant arise not because of a careful deliberation that the perceived (social) environmental benefits outweigh the private costs, but rather to express the values that this choice connotes (Sunstein & Reisch, 2013). However, as there is still a significant difference between the two groups, there is an indication that the framing has an effect, but it is likely that the respective proportions procuring efficient models (85% and 95% in the two versions, respectively) would be lower in real-life.

Hypothetical bias

The participants in the preference choice exercises did not have to spend their own money, and their choice had no implications on their real-life situation. This entails that there is a risk of hypothetical bias; the effect that participants' choices have been found to change depending on whether they bear the cost of this or not (Moser et al., 2014). This means that the decisions participants were found to make would likely not have been the same, if they had had to bear the costs of these decisions. In principle, all exercises except exercise 3 are affected by the (theoretical) presence of this bias, but in practice it is difficult to judge what effect his would have had on participant choice. This bias is assumed to be especially influential for testing the effect of defaults, and one can rightly question whether preference choice exercises can be used to test for the effect of defaults, or whether one should employ other methods?

It is not immediately clear whether better experimental design can completely overcome all these potential biases, but further research is warranted to establish the magnitude of these biases and the potential implications for results.

5.2 Discussion of Methodological Issues

5.2.1 Critique of experiments

The preference choice exercise consisted of 7 separate questions and was filled out by participants at a hardware store. The exercises were tested before the final version was applied in the field, but during and after research, a number of noteworthy learnings appeared. In exercise 1, several participants asked why they should pay to obtain information on their consumption; indeed a legitimate question, which perhaps diverted some of the attention towards that instead of selecting between the two. The energy label is missing from the first version (Q1) of exercise 2, which is a mistake as the question was intended to only test the effect of salience, not the presence of labels. As the information displayed in the label was also written in the question, it is assumed that this had little effect. The answer to exercise 3 is actually indirectly provided by exercise 2 for those participants given the second version (Q2) of the questionnaire, as the electricity price can be inferred from the total cost. Only one participant noted this, which indicates that the effect is probably limited. (It nicely sums up the inherent limitations to our ability to process information, even when present.) Exercise 3 worked fine, and although there is a slight difference between 330 kWh per month and 4,000 kWh per years, it is assumed that this is of less importance, since both are clearly larger than 4,000 DKK. Exercise 4 should have been turned into two separate questions, as at least some participants were confused as to whether they should answer only one of the two or answer both. This can perhaps explain why some participants have indicated a yes in 4b, but a no in 4a. Exercise 5 was too complex. Although the idea was to make it more difficult than exercise 4, the amount of people unable to answer the question indicates that the task was more complex than imagined. Exercise 6 had the same type of problem as exercise 1. Participants did not understand why a saving was not guaranteed, which removed focus from deciding between the two. The question in exercise 7 is too long (as noted by a participant), but it is unknown what effect this had.

The loss aversion experiment unfortunately had a very low number of participants. This was mainly caused by the fact that participants had to provide their consent to participating, i.e. in effect opting in. Furthermore, those not at home at the point of installation had to install the meter themselves, which led to even lower participation. It was not possible to get around these issues, as consent was needed due to the privacy issues. As only a limited number of meters were due for installation in the early summer months when the project was initiated, it was not possible to expand the initial sample. Despite numerous reminders, participants did not install meters and/or fill out questionnaires, meaning that the final sample was severely reduced. The difficulty of getting people to participate indicates how complicated conducting research on electricity consumption generally is. As the experiment took place over summer, there is a risk that some participants installed the meter and then went on vacation. This would obviously lead to lower consumption, as only stand-by and passive consumption is captured when participants are not at home. This should only affect the results for the daily consumption, meaning that the effect found might not be as pronounced as indicated by the result. As standby consumption is still consuming power when people are not at home, this should have little effect on the results for the standby experiment.

In general, the study was limited by a lack of access to electricity consumption data from Smart Meters, as shown by the sample containing data from only around 100 meters and the experiment only having 65 invited participants and 17 final participants. A number of utilities, DSOs and energy service providers were contacted, but only one company agreed to share consumption data and install a loss framing widget. The dataset for the Smart Meter analysis is de-limited both temporally and spatially, and thus most likely not representative. Secondly, the number of households and individuals willing and able to participate in interventions and experiments were limited, and none of the experiments can be said to be representative of the study area (Denmark) assuming standard error (5%) and standard confidence interval (95%). Thirdly, the experiments all took place during summer, were electricity consumption is low in DK (due to low penetration of air conditioning) and houses are often vacated due to the holiday season. This possibly affected the results.

Given the difficulties encountered in conducting this research, there are a number of things that should be done differently when a follow-up to this study is hopefully conducted one day. As it was not known which of the behavioural biases that could be expected to affect the effect of Smart Meters most, a number of these were tested. In hindsight, the study should have focused on just one or two biases in order to assess the effect of these in more detail. Ideally, the study should have focused only on loss aversion and salience and conducted a trial of the effect of this with a larger sample. When looking at the exercises, the added value provided by excercise 1 and 7 is limited, and these should have probably been left out.

5.2.2 Critique of conceptual framework

Naturally, behavioural economics has its critics. There are generally three main points of critique, each of which will be addressed briefly. The first is that BE rely extensively on laboratory and experimental studies, which means that the findings might not apply in real-world or market settings, or at least be less pronounced (Levitt & List, 2008; Etzioni, 2011; Cosmides & Tooby, 1996). This critique has some merit, as the strongest evidence of behavioural anomalies (as viewed from neoclassical economics) has emerged from the lab. This does not disqualify the anomalies found hitherto, but calls for extensive real-life or market experiments (Levitt & List, 2008). This author highly agrees with this, and sees extensive real-life experiments as an important line of future research. Secondly, it has been suggested (Etzioni, 2011) that the findings of BE might not apply in all cultural and social settings, a critique based on the fact that most studies and experiments have taken place in Western cultures. This notion is briefly discussed here as well. Finally, there has been critique of BE as promoting paternalistic approaches, in which the state or the policy maker exercises undue control, limiting the free choice of humans. This critique has been especially vocal in the US, and less so in Europe, and has been discussed extensively (e.g. Sunstein, 2013; Loewenstein et al., 2013; Lunn, 2014; John et al., 2013). This critique is briefly touched upon later. However, it is important to note that BE and the concept of "nudge," which is the target of most critique, are not interchangeable. The former is a scientific discipline or sub discipline, and thus has a positivist approach, while the latter is a method of applying behaviourally informed findings to public policy, and thus can be considered a normative approach (Lunn, 2014). This research has mostly concerned itself with how humans actually behave when confronted with behavioural biases (a positivist approach), and only to a lesser degree discussed how these biases should be used in practice (a normative approach).

Psychologists and sociologists have historically conducted most of the research on energy-related behaviour that does not apply a strict (neoclassical) economic framework (e.g. Bell et al., 1996; Stern, 2000a; b; 2011; Gifford, 2011, von Borgstede et al., 2013; Miller & Prentice, 2013; Bratt et al., 2014). The research by sociologists has especially focused on practice theory, as informed by Bourdieu (1977). While this strain of research is no doubt useful to understand how society shapes our general use of and approach to energy consumption, it has not been used here, as the approach taken here is fundamentally economic, informed not just by behavioural economics, but also to a certain degree by other schools of economics, such as New Institutional and environmental. Using a sociological approach would constitue a fundamental departure from economic research, rather than, as this thesis does, explore how economics can be used to understand human behaviour and decision-making with regards to energy and electricity.

5.3 Policy implications

5.3.1 Realising Smart Meter policy goals

The presence of a positive CBA in many countries hinges on whether the benefits from Smart Meter rollout can be realised by utilities, DSOs and consumers. Therefore, it is worth pausing to take a look at this. As mentioned in the introduction, Smart Meters will likely have several operational benefits to utilities such as elimination of meter reading, automatic or faster detection of power downs and grid problems, e.g. through proactive maintenance to correct sag and swell, and less electricity theft (Faruqui et al., 2010a; Krishnamurti et al., 2012; L. Elmegaard, personal communication, 4 June 2014). However, it is commonly acknowledged that meters do not on their own present a positive business case, as is noted by Owen and Ward (2006). For instance, a customer-owned Danish utility company installed Smart Meters at all their customer points at a cost of roughly 1,000 DKK (~€135) per customer. The company calculated that the project had an IRR of roughly 10 years, using a discount rate of 4%, a much longer payback and much lower discount rate than usually applied by private enterprises (L. Elmegaard, personal communication, 4 June 2014). Most benefits accrued from operational efficiency and avoidance of losses in the system.

Arguably, as has been amply discussed in this report, the main consumer benefit accrues from a reduction in consumption. The expected energy saving from the installation of Smart Meters in the MS CBAs are somewhat lower than that of the EC, ranging from 0 to 5%, with an average of 3%±1.3% (EC, 2014). Reviewing the CBAs of the various Member States reveal that consumer benefits in some instances are a significant part of the total benefit, which means that if consumers are not able to realise these benefits (i.e. reduce consumption), the CBA can become negative. This would make the argument for rolling out Smart Meters a lot weaker (Groothuis & Mohr, 2014). The CBAs reveal that consumer benefits make up half or more of the benefits in four countries (Austria, Greece, Netherlands, Northern Ireland), and electricity savings are expected to be above 3% in Austria, Greece, Luxembourg, Malta, Netherlands, Northern Ireland, Romania. Analysis reveal that end-user consumption reductions make up 55% of the total benefits in Austria, 44% in Greece, 15% in Netherlands, and 39% in Northern Ireland. A large-scale trial in the Netherlands (Huizing, 2014) found reductions of 0.6% as a result of Smart Meters coupled with bi-monthly home energy reports; markedly lower than expected reductions (3.2% for indirect feedback)[51]. This indicates that either action must be taken to increase the feedback achieved in many of these countries, or benefits must be realised elsewhere, unless the policy is to become a net cost to the society at large in those countries. An alternative interpretation is that the discrepancy between the behaviour assumed when conducting CBAs and actual behaviour displayed by market participants calls for alternative ways of conducting CBAs that take into account behavioural aspects (e.g. bounded rationality).

Increasing the number of households accessing feedback

Leaving concerns over rebound effects aside for a moment, the total amount of electricity that can be saved, and thus the total reduction in GHG emissions, depends on not just the amount reduced by each household, but also the number of households participating (Ehrhardt-Martinez et al., 2010). Therefore, it is important that this number is as high as possible. Figures from a Danish utility company (L. Elmegaard, personal communication, 4 June 2014) and the results from the Smart Meter experiment suggest that participation rates will be low if people have to sign up to receive this feedback. In the Danish case, less than 15% signed up, and less than 10% of the customers continued using the portal, while for this thesis, 75% of those invited to participate agreed to do so, while less than 25% actually installed the meter, and only around 10% installed the meter *and* filled in the questionnaire. Instead, if legally possible, participants could be automatically enrolled, but have the option to opt-out. Evidence from the Netherlands suggests that participation rates in such a case can be very high (98%), despite being voluntary (Huizing, 2014). An experimental study in Denmark found similar results; the acceptance rate to install a Smart Meter was higher if offered as "an 'opt-out' frame ("No, I would not like to have a Smart Meter with remote control installed in my home") than as an opt-in frame" (Sunstein & Reisch, 2013, see also Ölander & Thøgersen, 2014).

[51] To test whether alternative ways of providing feedback have an effect on consumption reductions, three alternative means of communication are being tested by DSO's: in-home display, web-based information systems and community-based concepts. These results are not yet available (Huizing, 2014).

Applying dynamic tariffs

If operational savings alone do not provide a positive CBA and if reductions are smaller than expected, benefits in other areas are needed. To this end, especially changes to peak demand will matter. Faruqui et al. (2010a) estimate the cost of installing Smart Meters in the EU to be €51 billion, while benefits from operational savings will amount to €26-41 billion, meaning that there is a gap between costs and benefits. They argue that this cost-benefit gap can be filled by adopting dynamic pricing, which supposedly can save up to €67 billion, mostly by reducing the need to build and maintain expensive peaking power plants. Two things are worth noting on the adoption of dynamic tariffs. Firstly, will consumers accept these, and secondly, will they have an affect? The results from the exercise indicate that under the right circumstance, consumers do seem willing to try these. However, it is important how the change is framed. Exercise 6 showed that people are willing to gamble to avoid a loss, but less willing to gamble if they risk losing a sure gain, while exercise 7 indicated that the notion of a gain incentivised people to change plan, meaning that communication to consumers about future electricity plans should be carefully considered. Ideally, various communication forms should be tested (as was done for tax returns in the UK (Hallsworth et al., 2014)) to test the effect of various frames in getting people to switch plans. There is also the option that people could automatically switch plans[52], though this has certain ethical implications. The evidence of the effect of changing plan, is, like the evidence of feedback in general, rather heterogeneous, meaning that there is a need to systematically test this. Some experiments find reductions in the 5% range, while others report savings upwards of 30% (Faruqui et al., 2010a; Owen & Ward, 2006). Generally, the more elaborate and automated the technologies are, the larger the response. Perhaps the most interesting finding is that not all customers seem to respond to price signals; in an experiment in California, about 80% of the total response came from 30% of the customers. Furthermore, the high reductions found in e.g. the US are probably not as applicable in Europe, as air-conditioning and electric space heating are generally not very common (Faruqui et al., 2010a). Furthermore, the social impact of dynamic tariffs needs to be taken into account. Carlsson-Kanyama & Lindén (2007, p. 2170) find evidence that "depending on how household's chores are divided between the sexes […], the extra workload induced by energy savings [e.g. doing chores at night or weekends] may at times be significant and fall upon women in a disproportional way" (p. 2170). Implementation of dynamic tariffs has to be accompanied by a certain degree of automatisation to ensure that disproportionate amounts of extra work do not fall on women or those undertaking significant amount of household work.

Potential rebound effects resulting from Smart Meter feedback

Finally, the presence of potential indirect rebound effects from Smart Meter implementation must be considered. If the installation of Smart Meters does lead to a reduction in electricity consumption, it will increase the disposable income of the consumer, which can then be used to procure other goods or services that require energy (e.g. money saved on electricity can be spent on travelling, obliterating the environmental reduction achieved). If this rebound effect is of significant size, there would be a need to counteract this. For instance, savings achieved as a result of a Smart Meter could be funnelled into an account that could finance home renovation or other EE measures, which would then provide further benefits, essentially generating an energy-saving, positive feedback loop. Joachain & Klopfert (2013) provide

[52] Once sufficient data had been collected to decide on a plan, the customer could, as a default, be switched to the appropriate plan, completely overcoming the transaction costs involved in switching. As noted earlier, evidence suggests that consumers would stay with the default plan, but should of course be given the option to manually switch plans. To make this less coercive, the consumers could opt out of this service (automatic plan switching), but, based on evidence on organ donation rates (Johnson & Goldstein, 2013), opting out should be the default, rather than opting in, as this significantly increases participation.

another interesting solution that electricity reductions could generate complimentary currencies, a form of social currency that, unlike conventional money, cannot be spent in stores, but instead, can only be spent in an environmentally friendly way, e.g. they can be used for public transportation, but not to buy gasoline. This issue is not discussed in any detail here, but is worthy of further research, especially if rebound effects are significant.

In conclusion, a number of factors related to consumer electricity reduction influence whether the Smart Meter policy will be a success. As this short discussion outlined, the effect of many of these factors is unknown, and there is a clear need to analyse the effect of these issues in greater detail.

5.3.2 Considerations for further development of Smart Metering and overall use of behavioural insights in public policy

Before impleting behavioural insights into electricity feedback on a large scale, a number of issues, ranging from the design of the feedback, the need for large-scale trials, technological considerations, and political and ethical considerations, are worth discussing and testing. With this in mind, a disclaimer is needed before providing policy recommendations. A significant amount of the findings informed by or taking a starting point in behavioural economics research suffer from low external validity; they are context specific and many of them have not be replicated in real-life settings, which makes suggesting general policy recommendations difficult (as noted by Faure & Luth, 2011). A certain amount of caution is therefore warranted when recommending future courses of action, but with this in mind, the author agrees with the view taken by Faure and Luth (2011) that “behavioural insights can and should be used to draft effective and efficient behaviourally informed consumer policy” (p. 355).

Systematic design of feedback

Electricity feedback to customers is in essence a form of communication by the utility or DSO. Research on risk communication has found that those who provide information to the public need to understand how people think about and respond to this information to successfully communicate it (Slovic, 1987). Relatively little work has been done on the best ways to present information in order to maximise electricity reductions, with Wood & Newborough (2003) and Karjalainen (2011) being the major exceptions. Karjalainen (2011) conducted a qualitative study where participants were asked which feedback they would find most useful, and similar work has been done by Anderson & White (2009). Results indicate that consumers preferred information on costs-over-time, appliance-specific breakdown and historical comparison. The problem is that asking people what they think works best might not actually be what works best. Studies (Nolan et al. 2008; Schultz et al., 2007; Wood & Newborough, 2007) suggest that “people hold incorrect beliefs about what motivates them to conserve [electricity] and may not be able to predict which strategies will be the most effective” (Nolan et al. 2008, p. 921). To that end, the EC has launched a survey on consumer understanding of energy labels (EC, 2011a), which might not be as effective as they could be, as this study pointed out (e.g. experiment 2). In general, it is not known how feedback should be provided, e.g. whether currency, environmental statement, or something else will have the largest effect on behaviour, but the underlying motivation to act (e.g. monetary or intrinsic) has been found to influence the extent to which people think feedback is worth responding to (Dogan et al., 2014). Following on from other parts of the research conducted for this thesis, it seems indisputable that there is a need to conduct a study of consumer understanding of energy information from Smart Meters.

Karjalainen (2011) suggest that when designing the feedback, utilities and DSOs should rely on knowledge from computer design specialists, since optimal display of data has long been an issue in the area of human-computer interaction. As anyone working with data visualisation can confirm, how data is visually presented has a huge impact on perception. As BE shows that humans are prone to biases stemming from reference point or salience, it is important that the display of data take these biases into account. This ranges from discussion of whether data should be shown as numericals or symbols, to whether or not to use bar/column charts or graphs and other graphical presentations, to whether the user will be only observing the information or have the ability to change the information displayed (Wood & Newborough, 2007). Weber (2013, p. 392) also points out the need to experiment with how to best provide feedback "without overstretching people's processing capacity or losing their attention over extended periods of time." Wilhite et al. (2002) and Egan (1999) are noteworthy examples of studies that explore these connections, but with the advent of Smart Meters, data visualisation is bound to become even more important. A thorough discussion of this is not possible here, but interested readers should consult Wood & Newborough (2007), Karjalainen (2011), as well as infographics websites[53].

Technological considerations

Because feedback studies are conducted using various media (e.g. some studies use IHDs, others use web-based solutions, while newer studies could use phone applications) and no studies have systemically tested these against each other, there is disagreement over what medium should be used to provide the feedback. Darby (2012) argues that "the picture is of broadly consistent and durable effects from the adoption and use of displays," but given the problems with concluding on the effect of feedback in general, this author find little support for this claim. In this regard, the recommendation by earlier research, primarily of British origin (e.g. Darby, 2006; 2012, Owen and Ward, 2006; van Elburg, 2009[54]), to require IHD's as part of the rollout already seem puzzling. As smart phones, tablets, and other devices become ubiquitous, a development, which was difficult to predict in 2006, but which seem obvious now, it is questionable whether consumers need yet another device in their home. Web-based solutions, as was used in the experiments for this thesis, have received little attention (most notable exception is the trials reported in Raw et al. (2011) and in Pyrko (2011) where some feedback is available online to customers), so it is difficult to draw any conclusions on the potential effect.

As feedback systems no doubt will become more sophisticated and automated as technology progress, there is no telling what future feedback will look like (Ehrhardt-Martinez et al., 2010). For this reason, focus should be on providing feedback to consumers in a way they can understand and act upon, rather than focusing exclusively on the medium through which this is provided. The rapid technological development within the sector calls for a focus on maintaining flexibility in the system and keeping an open-minded approach to the design of meters and feedback, in order to ensure that new findings can be incorporated into the existing system. As pointed out by Martiskainen & Coburn (2011), a trade-off between a rapid rollout and a more cautious approach to ensure technological maturity exist. The fast rollout of Smart Meters will provide the projected benefits at an earlier point, but due to the rapid development within the sector, there is a risk that today's Smart Meter will not be very 'smart' by 2020, and will need an update to comply with customer expectation, increasing the cost of the system. These potential problems have caused some to raise concern over the pace of the rollout and argue that a more cautious approach is needed to ensure that findings from real-

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[53] Noteworthy examples include: http://www.good.is/infographics; http://mashable.com/category/infographics/.

[54] Darby (2012) argues that "the inclusion of an in-home display [on the Smart Meter] is significant from the point of view of improving customer feedback." These have not been included in the early rollouts of Smart Meters (in Italy, Sweden, Denmark and Norway), but are part of the roll-out in the UK.

life trials and academia can be incorporated into policy (Martiskainen & Coburn, 2011). Given what is known from BE in general and this study in particular, it seems that a more inductive approach, where policy is formulated as knowledge develop, might lead to larger benefits overall, as the risk of buying into the wrong technology or basing the expected benefits on results never arising will be minimised with such an approach.

The case for a major trial

The research presented above is just a snapshot of the interventions possible and the resulting impacts, and there is a need for further studies evaluating the effectiveness of these interventions. These studies should rely on solid experimental research design, such as randomised controlled trials (RCT) (Haynes et al. 2012) that reveal the effectiveness of behavioural insights over various time frames. The tests should include treatment groups and control groups (Figure 5-1), and take to socio-economic backgrounds of the individuals/households participating in the studies into account. As it was generally hard to determine the long-term effect of the feedback studies reviewed, evaluations should test for both short-term and long-term impacts (Steg & Vlek, 2009). Furthermore, measures or interventions suggested by the Smart Meter need to be acceptable to customers (e.g. see work by Poortinga et al. (2003, p. 54pp). As has been pointed out, behaviourally informed interventions run the risk of being seen as paternalistic, and there is a need to test which interventions are acceptable to customers and which are not, to ensure that individual freedom is maintained and the Smart Meter is not seen as intrusive. Some major Smart Meter trials (similar to those presented Raw et al., 2011) are under way or planned in Member States, and present opportunities for exploring these research gaps, as well as implement some of the successful interventions found in this thesis, such as loss aversion and salience. Solid empirical evidence would allow for modification to national CBAs and better evaluation of Smart Meter policies (Owen & Ward, 2006).

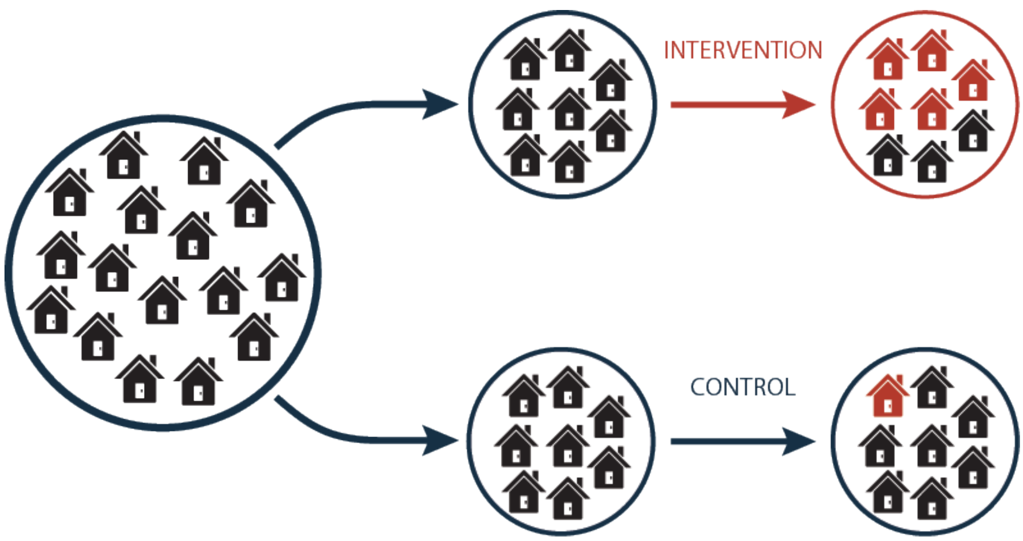


Figure 5-1 – Experimental research design should rely on control groups to determine the effect of interventions (Source: Author, after Haynes et al., 2012).

Incorporating behavioural insights into policy

Knowing that humans have certain biases that affect their economic decision making and that policies generally try to influence behaviour, an argument can be made that behavioural findings should have implications for policy (Lunn, 2014). One could even argue that BE is in a better position to provide policy suggestions than conventional economic theory, as it identifies the biases that lead to diversions from optimal decision making (Loewenstein et al., 2013). As many findings from BE are difficult to generalise, translating these into specific policy recommendations becomes difficult without large-scale, real-life trials. This calls for a more inductive policy approach, where hypotheses are formulated and then tested within the market in order to arrive at the/those idea(s) showing the most promising results (Lunn, 2014). As policies are needed to correct market failures and reduce externalities, there is a need to evaluate the effect of these, but policy evaluation has generally been lacking, especially so in the field of environmental policy (Mundaca, 2008). This is unfortunate, as a lack of *ex-ante* evaluation might result in the implementation of inefficient or ineffective policies, while a lack of *ex-post* evaluation might result in continuation of ineffective, inefficient or downright harmful policies (Mundaca, 2008). The normative approach taken by neoclassical economics means that very few *ex-ante* evaluations have been conducted, while the *ex-post* evaluations have tried to correct the human failures, rather than recognising that the policy might have failed. Changing this involves taking a more empirical approach to regulation, as is already done in some countries, most notably the UK (e.g. UK BIT). For Smart Meters, this has the implication that feedback studies should be conducted and results made publicly available, in order for others to learn from and replicate these[55]. Once determined which intervention that appeared most promising, policy could be formulated (mandating standards, rollout time, etc.). This calls for a more extensive role for the policymaker, but also holds the potential to induce confidence of the public in the regulatory process, as it could increase objectivity, rigour and openness, as the process is in essence more democratic.

Behavioural interventions as public policy

It is easy to demonstrate that the behavioural interventions that can possible be employed using Smart Meters are on a scale from very libertarian to more paternalistic or coercive. Some tools, such as having information provided as a forgone loss rather than a benefit, are very benign, and it is hard to see how these restrict freedom. Others, such as using behavioural patterns to detect which electricity plan fit a customer best, and automatically moving a consumer from their current plan to that plan, are clearly more paternalistic. It is also possible to completely circumvent behaviour and automate decisions, e.g. turning off all appliances when a person leaves the home, but it is easy to see that this has certain ethical implications, and such measures would need careful deliberation before implementation. Numerous authors have discussed the legitimacy of behavioural interventions. Some are critical of BE as a regulatory tool (see e.g. Bonell et al., 2011; Frerichs, 2011; Goodwin, 2012; Heilmann, 2014; Whitehead et al., 2011), some are cautious (see e.g. Cooper & Kovacic, 2012; Berggren, 2011; Hausman & Welch, 2010), while yet others encourage the use of these insights (see e.g. Sunstein & Thaler, 2003; Guldborg Hansen & Jespersen, 2013; Lunn, 2014). Finally, there are those who have tried to assess how the public feels about this, in order to understand if these insights should be used, and if so, how (see e.g. Felsen et al., 2013 and Branson et al., 2012). It is beyond the scope of this thesis to discuss these matters, but it is noted that a thorough discussion of these issues is needed before any BE-based insights, specifically those of more coercive character, are employed on a large scale.

[55] Leaving aside concerns over the replicability of reserach findings, a topic currently so heatedly debated by behavioural and psychological researchers that it has been given its own name: 'repligate' (Meyer & Chabris, 2014).

6 Conclusions

At the risk of oversimplifying, this thesis has argued that the existence of market barriers associated with lack of information (or information asymmetries), has led to the popularity of the 'Information-Deficit Model' in both academic and policy circles, due to the relatively simple policy advise: correct information barriers by providing consumers with better or more (technical) information. The expectation that provision of information would lead to reduction of electricity use by European households was argued to be a prominent feature in the EU policy on Smart Meter deployment in Member States.

As the success of this policy depend on whether such electricity reduction materialises, this thesis argued that it is of importance to better understand how, and to what extent, the provision of information can actually affect end-user behaviour with regards to electricity use. By taking insights from behavioural economics as a starting point, it was argued that the way information is presented to households has an impact on how it is perceived and acted on. It was argued that there is a lack of knowledge on if and how findings from behavioural economics can inform the provision of feedback to consumers, and what the effects of this would be.

- RQ #1: Which behavioural biases, as suggested by behavioural economics, are applicable when consumers are faced with energy-related decisions or provided with information on electricity consumption?

The thesis intended to explore which behavioural biases, as suggested by research in the field of behavioural economics, would be applicable when consumers faced energy-related decisions or were provided with information on electricity consumption. This question was addressed by conducting a number of field-based preference-choice exercises and a Smart Meter experiment. The preference-choice exercises tested five specific biases; above-average bias, information overload, salience, loss aversion, and defaults, by having participants answer questions related to these biases. The Smart Meter experiment focused on two of these biases: salience and loss aversion. The exercises and experiment showed that end-users are prone to several behavioural biases when faced with decisions relating to energy and/or electricity use, which have implications for the way in which information is understood and acted upon.

The exercise on *above-average bias* indicated that consumers hold incorrect beliefs about their electricity use, which warrants the provision of information on electricity, comparative and normative alike. The exercise on *information overload* found that the presence of additional options led to decisions of deteriorating quality, inconsistent with the axioms of EUT. The experiment indicated, again with due limitations, that more information is not necessarily better. The exercise on the effect of *default setting* found, again with due consideration, that consumers are willing to try new electricity tariff schemes. This indicated that Smart Meters might be a fitting place to provide information on dynamic pricing structures. The exercise on *loss aversion* found that framing an EE investment decision as reducing a loss, rather than as obtaining a gain, increased the number of participants willing to undertake risky investments, which suggests that using Smart Meters to frame EE investment decisions could potentially increase the uptake of these, which would increase the effect of the Smart Meters and help meet EU policy goals. The exercises on *salience* found that increasing the salience of information changed consumer preference, which is in conflict with EUT. This suggests that Smart Meters could be employed to display the electricity use cost, which would help close the EE gap by inducing consumers to purchase more efficient goods. Decreasing salience led to higher implicit discount rates among consumers, which indicated that consumer discount rates are not static. This warrants careful consideration of how EE-related information is provided to consumers, as this can potentially help close the EE gap. Together, the exercises demonstrated that consumers do not display rational behaviour, as understood by EUT, but that behavioural biases systematically influence electricity and energy-related decisions in such a way that especially the salience of the information provided, i.e. the mental capacity required to utilise this information, as well as the frame in which this is presented, impact our decisions.

- RQ #2: Using insights from behavioural economics, what may be the expected energy efficiency improvements on electricity use as a result of Smart Meter deployment, particularly in the field of controlled customer feedback?

The *Smart Meter analysis* was conducted to test the whether installing a Smart Meter could be expected to lead to a reduction in electricity consumption. Due to the structural differences between the households, large fluctuations within and between samples were found. It was therefore impossible to draw any statistically valid conclusions. To establish this with significance, a regression analysis with a larger sample would be needed. The effect found in the Smart Meter analysis generally aligned with electricity reductions found in previous research on the topic. Taken together, the review and analysis indicate that it is not unreasonable to expect a reduction in electricity use in the medium-term (weeks/months) of ~7%, but the findings suggest that this effect will likely diminish over time.

The *Smart Meter experiment with feedback* tested the effect of salience and loss aversion on two aspects of electricity consumption: total daily consumption and total standby consumption. It was originally planned to conduct an econometric analysis, but due to the lack of conclusive statistical power caused by the small sample size, alternative analyses were conducted. It was found that loss aversion does seem to have an effect on electricity consumption. In both of the analyses testing the effect on daily electricity use, the intervention group had a larger reduction than the reference group. This was also the case for both analyses of standby consumption, except the effect was much more pronounced here, which indicated that increasing salience of standby consumption is an effective way of achieving large electricity reductions. These results, coupled with the finding from the exercise on risk preferences, indicate that loss aversion indeed trigger behavioural responses, as theorised. However, it must be noted that the results are neither statistically robust nor representative for the case area.

The experiment was conducted in a real-life setting where consumers actually used and paid for their electricity. This means that the results have a high external and ecological validity, as the experiment took place in the home of the participants, indicating that this effect is likely to be found even if implemented in real life, but the low internal validity means that the effect found in this case cannot be assumed to be of the same magnitude once scaled to a population. It was discussed that if previous large-scale trials give any indication of future results, the effect on electricity use in a population of applying a loss aversion frame will likely be in the order of 4-6%. However, the reduction in electricity use found in the loss aversion experiment was higher than most other studies testing the effect of feedback, and especially the reduction in standby consumption was higher. This suggests that there is a need to conduct a study similar in design to what was originally intended for this study, i.e. a large-scale, longitudinal study were effects are determined using regression analysis, in order to establish whether these interventions can be said to work over time, and what the effect is likely to be.

- RQ #3: To what extent can research findings support and be utilized in public policy design?

The research conducted for this thesis has implications for *policy-makers*, because it highlights that information is not just about quantity (i.e. correcting the market failure), but that a policy prescribing the delivery of information to consumers need to take into account that how the information is *presented*, *framed*, and *designed* affects the impact that this information will have on consumer behaviour. The research highlighted that insights from BE could explain why some information is more effective than other, and that especially two features from BE, salience and loss aversion, seem to affect behaviour. This implies that when designing informative policies, there is a need to look beyond the information-deficit model, and view information as much in terms of quality as quantity. As the research is based on findings from Denmark, it might be of most value to policy-makers finding themselves in similar settings, e.g. Scandinavian or perhaps European countries.

The work conducted here contributed to existing research by showing that behavioural biases exist when humans are faced with electricity and energy-related decisions, and that these biases affect the decisions we make. It was shown that at least two of these biases; salience and loss aversion, can be utilised when providing feedback to consumers using Smart Meters, and that this is likely to increase the effectiveness of said feedback. Regarding the scope of this thesis, the research does not claim to provide conclusive knowledge on whether the behavioural interventions applied will increase the expected energy efficiency improvements on electricity use as a result of Smart Meter deployment, but rather that there seems to be a potential to increase the effectiveness by applying these insights.

This thesis provide evidence that Smart Meters do lead to reduced electricity consumption, at least in the short to medium term, but that these meters alone are unlikely to lead to the sustained behaviour change needed to meet EU policy goals. However, the research also indicates that the right combination of behavioural insights, informative policy instruments and Smart Meter technologies can lead to significant reductions in energy use, which can potentially achieve or even surpass the EU policy target.

This research is important to *utility companies* and practitioners working with electricity end-users, as it demonstrated that behavioural insights represent an opportunity to improve the effectiveness of initiatives aiming at energy efficiency improvements from a behavioural (demand) point of view. This includes inducing customers to save electricity overall and at peak hours (or use it more efficiently), getting end-users to accept dynamic tariff structures, or increase the uptake of energy efficiency measures in order to reduce heating, cooling, or other energy service demands.

To *researchers*, this thesis is important because it highlighted that our knowledge on the effect of information on human (economic) behaviour with regards to energy use is still incomplete, and it suggested several research gaps that need to be explored. It is hoped that academics will continue exploring the effect of some of the behavioural biases pointed out in this work in order to establish the likely impact of these on energy-related behaviour. Furthermore, as many feedback studies do not include statistical significance of results, this calls for further studies to employ regression analysis in order to separate the signal (the effect) from the noise (other variables).

The results generated by academia, hopefully in collaboration with utility companies, as was the case with the famous OPOWER experiment, are likely to be very important in furthering our understanding of consumer behaviour with regards to electricity use and energy-related decisions, and a proactive role by the sector would be conducive to knowledge-generation.

Bibliography

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2005). A review of intervention studies aimed at household energy conservation. *Journal of Environmental Psychology*, *25*(3), 273–291. doi:10.1016/j.jenvp.2005.08.002

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2007). The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents. *Journal of Environmental Psychology*, *27*(4), 265–276. doi:10.1016/j.jenvp.2007.08.002

Alcott, B. (2005). Jevons ' paradox, *Ecological Economics 54*, 9–21. doi:10.1016/j.ecolecon.2005.03.020

Allcott, H., & Mullainathan, S. (2010). Behavior and Energy Policy. *Science*, *327*, 1204–1205.

Allen, D., Janda, K., & College, O. (2006). The Effects of Household Characteristics and Energy Use Consciousness on the Effectiveness of Real-Time Energy Use Feedback : A Pilot Study Continuous Feedback: The Next Step In Residential Energy Conservation?, 1–12.

Amir, O., & Lobel, O. (2008). Stumble, Predict, Nudge: How Behavioral Economics Informs Law and Policy. *Columbia Law Review*, *108*(8), 2098–2137.

Anderson, B. W., & White, V. (2009). *Exploring consumer preferences for home energy display functionality*. Report to the Energy Saving Trust.

Ariely, D. (2008). *Predictably Irrational: The Hidden Forces That Shape Our Decisions*, 280 pp, New York, NY, USA: HarperCollins.

Attari, S. Z., DeKay, M. L., Davidson, C. I., & Bruine de Bruin, W. (2010). Public perceptions of energy consumption and savings. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(37), 16054–9. doi:10.1073/pnas.1001509107

Attari, B. S. Z., Dekay, M. L., Davidson, C. I., & Bruin, W. B. De. (2011). Changing Household Behaviors to Curb Climate Change : How Hard Can it Be?, *Sustainability 4*(1), 2010–2012. doi:10.1089/sus.2010.9724

Baddeley, M. (2011). *Energy, the Environment and Behaviour Change: A survey of insights from behavioural economics* (No. 1162) (p. 34). Cambridge, UK: Cambridge University

Barker T., I. Bashmakov, L. Bernstein, J. E. Bogner, P. R. Bosch, R. Dave, O. R. Davidson, B. S. Fisher, S. Gupta, K. Halsnæs, G.J. Heij, S. Kahn Ribeiro, S. Kobayashi, M. D. Levine, D. L. Martino, O. Masera, B. Metz, L. A. Meyer, G.-J. Nabuurs, A. Najam, N. Nakicenovic, H. -H. Rogner, J. Roy, J. Sathaye, R. Schock, P. Shukla, R. E. H. Sims, P. Smith, D. A. Tirpak, D. Urge-Vorsatz, D. Zhou (2007) Technical Summary. In: *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* [B. Metz, O. R. Davidson, P. R. Bosch, R. Dave, L. A. Meyer (eds)], Cambridge, UK and New York, NY, USA: Cambridge University Press.

Bell, P. A.; Greene, T. C.; Fisher, J. D. and Baum, A. (1996) Environmental Psychology, 4th Edition. Orlando, Fla., US: Harcourt Brace College Publishers.

Bemelmans-Videc, M-L.; Rist, R. C. and Vedung, E. (Eds.) (1998) Carrots, Sticks and Sermons: Policy Instruments and Their Evaluation. New Brunswick, US: Transaction Publishers.

Benders, R. M. J., Kok, R., Moll, H. C., Wiersma, G., & Noorman, K. J. (2006). New approaches for household energy conservation — In search of personal household energy budgets and energy reduction options. *Energy Policy*, *34*, 3612–3622. doi:10.1016/j.enpol.2005.08.005

Berg, N. (2003). Normative behavioral economics. *The Journal of Socio-Economics*, *32*(4), 411–427. doi:10.1016/S1053-5357(03)00049-0

Berggren, N. (2011). Time for behavioral political economy? An analysis of articles in behavioral economics. *The Review of Austrian Economics*, *25*(3), 199–221. doi:10.1007/s11138-011-0159-z

Bonell, C., McKee, M., Fletcher, A., Haines, A., & Wilkinson, P. (2011). Nudge smudge: UK Government misrepresents "nudge". *Lancet*, *377*(9784), 2158–9. doi:10.1016/S0140-6736(11)60063-9

Borchardt, K.-D. (2014). Benchmarking Smart Metering deployment in EU. In *European Conference on Smart Metering Deployment in the EU*. Brussels.

Bourdieu, P. (1977). *Outline of a Theory of Practice* (248 p.). Cambridge, UK: The Press Syndicate of the University of Cambridge.

Boyd, R., Gintis, H., & Bowles, S. (2010). Coordinated punishment of defectors sustains cooperation and can proliferate when rare. *Science*, *328*(5978), 617–20. doi:10.1126/science.1183665

Branson, C., Duffy, B., Perry, C., & Wellings, D. (2012). *Acceptable Behaviour?*, London, UK: Ipsos Mori(p. 26).

Bratt, C., Stern, P. C., Matthies, E., & Nenseth, V. (2014). Home, Car Use, and Vacation: The Structure of Environmentally Significant Individual Behavior. *Environment and Behavior*. Published online 27 February 2014, doi:10.1177/0013916514525038

Brown, I. (2014). Britain's Smart Meter programme: A case study in privacy by design. *International Review of Law, Computers & Technology*, *28*(2), 172–184. doi:10.1080/13600869.2013.801580

Brown, Z., Johnstone, N., Haščič, I., Vong, L., & Barascud, F. (2013). Testing the effect of defaults on the thermostat settings of OECD employees. *Energy Economics*, *39*, 128–134. doi:10.1016/j.eneco.2013.04.011

Bruni, L. & Sugden, R. (2007). The road not taken: how psychology was removed from economics, and how it might be brought back, *The Economic Journal, 117*(516), 146–173.

Bubb, R., & Pildes, R. H. (2013). *How Behavioral Economics Trims Its Sails and Why* (Working Paper No. 13-29) (pp. 1595–1678). New York, New York, USA.

Camerer, C. (1999). Behavioral economics: Reunifying psychology and economics. *Proceedings of the National Academy of Sciences*, *96*, 10575–10577. Retrieved from http://www.pnas.org/content/96/19/10575.short

Camerer, C., Issacharoff, S., Loewenstein, G., O'Donoghue, T., & Rabin, M. (2003). Regulation for Conservatives: Behavioral Economics and the Case for "Asymmetric Paternalism." *University of Pennsylvania Law Review*, *151*(3), 1211–1254.

Carlsson-Kanyama, A., & Lindén, A.-L. (2007). Energy efficiency in residences — Challenges for women and men in the North. *Energy Policy*, *35*, 2163–2172. doi:10.1016/j.enpol.2006.06.018

Carter, N. (2007). *The Politics of the Environment: Ideas, Activism, Policy*, 2nd Edition, Cambridge, UK: Cambridge University Press.

Centre d'analyse stratégique (2011) "Green nudges": new incentives for ecological behaviour, La Note d'Analyse, Social affairs no. 216. Accessed online June 2014: http://www.strategie.gouv.fr/system/files/2011-03-09-na-216-nudgesvertsgb_0.pdf.

Carroll, G. D., Choi, J. J., Laibson, D., Madrian, B. C., & Metrick, A. (2009). Optimal Defaults and Active Decisions. *The Quarterly Journal of Economics*, *124*(4), 1639–1674. Retrieved from http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=2798815&tool=pmcentrez&rendertype=abstract.

Christensen, T. H., Gram-Hanssen, K., & Friis, F. (2013a). Households in the smart grid – existing knowledge and new approaches, In: Hansson, L., Holmberg, U. & Brembeck, H. (Eds.)(2013). Making sense of consumption. Selections from the 2nd Nordic Conference on Consumer Research 2012. Göteborg: Centre for Consumer Science, University of Gothenburg. ISBN: 978-91-974642-6-0. Available online at http://hdl.handle.net/2077/34508 (pp. 333–348).

Christensen, T. H., Ascarza, A., Throndsen, W., Gram-Hanssen, K., & Friis, F. (2013b). The role of households in the smart grid : A comparative study. *ECEEE SUMMER STUDY PROCEEDINGS*, 2285–2296.

Cialdini, R. B., Reno, R. R. & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of Personality and Social Psychology, 58,* 1015-1026.

Coase, R. H. (1960). The problem of social cost. *Journal of Law and Economics,* 3: 1-44.

Cook, B., Gazzano, J., Gunay, Z., Hiller, L., Mahajan, S., Taskan, A., & Vilogorac, S. (2012). The Smart Meter and a smarter consumer: quantifying the benefits of Smart Meter implementation in the United States. *Chemistry Central Journal*, *6 Suppl 1*(Suppl 1), S5. doi:10.1186/1752-153X-6-S1-S5

Cooper, J. C., & Kovacic, W. E. (2012). Behavioral economics: implications for regulatory behavior. *Journal of Regulatory Economics*, *41*(1), 41–58. doi:10.1007/s11149-011-9180-1

Cosmides, L., & Tooby, J. (1996). Are humans good intuitive statisticians after all ? Rethinking some conclusions from the literature on judgment under uncertainty. *Cognition*, *58*, 1–73.

Costa, D. L., & Kahn, M. E. (2010). *Energy Conservation "Nudges" And Environmentalist Ideology: Evidence From A Randomized Residential Electricity Field Experiment* (NBER Working Paper Series No. 15939) (p. 33). Cambridge, MA: National Bureau of Economic Research.

Covrig, C. F., Ardelean, M., Vasiljevska, J., Mengolini, A., Fulli, G., Amoiralis, E., Jiménez, M. S., Filiou, C. (2014). *Smart Grid Projects Outlook 2014* (p. 156). European Commission Joint Research Centre. doi:10.2790/22075

Danziger, S., Levav, J., & Avnaim-Pesso, L. (2011). Extraneous factors in judicial decisions. *Proceedings of the National Academy of Sciences*, *108*(17), 6889–92. doi:10.1073/pnas.1018033108

Darby, S. (2006). *The Effectiveness of Feedback On Energy Consumption: A Review For Defra of The Literature On Metering, Billing and Direct Displays* (p. 24). Oxford, UK: University of Oxford

Darby, S. (2010). Smart Metering: what potential for householder engagement? *Building Research & Information*, *38*(5), 442–457. doi:10.1080/09613218.2010.492660

Darby, S. J. (2012). Metering: EU policy and implications for fuel poor households. *Energy Policy*, *49*, 98–106. doi:10.1016/j.enpol.2011.11.065

Dietz, T., Gardner, G. T., Gilligan, J., Stern, P. C., & Vandenbergh, M. P. (2009). Household actions can provide a behavioral wedge to rapidly reduce US carbon emissions. *Proceedings of the National Academy of Sciences*, *106*(44), 18452–18456.

Dinner, I., Johnson, E. J., Goldstein, D. G., & Liu, K. (2011). Partitioning Default Effects : Why People Choose Not to Choose. *Journal of Experimental Psychology*, *17*(4), 332–341. doi:10.1037/a0024354

[DG IPOL] Directorate General for Internal Policies. (2012). *Effect of Smart Metering on Electricity Prices: Briefing Note.* IP/A/ITRE/NT/2011-16. Brussels, Belgium: European Commission.

[DG Energy] Directorate General for Energy. (2007). 2020-vision: Saving our energy. Brussels, Belgium: European Commission. Retrieved 7 September 2014 from: http://ec.europa.eu/energy/action_plan_energy_efficiency/doc/2007_eeap_en.pdf.

[DG Energy] Directorate General for Energy. (2014). Single market for gas & electricity: Smart Grids. Brussels, Belgium: European Commission. Retrieved 10 July 2014, from http://ec.europa.eu/energy/gas_electricity/smartgrids/smartgrids_en.htm.

Dogan, E., Bolderdijk, J. W., & Steg, L. (2014). Making Small Numbers Count: Environmental and Financial Feedback in Promoting Eco-driving Behaviours. *Journal of Consumer Policy*, *37*(3), 413–422. doi:10.1007/s10603-014-9259-z

Draper, S. W. (2013) The Hawthorne, Pygmalion, Placebo and other effects of expectation: some notes. Accessed online 2 Sep 2014: http://www.psy.gla.ac.uk/~steve/hawth.html#Hawthorne%20overall.

Dromacque, C., Xu, S., & Baynes, S. (2013). *Case study on innovative smart billing for household consumers*, Report prepared by VaasaETT for the World Energy Council and ADEME, 72 pages.

Dubin, J. A., & McFadden, D. L. (1984). An Econometric Analysis of Residential Electric Appliance Holdings and Consumption. *Econometrica*, *52*(2), 345–362.

Dunning, D., Heath, C., & Suls, J. M. (2004). Flawed self-assessment: implications for health, education, and business. *Psychological Science in the Public Interest, 5*(3), 69–106.

Efthymiou, C., & Kalogridis, G. (2010). Smart Grid Privacy via Anonymization of Smart Metering Data. In *2010 First IEEE International Conference on Smart Grid Communications* (pp. 238–243). Ieee. doi:10.1109/SMARTGRID.2010.5622050

Egan, C. (1999). *Graphical Displays and Comparative Energy Information: What Do People Understand and Prefer?* In: ECEEE 1999 Summer Study Panel 11,13 (p. 13).

Ehrhardt-Martinez, K., Donnelly, K. A., & Laitner, J. A. S. (2010). *Advanced Metering Initiatives and Residential Feedback Programs: A Meta-Review for Household Electricity-Saving Opportunities,* Report E105, (p. 140). Washington, D.C., USA.

Endres, A. & Radke, V. (2012). *Economics for Environmental Studies,* Berlin, Germany: Springer-Verlag.

Epstein, R. A. (2006). Behavioral Economics: Human Errors and Market Corrections. *University of Chicago Law Review*, *111*(73), 111–132.

Ernst & Young. (2013). *„Kosten-Nutzen-Analyse für einen flächendeckenden Einsatz intelligenter Zähler“* (p. 239). Munich, Germany: Ernst & Young, GmbH

Ersson, E., & Pyrko, J. (2009a). *El-info via digitala kanaler: Potential att förändra elanvänding i bostäder. Fallstudie 1: "Min elförbrukning" hos Skånska Energi AB* (p. 82). Lund.

Ersson, E., & Pyrko, J. (2009b). *El-info via digitala kanaler: Potential att förändra elanvändning i bostäder. Fallstudie 2 "Dina sidor" hos Öresundskraft AB,* Elforsk rapport 09:92 (p. 59). Lund, Sweden.

Etzioni, A. (2011). Behavioural Economics: Next Steps. *Journal of Consumer Policy*, *34*(3), 277–287. doi:10.1007/s10603-011-9160-y

European Commission. (2006). *Directive 2006/32/EC on Energy End-use Efficiency and Energy Services*. Brussels, Belgium: European Commission.

European Commission. (2009). *Directive 2009/72/EC of The European Parliament and of The Council of 13 July 2009 concerning common rules for the internal market in electricity and repealing Directive 2003/54/EC*. Brussels, Belgium: European Commission.

European Commission (2011a). *COMMUNICATION FROM THE COMMISSION TO THE COUNCIL, THE EUROPEAN PARLIAMENT, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE – Energy Efficiency Plan 2011, COM(2011) 109 final/2 CORRIGENDUM* (16 pages). Brussels.

European Commission (2011b). Press Summary: "Next steps for smart grids: Europe's future electricity system will save money and energy," Brussels, 12 April 2011. Accessed online 10 July 2014: http://ec.europa.eu/energy/gas_electricity/smartgrids/doc/20110412_press_summary.pdf.

European Commission. (2011c). Smart Grid Mandate: Standardization Mandate to European Standardisation Organisations (ESOs) to support European Smart Grid deployment, *M/490 EN.*

European Commission. (2011d). *Special Eurobarometer 372: Climate change* (p. 85). Brussels, Belgium.

European Commission. (2012a). COMMISSION RECOMMENDATION of 9 March 2012 on preparations for the roll-out of Smart Metering systems (2012/148/EU). *Official Journal of the European Union*, 9–22.

European Commission. (2012b). *Directive 2012/27/EU of the European Parliament and of The Council of 25 October 2012 on energy efficiency, amending Directives 2009/125/EC and 2010/30/EU and repealing Directives 2004/8/EC and 2006/32/EC*. Brussels, Belgium: European Commission

European Commission. (2014). *Benchmarking Smart Metering deployment in the EU-27 with a focus on electricity, COM(2014) 356 final* (p. 10). Brussels, Belgium. Retrieved 11 July 2014 from: http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52014DC0356&from=EN.

European Council. (2014). European Council Conclusions, 20-21 March 2014, Nr.: EUCO 7/1/14, Retrieved from: http://www.consilium.europa.eu/uedocs/cms_data/docs/pressdata/en/ec/141749.pdf.

European Data Protection Supervisor. (2012). *Opinion of the European Data Protection Supervisor on the Commission Recommendation on preparations for the roll-out of Smart Metering systems* (pp. 1–18). Brussels, Belgium: European Data Protection Supervisor.

European Environment Agency. (2008). *Energy and environment report 2008*, EEA Report No 6/2008 (p. 100). Copenhagen, Denmark: European Environment Agency, doi:10.2800/10548

Eurostat (2014). Europe in figures - Eurostat yearbook. Brussels, Belgium: European Commission. Retrieved July 2014 from: http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Europe_in_figures_-_Eurostat_yearbook.

Faruqui, A., Harris, D., & Hledik, R. (2010a). Unlocking the €53 billion savings from Smart Meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investment. *Energy Policy*, *38*(10), 6222–6231. doi:10.1016/j.enpol.2010.06.010

Faruqui, A., Sergici, S., & Sharif, A. (2010b). The impact of informational feedback on energy consumption—A survey of the experimental evidence. *Energy*, *35*(4), 1598–1608. doi:10.1016/j.energy.2009.07.042

Faure, M. & Skogh, G. (2003). The Economic Analysis of Environmental Policy and Law, an Introduction. Cheltenham, UK: Edward Elgar Publishing, Ltd.

Faure, M. G., & Luth, H. A. (2011). Behavioural Economics in Unfair Contract Terms Cautions and Considerations. *Journal of Consumer Policy*, *34*, 337–358. doi:10.1007/s10603-011-9162-9

Fehr, E., & Fischbacher, U. (2003). The nature of human altruism. *Nature*, *425*(6960), 785–91. doi:10.1038/nature02043

Felsen, G., Castelo, N., & Reiner, P. B. (2013). Decisional enhancement and autonomy: public attitudes towards overt and covert nudges. *Judgment and Decision Making*, *8*(3), 202–213.

Fischer, C. (2008). Feedback on household electricity consumption: a tool for saving energy? *Energy Efficiency*, *1*(1), 79–104. doi:10.1007/s12053-008-9009-7

Flath, C., Nicolay, D., Conte, T., Dinther, C., & Filipova-Neumann, L. (2012). Cluster Analysis of Smart Metering Data. *Business & Information Systems Engineering*, *4*(1), 31–39. doi:10.1007/s12599-011-0201-5

Fleming, S., Thomas, C.L., & Dolan, R.J. (2010) Overcoming status quo bias in the human brain, *Proceedings of the National Academy of Science, 107*, 6005–6009.

Fox-Penner, P. (2010) Smart Power: Climate Change, the Smart Grid, and the Future of Electric Utilities, Washington, D.C.: Island Press

Frank, R. H. (1997). *Microeconomics and Behaviour*, 3rd Edition, Boston, MA: McGraw-Hill

Frederick, S., Loewenstein, G., & O'Donoghue, T. (2002). Time Discounting and Time Preference: A Critical Review. *Journal of Economic Literature*, *XL*(June), 351–401.

Frerichs, S. (2011). False Promises? A Sociological Critique of the Behavioural Turn in Law and Economics. *Journal of Consumer Policy*, *34*(3), 289–314. doi:10.1007/s10603-011-9164-7

Galley, A., Gold, J., & Johal, S. (2013). *Public Service Transformed - Harnessing the Power of Behavioural Insights* (p. 36). Toronto, ON.

Gans, W., Alberini, A., & Longo, A. (2013). Smart Meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland. *Energy Economics*, *36*, 729–743. doi:10.1016/j.eneco.2012.11.022

Gardner, G. T., & Stern, P. C. (2008). The Short List: The Most Effective Actions U.S. Households Can Take to Curb Climate Change. *Environment: Science and Policy for Sustainable Development*, *50*(5), 12–25. doi:10.3200/ENVT.50.5.12-25

Gately, D. (1980). Individual discount rates and the purchase and utilization of energy-using durables: comment. *The Bell Journal of Economics*, *11*(1), 373–374.

Gates, R. W. (1983). Investing in energy conservation: Are homeowners passing up high yields? *Energy Policy*, *11*(1), 63–71.

Gifford, R. (2011) The Dragons of Inaction: Psychological Barriers That Limit Climate Change Mitigation and Adaptation, *American Psychologist, Vol. 66*(4), 290-302.

Gilbert, B., & Graff Zivin, J. (2014). Dynamic salience with intermittent billing: Evidence from smart electricity meters. *Journal of Economic Behavior & Organization*, *In Press,* 1–15. doi:10.1016/j.jebo.2014.03.011

Giordano, V., Fulli, G., Jiménez, M. S., Onyeji, I., Colta, A., Papaioannou, I., Mengolini, A., Alecu, C., Ojala, T., Maschio, I. (2011). *Smart Grid projects in Europe: lessons learned and current developments* (p. 118). Luxembourg: Publications Office of the European Union. doi:10.2790/32946

Gleerup, M., Larsen, A., Leth-Petersen, S., & Togeby, M. (2010). The Effect of Feedback by Text Message(SMS) and Email on Household Electricity Consumption: Experimental Evidence. *Energy Journal*, *31*(3), 113-132.

Goldstein, N. J., Cialdini, R. B., & Griskevicius, V. (2008a). A Room with a Viewpoint: Using Social Norms to Motivate Environmental Conservation in Hotels. *Journal of Consumer Research*, *35*(August). doi:10.1086/586910

Goodwin, T. (2012). Why We Should Reject "Nudge." *Politics*, *32*(2), 85–92. doi:10.1111/j.1467-9256.2012.01430.x

Gowdy, J. M. (2008) Behavioral economics and climate change policy, *Journal of Economic Behavior & Organization, Vol. 68*, pp. 632–644.

Gowdy, J. (2010) Behavioral Economics, Neuroeconomics, and Climate Change Policy, Baseline Review for the Garrison Institute Initiative on Climate Change Leadership, Garrison, NY: Garrison Institute.

Gram-Hanssen, K. (2003). *By og Byg Resultater 029: Boligers energiforbrug – sociale og tekniske forklaringer på forskelle* (p. 132). Hørsholm, Denmark.

Gram-Hanssen, K. (2013). Efficient technologies or user behaviour, which is the more important when reducing households' energy consumption? *Energy Efficiency*, *6*(3), 447–457. doi:10.1007/s12053-012-9184-4

Gram-Hanssen, K., Kofod, C., & Petersen, K. N. (2004). Different Everyday Lives - Different Patterns of Electricity Use. In *Proceedings of the 2004 American Council for an Energy Efficient Economy Summerstudy in Buildings.* (p. 13). Washington, D.C., USA.

Greening, L. A., Greene, D. L., & Difiglio, C. (2000). Energy efficiency and consumption - the rebound effect - a survey. *Energy Policy*, *28*, 389–401.

Grønhøj, A., & Thøgersen, J. (2011). Feedback on household electricity consumption: learning and social influence processes. *International Journal of Consumer Studies*, *35*(2), 138–145. doi:10.1111/j.1470-6431.2010.00967.x

Groothuis, P. a., & McDaniel Mohr, T. (2014). Do Consumers Want Smart Meters? Incentives or Inertia: Evidence from North Carolina and Lessons for Policy. *Economics of Energy & Environmental Policy*, *3*(1), 53–67. doi:10.5547/2160-5890.3.1.pgro

Gsottbauer, E. and van den Bergh, J. C. J. M. (2011) Environmental Policy Theory Given Bounded Rationality and Other-regarding Preferences, *Environmental Resource Economics, 49*, pp. 263–304

Guldborg Hansen, P., & Jespersen, A. M. (2013). Nudge and the Manipulation of Choice A Framework for the Responsible Use of the Nudge Approach. *European Journal of Risk Regulation*, *1*, 3–28.

Hallsworth, M., List, J. A., Metcalfe, R. D. & Vlaev, I. (2014). The Behavioralist As Tax Collector: Using Natural Field Experiments to Enhance Tax Compliance, *NBER Working Paper No. 20007*, Retrieved August 2014 from: http://www.nber.org/papers/w20007.

Hanks, A. S., Just, D. R., Smith, L. E., & Wansink, B. (2012). Healthy convenience: nudging students toward healthier choices in the lunchroom. *Journal of Public Health*, *34*(3), 370–6. doi:10.1093/pubmed/fds003

Hansen, J., Kharecha, P., Sato, M., Masson-Delmotte, V., Ackerman, F., Beerling, D. J., Hearty, P. J., Hoegh-Guldberg, O., Hsu, S.-L., Parmesan, C., Rockstrom, J., Rohling, E. J., Sachs, J., Smith, P., Steffen, K., van Susteren, L., von Schuckmann, K. & Zachos, J. C. (2013). Assessing "dangerous climate change": required reduction of carbon emissions to protect young people, future generations and nature. *PloS One*, *8*(12), e81648. doi:10.1371/journal.pone.0081648

Hargreaves, T. (2011). Practice-ing behaviour change: Applying social practice theory to pro-environmental behaviour change. *Journal of Consumer Culture*, *11*(1), 79–99. doi:10.1177/1469540510390500

Hargreaves, T., Nye, M., & Burgess, J. (2010). Making energy visible: A qualitative field study of how householders interact with feedback from smart energy monitors. *Energy Policy*, *38*(10), 6111–6119. doi:10.1016/j.enpol.2010.05.068

Hargreaves, T., Nye, M., & Burgess, J. (2013). Keeping energy visible ? Exploring how householders interact with feedback from smart energy monitors in the longer term. *Energy Policy*, *52*, 126–134. doi:10.1016/j.enpol.2012.03.027

Hassett, K. A., & Metcalf, G. E. (1993). Energy conservation investment: Do consumers discount the future correctly? *Energy Policy*, *21*, 710–716.

Hausman, J. A. (1979). Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables. *The Bell Journal of Economics*, *10*(1), 33–54.

Hausman, D. M., & Welch, B. (2010). Debate: To Nudge or Not to Nudge. *Journal of Political Philosophy*, *18*(1), 123–136. doi:10.1111/j.1467-9760.2009.00351.x

Haynes, L., Service, O., Goldacre, B., & Torgerson, D. (2012). *Test , Learn , Adapt: Developing Public Policy with Randomised Controlled Trials* (p. 35). London, UK: United Kingdom Cabinet Office Behavioural Insights Team

Heilmann, C. (2014). Success conditions for nudges: a methodological critique of libertarian paternalism. *European Journal for Philosophy of Science*, *4*(1), 75–94. doi:10.1007/s13194-013-0076-z

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., & McElreath, R. (2001). In Search of Homo Economicus: Behavioral Experiments in 15 Small-Scale Societies. In *AEA PAPERS AND PROCEEDINGS* (pp. 73–78).

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *The Behavioral and Brain Sciences*, *33*(2-3), 61–83; discussion 83–135. doi:10.1017/S0140525X0999152X

Hoenkamp, R., Huitema, G. B., & Vugt, A. J. C. D. M. Van. (2014). The Neglected Consumer : The Case of the Smart Meter Rollout in the Netherlands. *Renewable Energy Law and Policy*, *4*, 269–282.

Houston, D. A. (1983). Implicit Discount Rates and the Purchase of Untried, Energy-Saving Durable Goods. *Journal of Consumer Research*, *10*(2), 236–246.

Howarth, R. B., & Sanstad, A. H. (1995). Discount rates and energy efficiency. *Contemporary Economic Policy,* 13(3): 101-109.

Huizing, I. (2014). Smart Meter roll-out in The Netherlands. In *European Conference on Smart Metering Deployment in the EU* (p. 7). Brussels, Belgium.

Hwang, M. I. & Lin, J. W. (1999) Information dimension, information overload and decision quality, *Journal of Information Science, 25*, 213-218, doi:10.1177/016555159902500305

International Energy Agency. (2010). *2010 Key World Energy Statistics* (p. 82). Paris, France.

[IPCC] Intergovernmental Panel on Climate Change (2013). Summary for Policymakers. In: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)], Cambridge, UK and New York, NY, USA: Cambridge University Press.

[IPCC] Intergovernmental Panel on Climate Change (2014). Summary for Policymakers, In: Climate Change 2014, Mitigation of Climate Change. *Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge, UK and New York, NY, USA: Cambridge University Press.

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: can one desire too much of a good thing? *Journal of Personality and Social Psychology*, *79*(6), 995–1006. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11138768.

Jackson, T. (2005). *Motivating sustainable consumption, a review of evidence on consumer behaviour and behavioural change.* Report to the Sustainable Development Research Network. Guildford, UK: University of Surrey. Retrieved from: http://www.sustainablelifestyles.ac.uk/sites/default/files/motivating_sc_final.pdf.

Jacoby, J. (1984) Perspectives on Information Overload, *Journal of Consumer Research, 10*(4), 432-435.

Jaffe, A. B., & Stavins, R. N. (1994a). The energy paradox and the diffusion of conservation technology. *Resource and Energy Economics,* 16(2): 91-122.

Jaffe, A. B., & Stavins, R. N. (1994b). The energy-efficient gap: What does it mean? *Energy Policy,* 22(10): 804.

Jennings, M. G. (2013). A smarter plan? A policy comparison between Great Britain and Ireland's deployment strategies for rolling out new metering technologies. *Energy Policy*, *57*, 462–468. doi:10.1016/j.enpol.2013.02.017

Jessoe, K., & Rapson, D. (2013). *Knowledge is (Less) Power: Experimental Evidence from Residential Energy Use,* WP 241 (pp. 1–32). Berkeley, CA: Energy Institute, Haas School of Business, Joachain, H., & Klopfert, F. (2013). *Smart Meters as an opportunity to motivate households for energy savings? Designing innovative policy instruments based on the coupling of Smart Meters and non-financial incentives,* CEB Working Paper (No. 13/008) (p. 28). Brussels, Belgium: Solvay Brussels School of Economics and Management

John, P., Smith, G. & Stoker, G. (2009) Nudge nudge, think think: two strategies for changing civic behaviour. *Political Quarterly, Vol. 80*(3), pp. 361-370.

John, P., Cotterill, S., Moseley, A., Richardson, L., Smith, G., Stoker, G. & Wales, C. (2013) *Nudge, Nudge, Think, Think: Experimenting with Ways to Change Civic Behaviour.* Revised paperback edition. London, UK: Bloomsbury

Johnson, E. J., & Goldstein, D. G. (2003). Do Defaults Save Lives ? *Science*, *302*, 1338–1339.

Johnson, E. J., & Goldstein, D. G. (2013). Decision by Default. In: Shafir, E. (Ed.) *The Behavioral Foundations of Public Policy*, Princeton, NJ, US: Princeton University Press.

Johnson, E. J., Shu, S. B., Dellaert, B. G. C., Fox, C., Goldstein, D. G., Häubl, G., Larrick, R. P., Payne, J. W., Peters, E., Schkade, D., Wansink, B. & Weber, E. U. (2012). Beyond nudges: Tools of a choice architecture. *Marketing Letters*, *23*(2), 487–504. doi:10.1007/s11002-012-9186-1

Kahan, D. M. (2002). *The Logic of Reciprocity: Trust, Collective Action, and Law*, John M. Olin Center for Studies in Law, Economics, and Public Policy Working Papers. (No. 281) (p. 36). New Haven, CT: Yale University

Kahneman, D. (2003). Maps of Bounded Rationality: Psychology for Behavioral Economics. *The American Economic Review*, *93*(5), 1449–1475.

Kahneman, D. (2011) *Thinking, Fast and Slow*. London, UK: Penguin Books.

Kahneman, D., & Tversky, A. (1984). Choices, Values, and Frames. *American Psychologist*, *39*(4), 341–350.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–292.

Kahneman, D., Knetsch, J., & Thaler, R. (1990). Experimental tests of the Endowment Effect and the Coase Theorem. *Journal of Political Economy*, *98*(6), 1325–1348. Retrieved from http://www.jstor.org/stable/2937761

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias. *Journal of Economic Perspectives*, *5*(1), 193–206. doi:10.1257/jep.5.1.193

Kallbekken, S., Sælen, H., & Hermansen, E. A. T. (2013). Bridging the energy efficiency gap: A field experiment on lifetime energy costs and household appliances. *Journal of Consumer Policy*, *36*(1), 1–16. doi:10.1007/s10603-012-9211-z

Karjalainen, S. (2011). Consumer preferences for feedback on household electricity consumption. *Energy and Buildings*, *43*(2-3), 458–467. doi:10.1016/j.enbuild.2010.10.010

Kavousian, A., Rajagopal, R., & Fischer, M. (2013). Determinants of residential electricity consumption: Using Smart Meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior. *Energy*, *55*, 184–194. doi:10.1016/j.energy.2013.03.086

Khazzoom, J. D. (1980). Economic Implications of Mandated Efficiency in Standards for Household Appliances. *The Energy Journal*, *1*(4), 21–40.

Khazzoom, J. D. (1987). Energy Saving Resulting from the Adoption of More Efficient Appliances. *The Energy Journal*, *8*(4), 85–89.

Kinzig, A. P., Ehrlich, P. R., Alston, L. J., Arrow, K., Barrett, S., Buchman, T. G., Daily, Gretchen C., Levin, B., Levin, S., Oppenheimer, M., Ostrom, E., & Saari, D. (2013). Social Norms and Global Environmental Challenges: The Complex Interaction of Behaviors, Values, and Policy. *BioScience*, *63*(3), 164–175. doi:10.1525/bio.2013.63.3.5

Klopfert, F., & Wallenborn, G. (2011). *Empowering Consumers Through Smart Metering,* report for the BEUC, the European Consumer Organisation, 22 December 2011, pp. 57). Brussels.

Klos, M. (2009). *Impact Evaluation of OPOWER SMUD Pilot Study* (35 p.). Boulder, CO: Summit Blue Consulting

Kluger, A. N., & DeNisi, A. (1996). The Effects of Feedback Interventions on Performance: A Historical Review, a Meta-Analysis, and a Preliminary Feedback Intervention Theory. *Psychological Bulletin*, *119*(2), 254–284.

Knetsch, J. L., & Wong, W. (2009). The endowment effect and the reference state: Evidence and manipulations. *Journal of Economic Behavior & Organization*, *71*, 407–413. doi:10.1016/j.jebo.2009.04.015

Kollmuss, A., & Agyeman, J. (2002). Mind the Gap: Why do people act environmentally and what are the barriers to pro- environmental behavior ? *Environmental Education Research*, *8*(3), 239–260.

Kolstad C., Urama, K., Broome, J., Bruvoll, A., Cariño Olvera, M., Fullerton, D., Gollier, C., Hanemann, W.M, Hassan, R., Jotzo, F., Khan, M.R., Meyer, L. & Mundaca, L. (2014). Social, Economic and Ethical Concepts and Methods. In: *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge, UK and New York, NY, USA: Cambridge University Press.

Krishnamurti, T., Schwartz, D., Davis, A., Fischhoff, B., de Bruin, W. B., Lave, L., & Wang, J. (2012). Preparing for smart grid technologies: A behavioral decision research approach to understanding consumer expectations about Smart Meters. *Energy Policy*, *41*, 790–797. doi:10.1016/j.enpol.2011.11.047

Kruger, J. (1999). Lake Wobegon be gone! The "below-average effect" and the egocentric nature of comparative ability judgments, *Journal of Personality and Social Psychology, 77*(2), 221-232. doi: 10.1037/0022-3514.77.2.221.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, *112*(2), 443–477.

Levitt, S. D., & List, J. a. (2007). Viewpoint: On the generalizability of lab behaviour to the field. *Canadian Journal of Economics/Revue Canadienne D'économique*, *40*(2), 347–370. doi:10.1111/j.1365-2966.2007.00412.x

Levitt, S. D., & List, J. a. (2008). Homo economicus Evolves. *Science*, *319*(5865), 909–910. doi:10.1126/science.1153640

Lissowska, M. (2011). Overview of Behavioural Economics Elements in the OECD Consumer Policy Toolkit. *Journal of Consumer Policy*, *34*, 393–398. doi:10.1007/s10603-011-9167-4

Loewenstein, G., John, L. & Volpp, K. G. (2013) Using decision Errors to Help People Help Themselves. In: Shafir, E. (Ed.) *The Behavioral Foundations of Public Policy*, Princeton, NJ, US: Princeton University Press.

Lopes, M. A. R., Antunes, C. H., & Martins, N. (2012). Energy behaviours as promoters of energy efficiency: A 21st century review. *Renewable and Sustainable Energy Reviews*, *16*(6), 4095–4104. doi:10.1016/j.rser.2012.03.034

Lucon O., D. Ürge-Vorsatz, A. Zain Ahmed, H. Akbari, P. Bertoldi, L.F. Cabeza, N. Eyre, A. Gadgil, L.D.D. Harvey, Y. Jiang, E. Liphoto, S. Mirasgedis, S. Murakami, J. Parikh, C. Pyke, and M.V. Vilariño (2014). Buildings. In: *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge, UK and New York, NY, USA: Cambridge University Press.

Lundgren, L. J. (ed.) (1999) Changing Environmental Behaviour. Stockholm: Swedish Environmental Protection Agency.

Lunn, P. (2014). *Regulatory Policy and Behavioural Economics.* Paris, France: OECD Publishing.

Malhotra, N. K. (1984) Reflections on the Information Overload Paradigm in Consumer Decision Making, *Journal of Consumer Research, 10*(4), 436-440.

Maréchal, K. (2010). Not irrational but habitual: The importance of "behavioural lock-in" in energy consumption. *Ecological Economics*, *69*(5), 1104–1114. doi:10.1016/j.ecolecon.2009.12.004

Martiskainen, M., & Coburn, J. (2011). The role of information and communication technologies (ICTs) in household energy consumption—prospects for the UK. *Energy Efficiency*, *4*(2), 209–221. doi:10.1007/s12053-010-9094-2

Matsukawa, I. (2004). The Effects of Information on Residential Demand for Electricity. *The Energy Journal*, *25*(1), 1–17.

McKenzie, C. R. M., Liersch, M. J., & Finkelstein, S. R. (2006). Recommendations Implicit in Policy Defaults. *Psychological Science*, *17*(5), 414–420.

McKerracher, C., & Torriti, J. (2013). Energy consumption feedback in perspective: integrating Australian data to meta-analyses on in-home displays. *Energy Efficiency*, *6*(2), 387–405. doi:10.1007/s12053-012-9169-3

McKinsey & Company. (2010). Impact of the financial crisis on carbon economics: Version 2.1 of the Global Greenhouse Gas Abatement Cost Curve. Retrieved 8 September 2014 from: http://www.mckinsey.com/client_service/sustainability/latest_thinking/greenhouse_gas_abatement_cost_curves.

McNamara, S., & Grubb, M. (2011). *The Psychological Underpinnings of the Consumer Role in Energy Demand and Carbon Abatement The Psychological Underpinnings of the Consumer Role in Energy Demand and Carbon Abatement,* EPRG Working Paper (No. 1110). Cambridge, UK: Cambridge University

Meyer, M. N. & Chabris, C. (2014). Why Psychologists' Food Fight Matters, *Slate,* 31 July 2014, Retrieved 6 September 2014 from: http://www.slate.com/articles/health_and_science/science/2014/07/replication_controversy_in_psychology_bullying_file_drawer_effect_blog_posts.1.html.

Midden, C. J. H., Meter, J. F., Weenig, M. H., & Zieverink, H. J. A. (1983) Using feedback, reinforcement and information to reduce energy consumption in households: A field-experiment, *Journal of Economic Psychology, 3*(1), 65-86, http://dx.doi.org/10.1016/0167-4870(83)90058-2.

Micklitz, H.-W., Reisch, L. A., & Hagen, K. (2011). An Introduction to the Special Issue on "Behavioural Economics, Consumer Policy, and Consumer Law." *Journal of Consumer Policy*, *34*(3), 271–276. doi:10.1007/s10603-011-9166-5

Miller, D. T. & Prentice, D. A. (2013) Psychological Levers of Behavior Change. In: Shafir, E. (Ed.) *The Behavioral Foundations of Public Policy*, Princeton, NJ, US: Princeton University Press.

Mills, B., & Schleich, J. (2012). Residential energy-efficient technology adoption, energy conservation, knowledge, and attitudes: An analysis of European countries. *Energy Policy*, *49*, 616–628. doi:10.1016/j.enpol.2012.07.008

Moser, R., Raffaelli, R., & Notaro, S. (2014). Testing hypothetical bias with a real choice experiment using respondents' own money. *European Review of Agricultural Economics, 41*(1): 25-46, doi: 10.1093/erae/jbt016

Mullainathan, S., & Thaler, R. H. (2000). *Behavioural Economics*, NBER Working Paper Series (No. 7948), Cambridge, MA: National Bureau of Economic Research

Mundaca, L. A. (2008). *Markets for Energy Efficiency Exploring the new horizons of tradable certificate schemes, Doctoral Dissertation , September 2008, Lund, Sweden: The International Institute for Industrial Environmental Economics*.

Mundaca, L.; Neij, L.; Worrell, E. and McNeil, M. (2010) Evaluating Energy Efficiency Policies with Energy-Economy Models, *Annual Review of Environmental Resources, Vol. 35*, pp. 305–44.

Mundaca, L., Mansoz, M., Neij, L., & Timilsina, G. R. (2013). Transaction costs analysis of low carbon technologies. *Climate Policy*, *13*(4), 490–513. doi:10.1080/14693062.2013.781452

Murphy, R., & Jaccard, M. (2011). Energy efficiency and the cost of GHG abatement: A comparison of bottom-up and hybrid models for the US. *Energy Policy*, *39*, 7146–7155. doi:10.1016/j.enpol.2011.08.033

Newell, R. G., & Siikamäki, J. (2013). *Nudging Energy Efficiency Behavior: The Role of Information Labels*, RFF Discussion Paper (13-17) (41 p.). Washington, D.C., USA: Resources for the Future

Nolan, J. M., Schultz, P. W., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2008). Normative social influence is underdetected. *Personality & Social Psychology Bulletin*, *34*(7), 913–23. doi:10.1177/0146167208316691

NorthQ. (2013). Normalized household electricity consumption data (raw data hosed by Dansk Energi & www.energinet.dk).

Nässén, J., & Holmberg, J. (2009). Quantifying the rebound effects of energy efficiency improvements and energy conserving behaviour in Sweden. *Energy Efficiency*, *2*(3), 221–231. doi:10.1007/s12053-009-9046-x

Olson, R., Verley, J., Santos, L. & Salas, C. (1994) What we teach students about the Hawthorne studies: A review of content within a sample of introductory I-O and OB textbooks, *The Industrial-Organizational Psychologist, 41*(3), 23-39.

Osbaldiston, R., & Schott, J. P. (2011). Environmental Sustainability and Behavioral Science: Meta-Analysis of Proenvironmental Behavior Experiments. *Environment and Behavior*, *44*(2), 257–299. doi:10.1177/0013916511402673

Owen, G., & Ward, J. (2006). *Smart Meters: Commercial, Policy and Regulatory Drivers* (pp. 1–54). London, UK: Sustainability First

Owens, S., & Driffill, L. (2008). How to change attitudes and behaviours in the context of energy. *Energy Policy*, *36*(12), 4412–4418. doi:10.1016/j.enpol.2008.09.031

Ölander, F., & Thøgersen, J. (2014). Informing Versus Nudging in Environmental Policy. *Journal of Consumer Policy*, *37*(3), 341–356. doi:10.1007/s10603-014-9256-2

Pasche, M. (2014). *Topics in Behavioral Economics,* Module MW21.6. (pp. 1–205). Retrieved from http://www.wiwi.uni-jena.de/Makro/lehre/BR/slides_BE.pdf

Petersen, J. E., Shunturov, V., Janda, K., Platt, G., Weinberger, K., Corfas, R., Dennis, L., Derry, R., Epstein, C., Grossman, J. (2007). Dormitory residents reduce electricity consumption when exposed to real-time visual feedback and incentives. *International Journal of Sustainability in Higher Education*, *8*(1), 16–33. doi:10.1108/14676370710717562

Pichert, D. and Katsikopoulos, K. V. (2008) Green defaults: Information presentation and pro-environmental behaviour, *Journal of Environmental Psychology, 28*, pp. 63–73.

Platchkov, L. M., & Pollitt, M. G. (2011). *The Economics of Energy (and Electricity) Demand*, (EPRG Working Paper 1116, Cambridge Working Paper in Economics 1137 (p. 37). Cambridge, UK: University of Cambridge

Poortinga, W., Steg, L., & Vlek, C. (2003). Household preferences for energy-saving measures: A conjoint analysis. *Journal of Economic Psychology*, *24*, 49–64.

Popper, K. R. (1973) *Kritisk Rationalisme: Udvalgte essays om videnskab og samfund*. Copenhagen, Denmark: Nyt Nordisk Forlag Arnold Busck.

Pyrko, J., & Darby, S. (2009). Conditions of behavioural changes towards efficient energy use – a comparative study between Sweden and the UK. In *ECEEE 2009 Summer Study proceedings* (pp. 1–14).

Pyrko, P. J. (2011). "Am I as smart as my Smart Meter is?" – Swedish experience of statistics feedback to households. *ECEEE 2011 Summer Study*, 1837–1841.

Rabin, M., & Thaler, R. H. (2001). Anomalies: Risk Aversion. *The Journal of Economic Perspectives*, *15*(1), 219–232.

Raw, G., Ross, D., & Cripps, A. (2011). *Energy Demand Research Project: Final Analysis* (p. 179). Hertfordshire, UK: AECOM.

Read, D. (2002). Book Review: Choices, Values and Frames. *Journal of Behavioral Decision Making*, *15*, 467–473.

Reiss, P. C., & White, M. W. (2008). What changes energy consumption? Prices and public pressures. *The RAND Journal of Economics*, *39*(3), 636–663.

Roe, B. E., & Just, D. R. (2009). Internal and External Validity in Economics Research : Trade-offs Between Experiments and Field Data. *Amer. J. Agr. Econ., 91*(5), 1266–1271.

Romanach, L.; Hall, N. & Cook, S. (2013) Behaviour change and energy consumption: a case study on engaging and retaining participation of low-income individuals, *Community Development Journal*, p. 1-16.

Ruderman, H., Levine, M. D., & McMahon, J. E. (1987). The Behavior of the Market for Energy Efficiency Appliances Including Heating and Cooling Equipment. *The Energy Journal*, *8*(1), 101–124.

Samuelson, W., & Zeckhauser, R. (1988). Status Quo Bias in Decision Making. *Journal of Risk and Uncertainty*, *1*, 7–59.

Sanstad, A. H., & Howarth, R. B. (1994). "Normal" markets, market imperfections and energy efficiency. *Energy Policy,* 22(10): 811-819.

Sathaye, J. & Murtishaw, S. (2004). *Market Failures, Consumer Preferences, and Transaction Costs in Energy Efficiency Purchase Decisions*, Lawrence Berkeley National Laboratory for the California Energy Commission, PIER Energy-Related Environmental Research. CEC-500-2005-020.

Schleich, J., Klobasa, M., Brunner, M., Gölz, S., Götz, K. & Sunderer, G. (2011). *Smart Metering in Germany and Austria – results of providing feedback information in a field trial*, Working Paper Sustainability and Innovation No. S 6/2011, Karlsruhe, Germany: Fraunhofer ISI. Retrieved from http://www.isi.fraunhofer.de/isi-de/service/presseinfos/2011/pri11-13.php.

Schleich, J., Klobasa, M., Gölz, S., & Brunner, M. (2013). Effects of feedback on residential electricity demand—Findings from a field trial in Austria. *Energy Policy*, *61*, 1097–1106. doi:10.1016/j.enpol.2013.05.012

Schultz, P. W. (1998) Changing Behavior with Normative Feedback Interventions: A Field Experiment on Curbside Recycling, *Basic and Applied Social Psychology, 2*(1), pp. 25-36.

Schultz, P. W. (2014). Strategies for Promoting Proenvironmental Behavior: Lots of Tools but Few Instructions. *European Psychologist*, *19*(2), 107–117. doi:10.1027/1016-9040/a000163

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms. *Psychological Science*, *18*(5), 429–34. doi:10.1111/j.1467-9280.2007.01917.x

Schwartz, B. (2004) The Paradox of Choice: Why More is Less. New York, NY: HarperCollins.

Scott, J. and Marshall, G. (2009) Oxford Dictionary of Sociology (3 rev. ed.), Oxford, UK: Oxford University Press (Current Online Version: 2014: eISBN: 9780191726842).

Shogren, J. F. (2002). A behavioral mindset on environment policy. *The Journal of Socio-Economics*, *31*(4), 355–369. doi:10.1016/S1053-5357(02)00175-0

Shogren, J. F., & Taylor, L. O. (2008). On Behavioral-Environmental Economics. *Review of Environmental Economics and Policy*, *2*(1), 26–44. doi:10.1093/reep/rem027

Shogren, J. F., Parkhurst, G. M., & Banerjee, P. (2010). Two Cheers and a Qualm for Behavioral Environmental Economics. Environmental and Resource Economics, 46(2), 235–247.

Silver, N. (2012). *The Signal and the Noise: Why So Many Predictions Fail-but Some Don't.* London, UK: Penguin

Simon, H. A. (1959). Theories of Decision-Making in Economics and Behavioral Science. *The American Economic Review*, *49*(3), 253–283.

Simon, H. A. (1982). *Models of bounded rationality: Empirically grounded economic reason* (Vol. 3). Cambridge, MA: MIT Press.

Simon, H. A. (1986) Rationality in Psychology and Economics, *The Journal of Business, 59*(4, Part 2), S209-S224.

Simon, H. A. (1987). Behavioural Economics. In: Eatwell, J.; Milgate, M. and Newman, P. (eds.) (1987) The New Palgrave; A Dictionary of Economics, Vol. 1, A-D, p. 221.

Stavins, R. N. (2001). *Experience with market-based environmental policy instruments*. Retrieved August 2014, from http://www.rff.org/documents/RFF-DP-01- 58.pdf.

Slovic, P. (1987). Perception of Risk. *Science*, *236*(4799), 280–285.

Slovic, P., Finucane, M., Peters, E., & Macgregor, D. G. (2002). Rational actors or rational fools: implications of the affect heuristic for behavioral economics. *Journal of Socio-Economics*, *31*, 329–342.

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2007). The affect heuristic. *European Journal of Operational Research*, *177*(3), 1333–1352. doi:10.1016/j.ejor.2005.04.006

Staats, H., Harland, P., & Wilke, H. a. M. (2004). Effecting Durable Change: A Team Approach to Improve Environmental Behavior in the Household. *Environment & Behavior*, *36*(3), 341–367. doi:10.1177/0013916503260163

Statistics Denmark (Danmarks Statistik) (2012). Denmark in Numbers 2012 (Danmark i tal 2012). Retrieved 26 August 2014 from: http://www.dst.dk/pukora/epub/upload/14849/dkital.pdf.

Statistics Denmark (Danmarks Statistik) (2014). Statistics on Danish Households (FAM55N) (Husstande i Danmark). Retrieved 26 August 2014 from: http://www.dst.dk/da/Statistik/emner/husstande-familier-boern/husstande.aspx.

Steg, L. (2008). Promoting household energy conservation. *Energy Policy*, *36*(12), 4449–4453. doi:10.1016/j.enpol.2008.09.027

Steg, L. and Vlek, C. (2009) Encouraging pro-environmental behaviour: An integrative review and research agenda, *Journal of Environmental Psychology, 29*, pp. 309–317.

Stern, P. C. (2000a). Toward a Coherent Theory of Environmentally Significant Behavior. *Journal of Social Issues*, *56*(3), 407–424.

Stern, P. C. (2000b). Information, Incentives, and Proenvironmental Consumer Behavior. *Journal of Consumer Policy*, *22*, 461–478.

Stern, P. C. (2011) Contributions of Psychology to Limiting Climate Change, *American Psychologist, Vol. 66*(4), pp. 303–314.

Sunstein, C. R. (2010). Empirically Informed Regulation. *The University of Chicago Law Review*, *78*, 1349–1430.

Sunstein, C. R. (2013) If Misfearing is the Problem, Is Cost-Benefit Analysis the Solution? In: Shafir, E. (Ed.) The Behavioral Foundations of Public Policy, Princeton, NJ, US: Princeton University Press.

Sunstein, C. R. (2014) *Why Nudge? The Politics of Libertarian Paternalism*. New Haven, CT: Yale University Press

Sunstein, C. R. and Thaler, R. H. (2003) Libertarian Paternalism Is Not an Oxymoron, *The University of Chicago Law Review, Vol. 70*(4), pp. 1159-1202.

Sunstein, C. R., & Reisch, L. a. (2013). Green by Default. *Kyklos*, *66*(3), 398–402. doi:10.1111/kykl.12028

Sutherland, R. J. (1991). Market barriers to energy-efficiency investments. *Energy Journal,* 12(3): 15-34.

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization*, *1*(1), 39–60. doi:http://dx.doi.org/10.1016/0167-2681(80)90051-7

Thaler, R. H. (2000). From Homo Economicus to Homo Sapiens. *Journal of Economic Perspectives*, *14*(1), 133–141.

Thaler, R. H., & Sunstein, C. R. (2001). Libertarian Paternalism. *The American Economic Review*, *93*(2), 175–179.

Thaler, R. H. and Sunstein, C. R. (2009) Nudge: Improving decisions about health, wealth and happiness. London, UK: Penguin Books.

Thaler, R. H., & Tucker, W. (2013). Smarter Information, Smarter Consumers. *Harvard Business Review*, (February), 2–11.

Train, K. (1985). Discount rates in consumers' energy related decisions: A review of the literature. *Energy,* 10(2): 1243-1253.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, *185*(4157), 1124–1131. doi:10.1126/science.185.4157.1124

Tversky, A., & Kahneman, D. (1981). The Framing of Decisions and the Psychology of Choice. *Science*, *211*(4481), 453–458.

Tversky, A., & Kahneman, D. (1986). Rational Choice and the Framing of Decisions. *The Journal of Business*, *59*(4, Part 2), S251–S278.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323. doi:10.1007/BF00122574

[UK BIT] United Kingdom Cabinet Office Behavioural Insights Team (2011) Behaviour Change and Energy Use. London, UK: United Kingdom Cabinet Office.

[UK BIT] United Kingdom Cabinet Office Behavioural Insights Team (2012) Better Choices: Better Deals – Consumers Powering Growth. London, UK: United Kingdom Cabinet Office.

United Kingdom Cabinet Office (2010) Mindspace: Influencing behaviour through public policy, London: Institute for Government.

van Bavel, R.; Herrmann, B.; Esposito, G. and Proestakis, A. (2013) Applying Behavioural Sciences to EU Policy-making, European Commission Joint Research Centre, Scientific and Policy Report EUR 26033 EN, Luxembourg: Publications Office of the European Union.

van Dam, S. S., Bakker, C. A., & van Hal, J. D. M. (2010). Home energy monitors: impact over the medium-term. *Building Research & Information*, *38*(5), 458–469. doi:10.1080/09613218.2010.494832

van Dijk, E., & van Knippenberg, D. (1996). Buying and selling exchange goods: Loss aversion and the endowment effect. *Journal of Economic Psychology*, *17*, 517–524.

van Elburg, H. (2009). Smart Metering and in-home energy feedback; enabling a low carbon life style. In *ECEEE 2009 SUMMER STUDY* (pp. 1745–1750).

Vandenbergh, M. P., Stern, P. C., Gardner, G. T., Dietz, T., & Gilligan, J. M. (2010). Implementing the Behavioral Wedge : Designing and Adopting. *Environmental Law Reporter*, *40*(6), 10547–10554.

Venkatachalam, L. (2008). Behavioral economics for environmental policy. Ecological Economics, 67(4), 640–645. doi:10.1016/j.ecolecon.2008.01.018

Vedung, E. (1998). Policy instruments: Typologies and theories. In Bemelmans-Videc, M., Rist, R., & Vedung, E. (Eds.) *Carrots, sticks and sermons* (pp. 21- 58). New Brunswick NJ: Transaction Publishers.

Verbong, G. P. J., Beemsterboer, S., & Sengers, F. (2013). Smart grids or smart users? Involving users in developing a low carbon electricity economy. *Energy Policy*, *52*, 117–125. doi:10.1016/j.enpol.2012.05.003

Vine, D., Buys, L., & Morris, P. (2013). The Effectiveness of Energy Feedback for Conservation and Peak Demand: A Literature Review. *Open Journal of Energy Efficiency*, *2*, 7–15.

Von Borgstede, C., Andersson, M., & Johnsson, F. (2013). Public attitudes to climate change and carbon mitigation—Implications for energy-associated behaviours. *Energy Policy*, *57*, 182–193. doi:10.1016/j.enpol.2013.01.051

Weber, E. (2013) Doing the Right Thing Willingly: Using the Insights of Behavioral Decision Research for Better Environmental Decisions. In: Shafir, E. (Ed.) The Behavioral Foundations of Public Policy, Princeton, NJ, US: Princeton University Press.

Whitehead, M., Jones, R., & Pykett, J. (2011). Governing irrationality, or a more than rational government? Reflections on the rescientisation of decision making in British public policy. *Environment and Planning A*, *43*(12), 2819–2837. doi:10.1068/a43575

Wilhite, H. & Ling, R. (1995). Measured energy savings from a more informative energy bill. *Energy and Buildings, 22*, 145–155.

Wilhite, H., Høivik, A., & Olsen, J.-G. (1999). Advances in the use of consumption feedback information in energy billing: the experiences of a Norwegian energy utility. In *ECEEE Summer Study proceedings*.

Wood, G., & Newborough, M. (2003). Dynamic energy-consumption indicators for domestic appliances: environment, behaviour and design. *Energy and Buildings*, *35*, 821–841. doi:10.1016/S0378-7788(02)00241-4

Wood, G., & Newborough, M. (2007). Energy-use information transfer for intelligent homes: Enabling energy conservation with central and local displays. *Energy and Buildings*, *39*(4), 495–503. doi:10.1016/j.enbuild.2006.06.009

Appendices

6.1 Appendix I – Questionnaires

6.1.1 Questionnaire 1

Please indicate your answer to the following questions by ticking the box. The questionnaire is anonymous. NB! There are no right answers or wrong answers. A guess is better than no answer.

Question 1:

Imagine that you have installed a new electronic electricity meter (Smart Meter) in your home. With the Smart Meter you have the opportunity to log on to a website and check your consumption. You can also choose to have a detailed consumption report sent to on e-mail or phone. Which of the following solutions would you choose?

☐ Online access to check your consumption (price: 10 DKK per year)
☐ Online access to check your consumption as well as a detailed daily, weekly and monthly consumption report sent to my email and phone (price: 25 DKK per year)

Question 2:

Imagine that you are about to buy a new fridge. Which of the following two models would you buy?

	☐ Fridge A	☐ Fridge B
Price	5.599 DKK (≈€750)	3.805 DKK (≈€507)
Type	Combined fridge & freezer	Combined fridge & freezer
Energy label	A+++	A+
Energy consumption (kWh/year)	150	274
Volume fridge/freezer (litre)	215 / 89	215 / 94
Size (HxWxD) (cm)	186 x 60 x 65	186 x 60 x 65

Question 3:

Which of the following constitutes the largest monetary cost per year?

☐ An electricity consumption of 4,000 kWh per year
☐ An electricity bill of 4,000 DKK per year
☐ I do not know

Question 4

Imagine that you receive an offer for an energy efficiency renovation of your home. Please state whether you would accept the following offer (yes/no):

a) Would you be willing to spend 1,000 DKK on an energy efficiency investment if you could save 250 DKK on your yearly heat and electricity bill? □ Yes □ No
b) Would you be willing to spend 3,000 DKK on an energy efficiency investment if you could save 500 DKK on your yearly heat and electricity bill? □ Yes □ No

Question 5:

If an energy saving device with a long life time could be bought and installed in your home for 500 DKK, how large would your yearly saving on your electricity bill have to be before you would be willing to install such a device? (please state an amount in DKK):

____

Question 6:

Imagine that you have installed a heat pump in your home. The pump costs 600 DKK per year in electricity consumption. Your electrician says that he can installed one of the following two devices, which would cut the electricity consumption. Which of the following two devices would you choose?

□ Device A guarantees a saving of 200 DKK per year.
□ Device B has 1/3 probability that you can save 600 DKK and 2/3 probability that you will not save anything at all (0 DKK)

Question 7:

Imagine that you have an opportunity to participate in an experiment at your utility company where you will pay variable prices for your electricity depending on when you use the electricity. The utility company believes that you can save about 5% on your electricity bill compared to the normal plan, but they cannot guarantee anything. You have the option to call your utility company and tell them that you wish to participate. Choose one of the following two:

□ I would like to keep my current plan.
□ I would like to call the utility company, so I can be moved to the new experimental plan.

Final questions:

Gender: □ Male □ Female

Age: __________________________

THANK YOU VERY MUCH FOR YOUR PARTICIPATION! ☺

6.1.2 Questionnaire 2

Please indicate your answer to the following questions by ticking the box. The questionnaire is anonymous. NB! There are no right answers or wrong answers. A guess is better than no answer.

Question 1:

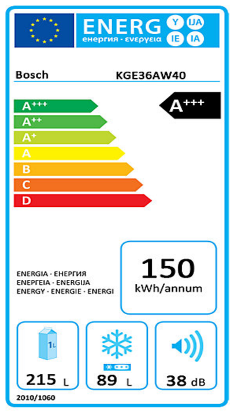
Imagine that you have installed a new electronic electricity meter (Smart Meter) in your home. With the Smart Meter you have the opportunity to log on to a website and check your consumption. You can also choose to have a detailed consumption report sent to on e-mail or phone. Which of the following solutions would you choose?

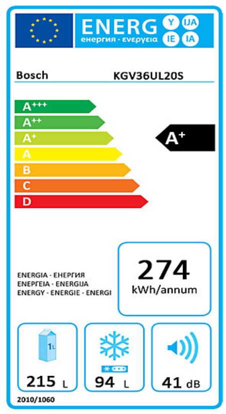
- ☐ Online access to check your consumption (price: 10 DKK per year)
- ☐ Detailed daily, weekly and monthly consumption report sent to my email and phone (price: 25 DKK per year)
- ☐ Online access to check your consumption as well as a detailed daily, weekly and monthly consumption report sent to my email and phone (price: 25 DKK per year)

Question 2:

Imagine that you are about to buy a new fridge. Which of the following two models would you buy?

	☐ Fridge A	☐ Fridge B
Price	5,599 DKK (≈€750)	3.805 DKK (≈€507)
Expected electricity costs over lifetime (12 years)	3,960 DKK (≈€530)	7,234 DKK (≈€965)
Type	Combined fridge & freezer	Combined fridge & freezer
Energy label	A+++	A+
Energy consumption (kWh/year)	150	274
Volume fridge/freezer (litre)	215 / 89	215 / 94
Size (HxWxD) (cm)	186 x 60 x 65	186 x 60 x 65





Question 3:

Which of the following constitutes the largest monetary cost per year?

- ☐ An electricity bill of 4,000 DKK per year
- ☐ An electricity consumption of 330 kWh per month
- ☐ I do not know

Question 4:

Imagine that you receive an offer for an energy efficiency renovation of your home. Please state whether you would accept the following offer (yes/no):

a) Would you be willing to spend 10,000 DKK on an energy efficiency investment if you could save 2,500 DKK on your yearly heat and electricity bill? ☐ Yes ☐ No
b) Would you be willing to spend 30,000 DKK on an energy efficiency investment if you could save 5,000 DKK on your yearly heat and electricity bill? ☐ Yes ☐ No

Question 5:

If an energy saving device with a long life time could be bought and installed in your home for 500 DKK, how large would your yearly saving on your electricity bill have to be before you would be willing to install such a device? (please state an amount in DKK):_________

Question 6:

Imagine that you have installed a heat pump in your home. The pump costs 600 DKK per year in electricity consumption. Your electrician says that he can installed one of the following two devices, which would cut the electricity consumption. Which of the following two devices would you choose?

☐ Device A guarantees that your cost for the pump would be 400 DKK per year.
☐ Device B has 1/3 probability that your cost would be 0 DKK per year and 2/3 probability that your cost will be 600 DKK per year

Question 7:

Imagine that you have been moved to a new electricity plan by your utility company where you will pay variable prices for your electricity depending on when you use the electricity. The utility company believes that you can save about 5% on your electricity bill compared to the normal plan that you previously had, but they cannot guarantee anything. You have the option to call your utility company and tell them that you wish to be moved to your old plan. Choose one of the following two:

☐ I would like to keep my new plan.
☐ I would like to call the utility company, so I can be moved back to the normal plan.

Final questions:

Gender: ☐ Male ☐ Female

Age: ___________________________

THANK YOU VERY MUCH FOR YOUR PARTICIPATION! ☺

6.2 Appendix II – Chi-square (X^2) goodness-of-fit test

Chi-square is a method to determine if a significant difference exists between a set of observed frequencies and the corresponding expected frequencies.
The null hypothesis (H_0) states that the population from which the sample has been drawn fits an expected frequency distribution, i.e. H_0 assumes no difference between observed and expected frequency counts.

Conversely, the alternative hypothesis (H_A) states that there is a significant difference between observed and expected frequencies.

The formula for the chi-square test is:

$$x^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i}$$

where,
O_i = observed frequency count in the i^{th} category
E_i = expected frequency count in the i^{th} category
k = number of nominal or ordinal categories

If the calculated value is greater than critical value under the given degrees of freedom, the null hypothesis (H_0) is rejected, meaning that there is a significant difference between the observed and the expected values. The degrees of freedom is calculated as:

(df) = n-1,
where n is the number of classes

Upper-tail critical values of chi-square distribution with *v* degrees of freedom:

Degrees of freedom (v)	Level of significance	
	95%	*99%*
1	3.841	6.635
2	5.991	9.210
3	7.815	11.345
4	9.488	13.277

(after McGrew & Monroe, 2000, p. 155).

6.3 Appendix III – Letter to Participants in Smart Meter Loss Aversion experiment

Spørgeskema til beboerne i Grøndalsvænge i forbindelse med opsætning af elektroniske elmålere fra NorthQ

København, 26 Maj 2014

Kære beboere i Grøndalsvænge Andelsforening

I forbindelse med opsætningen af såkaldte Power Readers (elektroniske el-målere) fra NorthQ, vil der blive foretaget et forsøg, der skal forbedre effekten af disse målere. For at kunne foretage dette forsøg har vi brug for Jeres tilsagn, samt information om de enkelte husstande.

Ønsker I at deltage i dette forsøg, bedes vedlagte spørgeskema udfyldes. Heri bedes du/I angive husstandens størrelse, elforbrug, og enkelte andre parametre. Jo mere detaljeret og korrekt spørgeskemaet udfyldes, des bedre bliver resultaterne, der kan indhentes. Da disse resultater bruges til at forbedre funktionaliteten af den nye elmåler er det vigtigt at spørgeskemaet udfyldes korrekt og efter bedste evne.

Har du spørgsmål angående spørgeskemaet er du velkommen til at kontakte Simon Bager.

Med venlig hilsen

Christian von Scholten, NorthQ
Steen Hartvig, Rubrik
Hans Gyum Larsen, IT-energy

Simon Bager, Lunds Universitet (simonbager@gmail.com)

Spørgeskema i forbindelse med opsætning af elektroniske elmålere fra NorthQ

Navn:
Adresse:
Postnummer og by:

Spørgsmål	**Svar**	**Eventuelle kommentarer**
Angiv engangskode (PIN-kode) vedlagt Power Reader pakken (8 cifret kode)	Kode:___________________	
Elforbrug i foregående år Angiv venligst husstandens elforbrug (årsbasis) for de tre foregående år i antal kilowatttimer (angives i antal kWh → xxxx kWh).	2011:___________________ 2012:___________________ 2013:___________________	
Antal beboere i husstanden: Hvor mange beboere er der i husstanden?	Antal beboere:_____________	
Alder på husstandens beboere Hvor gamle er beboerne i husstanden? (Angiv alder på alle beboere)	Person 1: Person 2: Person 3: Person 4: Person 5: Person 6:	
Husets størrelse Angiv husets størrelse (i kvadratmeter) som angivet i kontrakt/ejerbevis.	_______________m2	
Årlig husstandsindkomst Hvor stor er husstandens årlige indkomst? (Vælg den af de bokse der kommer nærmest husstandens samlede årlige indkomst før skat).	□ 0-250.000 DKK □ 251.000-400.000 DKK □ 401.000-600.000 DKK □ +601.000 □ Ønsker ikke at oplyse	
Antal elektriske eller elektroniske apparater i husstanden Hvor mange elektroniske og elektriske apparater (f.eks. ovn, fjernsyn, mikroovn, computer, elkedel, brødrister, kogeplade, vaskemaskine, køleskab, kaffemaskine, tørretumbler, fryser) findes i husstanden?	□ 0-9 □ 10-19 □ 20-29 □ 30-39 □ 40+	(Antal lamper, pærer, mv. skal ikke medregnes)
Opholdstid i hjemmet Hvor mange timer i døgnet opholder husets beboere sig i hjemmet? (Angiv antal timer beboerne er i hjemmet i de tre intervaller)	kl. 07-15:______________ kl. 15-23:______________ kl. 23-07:______________	
Miljøbevidsthed Anser du/I husstandens beboere som værende miljøbevidste?	□ Ja □ Nej	

6.4 Appendix IV – Statistical tests from knowledge exercise (#3)

Results from chi-squared tests:

Experiment 3 – Knowledge (all)			
Observed	*Version 1*	*Version 2*	*Total*
DKK	16	27	43
kWh	78	69	147
Don't know	36	48	84
Total	130	144	274
Expected	*Version 1*	*Version 2*	*Total*
DKK	20.40145985	22.59854015	43
kWh	69.74452555	77.25547445	147
Don't know	39.8540146	44.1459854	84
Total	130	144	274
Squares	0.9495815	0.857261076	
	0.977178609	0.882175133	
	0.372695917	0.336461592	
Sum	4.375353827	p-value	0.112177043
No significant difference between version 1 & 2 at 95% confidence interval			

Experiment 3 – Knowledge: Difference between old and young participants			
Observed	*Young*	*Old*	*Total*
DKK	14	29	43
kWh	39	106	145
Don't know	29	54	83
Total	82	189	271
Expected	*Young*	*Old*	*Total*
DKK	13.01107	29.98892989	43
kWh	43.87454	101.1254613	145
Don't know	25.11439	57.88560886	83
Total	82	189	271
Squares	0.075165403	0.032611445	
	0.541569864	0.234966819	
	0.601167518	0.260824002	
Sum	1.746305051	p-value	0.417632874
No significant difference between version 1 & 2 at 95% confidence interval			

Experiment 3 – Knowledge (men)			
Observed	*Version 1*	*Version 2*	*Total*
DKK	7	24	31
kWh	57	55	112
Don't know	15	23	38
Total	79	102	181
Expected	*Version 1*	*Version 2*	*Total*
DKK	13.53038674	17.46961326	31
kWh	48.8839779	63.1160221	112
Don't know	16.58563536	21.41436464	38
Total	79	102	181
Squares	3.151864895	2.441150262	
	1.347472476	1.043630643	
	0.151591388	0.117409017	
Sum	8.25311868	p-value	0.01613831
Significant difference between version 1 & 2 at 95% confidence interval			

Experiment 3 – Knowledge (women)			
Observed	*Version 1*	*Version 2*	*Total*
DKK	9	3	12
kWh	21	14	35
Don't know	21	24	45
Total	51	41	92
Expected	*Version 1*	*Version 2*	*Total*
DKK	6.652173913	5.347826087	12
kWh	19.40217391	15.59782609	35
Don't know	24.94565217	20.05434783	45
Total	51	41	92
Squares	0.828644501	1.030752916	
	0.131585678	0.163679745	
	0.624083546	0.776299046	
Sum	3.555045433	p-value	0.16905643
No significant difference between X & Y at 90% confidence interval			

6.5 Appendix V – Results from salience exercise (#2):

Exercise 2 – Purchase of refrigerator (all participants)			
Observed	*Version 1*	*Version 2*	*Total*
Fridge A (efficient fridge)	112	138	250
Fridge B (average fridge)	19	7	26
Total	131	145	276
Expected	*Version 1*	*Version 2*	*Total*
Fridge A (efficient fridge)	118.6594203	131.3405797	250
Fridge B (average fridge)	12.34057971	13.65942029	26
Total	131	145	276
Squares	0.373740901	0.337655572	
	3.593662505	3.246688194	
Sum	7.551747172	p-value	0.005995192
Significant at 99% confidence level			

Exercise 2 – Purchase of refrigerator (all women)			
Observed	*Version 1*	*Version 2*	*Total*
Fridge A (efficient fridge)	46	38	84
Fridge B (average fridge)	5	3	8
Total	51	41	92
Expected	*Version 1*	*Version 2*	*Total*
Fridge A (efficient fridge)	46.56521739	37.43478261	84
Fridge B (average fridge)	4.434782609	3.565217391	8
Total	51	41	92
Squares	0.006860715	0.00853406	
	0.072037511	0.089607635	
Sum	0.177039922	p-value	0.673929524
Not significant			

Exercise 2 – Purchase of refrigerator (all men)			
Observed	*Version 1*	*Version 2*	*Total*
Fridge A (efficient fridge)	66	98	164
Fridge B (average fridge)	14	4	18
Total	80	102	182
Expected	*Version 1*	*Version 2*	*Total*
Fridge A (efficient fridge)	72.08791209	91.91208791	164
Fridge B (average fridge)	7.912087912	10.08791209	18
Total	80	102	182
Squares	0.5141316	0.403240471	
	4.684310134	3.673968733	
Sum	9.275650938	p-value	0.002322201
Significant at 99% confidence level			

6.6 Appendix VI – Results from energy-use awareness exercise

Results:

	Me	Danes
Mean (m)	5.828125	5.046875
Standard deviation (SD)	2.020173555	1.798411279
Count (n)	64	67
Median (M)	6	5

***t*-test:**

f-test	0.351476386	homoscedatic (f-test > 0.05)
t-test (two-tailed)	0.028697343	p-value < 0.05
	Significant difference	

Answers:

Awareness (scale 1-10)	**Me**	**Danes**
1	1	0
2	3	6
3	4	5
4	11	12
5	10	23
6	4	8
7	16	5
8	11	4
9	4	4
10	0	0

6.7 Appendix VII – Results from risk aversion exercise (#6)

Results of chi-squared test:

Experiment 6 – Risk aversion (all)			
Observed	*Gain frame (Q1)*	*Loss frame (Q2)*	*Total*
Risk averse (A)	114	100	214
Risk seeking (B)	14	39	53
Total	128	139	267
Expected	*Gain frame (Q1)*	*Loss frame (Q2)*	*Total*
Risk averse (A)	102.5917603	111.4082397	214
Risk seeking (B)	25.4082397	27.5917603	53
Total	128	139	267
Squares	1.268600253	1.168207427	
	5.122272719	4.716913008	
Sum	12.27599341	p-value	0.000458822
Significant at 99.9% confidence level			

Experiment 6 – Risk aversion (women)			
Observed	*Gain frame (Q1)*	*Loss frame (Q2)*	*Total*
Risk averse (A)	48	26	74
Risk seeking (B)	3	12	15
Total	51	38	89
Expected	*Gain frame (Q1)*	*Loss frame (Q2)*	*Total*
Risk averse (A)	42.40449438	31.59550562	74
Risk seeking (B)	8.595505618	6.404494382	15
Total	51	38	89
Squares	0.738357657	0.990953698	
	3.642564442	4.888704908	
Sum	10.2605807	p-value	0.001359029
Significant at 99% confidence level			

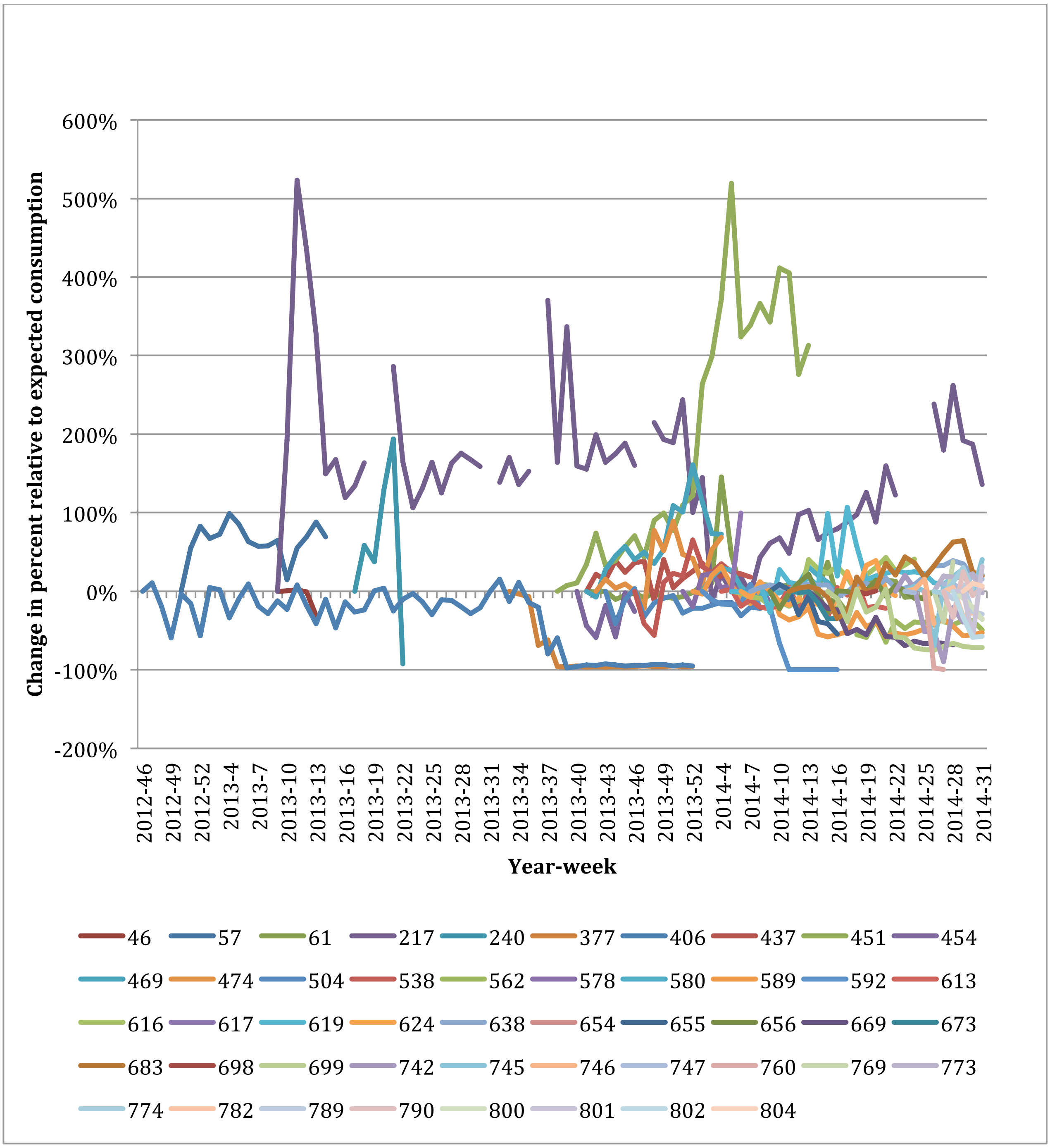
Experiment 6 – Risk aversion (men)			
Observed	*Gain frame (Q1)*	*Loss frame (Q2)*	*Total*
Risk averse (A)	66	74	140
Risk seeking (B)	11	27	38
Total	77	101	178
Expected	*Gain frame (Q1)*	*Loss frame (Q2)*	*Total*
Risk averse (A)	60.56179775	79.43820225	140
Risk seeking (B)	16.43820225	21.56179775	38
Total	77	101	178
Squares	0.488328365	0.372289942	
	1.799104503	1.371594522	
Sum	4.031317332	p-value	0.044663053
Significant difference at 95%-confidence level			

Experiment 6 – Risk aversion (version one – gain framing)			
Observed	*Men*	*Women*	*Total*
Risk averse (A)	66	48	114
Risk seeking (B)	11	3	14
Total	77	51	128
Expected	*Men*	*Women*	*Total*
Risk averse (A)	68.578125	45.421875	114
Risk seeking (B)	8.421875	5.578125	14
Total	77	51	128
Squares	0.096921992	0.146333204	
	0.789221939	1.191570378	
Sum	2.224047514	p-value	0.13587643
Not significant at 95%			

Experiment 6 – Risk aversion (version two – loss framing)			
Observed	*Men*	*Women*	*Total*
Risk averse (A)	74	26	100
Risk seeking (B)	27	12	39
Total	101	38	139
Expected	*Men*	*Women*	*Total*
Risk averse (A)	72.6618705	27.3381295	100
Risk seeking (B)	28.3381295	10.6618705	39
Total	101	38	139
Squares	0.024642781	0.065497917	
	0.063186617	0.167943378	
Sum	0.321270694	p-value	0.570845003
No significant difference between the two genders			

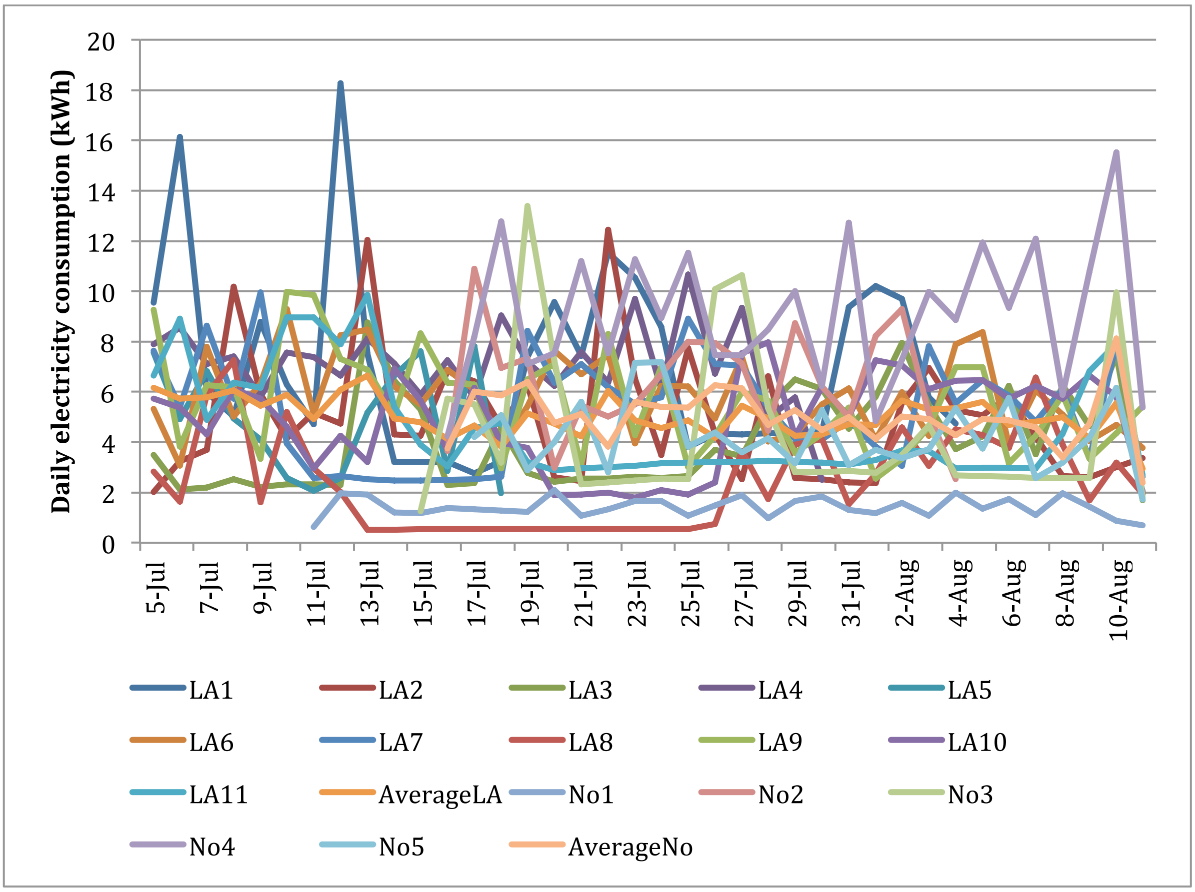
6.8 Appendix VIII – Results from Smart Meter consumption data

Including the two observations discarded earlier changes the result to plus 10%(±83%, n=49). As can be seen from the figure below, the deviations from the two meter readings excluded are very large and distorts the overall signal.

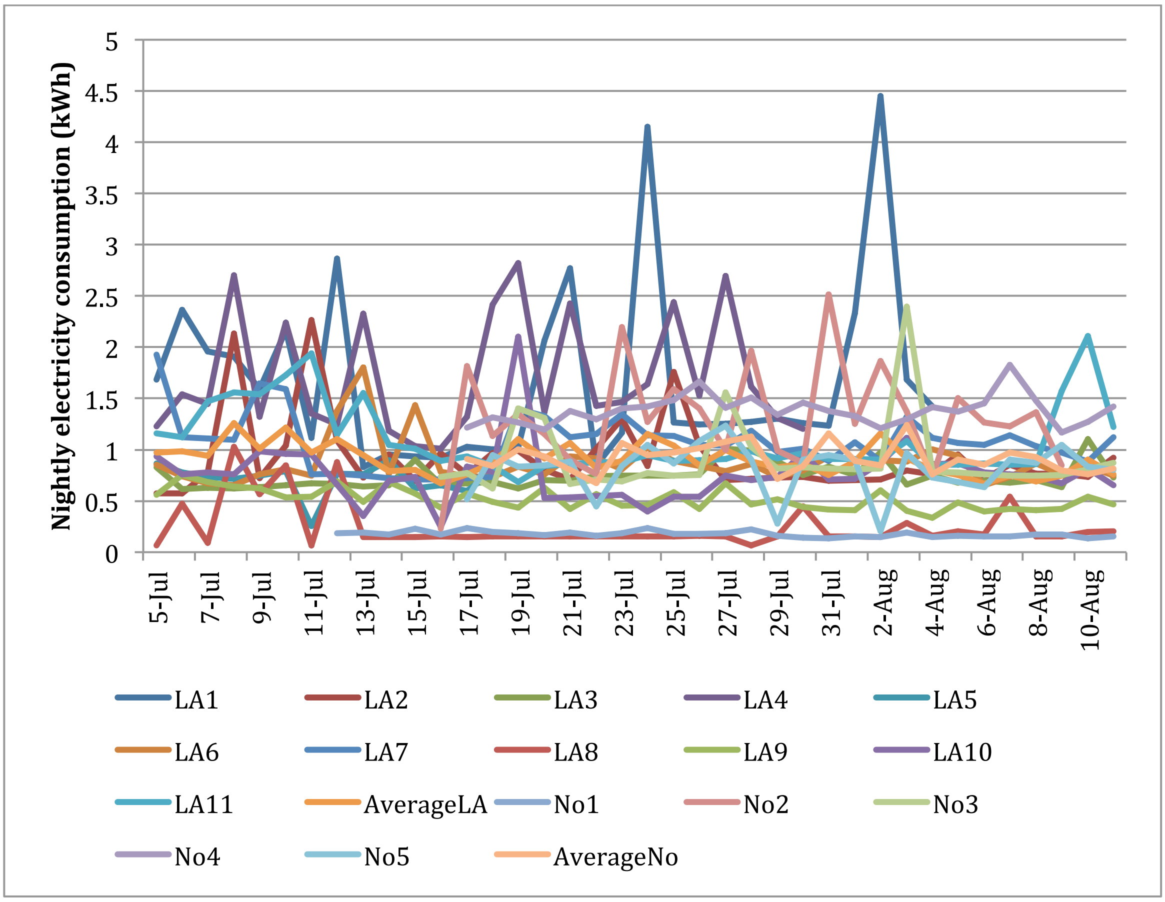


6.9 Appendix IX – Results from Loss Aversion and Smart Meter experiment

Data series for daily consumption



Data series for nightly consumption



6.10 Appendix X – Smart Meter feedback studies included in literature review

Author	**Description of intervention** *** Average change in electricity consumption (in percentage) (from feedback)** **** Intervention period, days**	**Type of feedback**	*****	**Sample size**	**Duration**	******
McClelland & Cook (1979) in Abrhamse et al (2005)	Households continuous feedback over a period of 11 months about monetary costs of electricity use by means of a monitor displaying electricity use in cents per hour. On average, households who had a monitor installed in their homes used 12% less electricity than a control group	Monthly	-12.0%		11 months	330
Bittle et al (1979) in Abrahamse et al (2005)	Households were assigned to either a daily feedback group or a control group. The feedback group saved an average of 4% on their electricity use (compared to baseline consumption), and also saved more than the control group.	Daily	-4.0%	30 households	42 days	42
Katzev et al (1981) after Abrahamse et al (2005).	Households were given either daily feedback about electricity use (kWh, cost and compared to other households), feedback every third day (kWh, cost, and compared to others), or noncontingent (viz., regardless of whether households had actually saved electricity or not) feedback (kWh and cost). No significant group differences in electricity use were found, possibly due to a low number of respondents in each experimental group.	Daily	0.0%	44	4 weeks	28
Winett et al (1979) in Abrahamse et al (2005)	Households were given information about how to conserve and they were asked to choose an energy conservation goal. Results show that households who had received daily feedback used 13% less electricity, and households who were taught to read their outdoor meters (self-monitoring) used 7% less electricity than did a control group. The effect was still present during a follow-up measurement.	Daily	-13.0%	71	1 month	30
Seligman and Darley (1977) in Abrahamse et al (2005)	All participating households were told that air conditioners were the largest users of electricity in homes. Half of them received feedback about electricity savings (four times a week during one month), while the other half did not receive any feedback. Households in the feedback group used 10.5% less electricity than the control group did. There was no follow-up measurement to determine whether the effect was maintained.	Weekly	-10.5%	40	1 month	30

Hayes & Cone (1981) in Abrahamse et al (2005)	The effect of monthly feedback on electricity use, both in terms of kWh as well as in terms of money was examined. Households who had received feedback reduced electricity use by 4.7%, while households in the control group increased electricity use by 2.3%.	Monthly	-4.7%	40	4 months	120
Midden et al. (1983) in Abrahamse et al (2005)	The effectiveness of comparative feedback, individual feedback, monetary rewards and information was tested. The comparative feedback consisted of a comparison with consumption levels of households in similar settings. For individual feedback and information, the savings were 18,8% for electricity.	Weekly	-18.8%	91	12 weeks	84
Matsukawa (2004)	Matsukawa (2004) finds that 113 Japanese households, who had feedback provided by a continuous display installed in the residence and giving information about consumption, were observed with a level of electricity consumption that was 1.5 % lower than that of a control group	?	-1.5%	319 households (113 reference and 206 control)		68
Gleerup et al (2009)	The effect of feedback by text message and email sent out at a daily frequency. The experiment ran for an entire year. Email and SMS messaging that communicated timely information about a household's 'exceptional' consumption periods (e.g. highest week of electricity use in past quarter) produced average reductions in total annual electricity use of about 3%.	Daily	-3.0%	Control (205, 189), test (333, 325, 345)	1 year	365
Dobson & Griffin (1992) in Fischer (2008)	Field experiment. Continuous feedback on consumption and cost, broken down to various appliances and time intervals. Measurement of consumption. 12.9% less consumption than control groups	Daily	-12.9%	100 households (25 test, 75 control)	60 days	60
Haakana et al (1997) in Fischer (2008)	Field experiment. Various combinations of monthly feedback (written or video) and advice. Questionnaire on satisfaction and conservation activities, calculation of savings from the activities. Average reduction in first half of feedback period: "feedback plus video information" group: 21%, "feedback plus written information" group: 19%, "feedback only" group: 17%, control group: 14%	Monthly	-3.0%		17 months	510
Mack and Hallmann (2004) in Fischer (2008).	30 households in German neighborhood. Field experiment. Weekly written feedback. Meter readings, interviews. Baseline interval: average of 6 measurements during 3 months before treatment (temperature corrected). Control group 4 weekly measurements during intervention, 30 measurements over 10 months after treatment, divided in 5 intervals with 6 measurements each. Reduction during treatment period that can be attributed to the treatment: 2.9%.	Weekly	-2.9%	30 households (19 experimental group, 10 control group)		1

Ueno et al (2005) in Fischer (2008)	Computerized interactive tool with daily feedback on consumption and cost; breakdown. Electricity consumption measurement, monitoring of feedback tool usage, questionnaire. electricity consumption reduced by 17.8% (control group 4.7%).	Daily	-13.1%	19 households	4 weeks	28
Schleich et al (2013)	The effects of providing feedback on electricity consumption in a field trial involving more than 1500 households in Linz, Austria. About half of these households received feedback together with information about electricity-saving measures (pilot group), while the remaining households served as a control group. Participation in the pilot group was random, but households were able to choose between two types of feedback: access to a web portal or written feedback by post.	Daily (web based), Monthly (written)	-4.5%	1525 households 775 (pilot group) 750 (control group).	11 months	330
Gaskell, Ellis and Pike (1982) in Darby (2006)	Feedback type: Meter readings. weekly visits, daily diaries. 9% from feedback, 11% from feedback + information	Weekly	-9.0%	160 households	4 weeks	28
Winett et al (1982) in Darby (2006)	Daily, plus weekly visits from experimenters. 3-week baseline + 5- week intervention, winter and summer. 15% against controls for feedback and/or video message.	Daily	-15.0%	85 winter, 53 summer	3 weeks baseline, 5 weeks intervention	35
Nielsen (1993) in Darby (2006).	Feedback: meter reading, written information. Flats. 1% (flats), 10% (houses)	Unknown	-1.0%	app. 1500 households	3 years	1095
	Same as above, but for houses.	Unknown	-10.0%	app. 1500 households	3 years	1095
Mountain (2006) in Darby (2006)	Portable monitor with instantaneous feedback, consumption in kWh, $ and CO2, per hour, in total and predicted. 6.5% against baseline (adjusted for weather, appliances, demographics). Response was persistent across the study period.	Daily (hourly)	-6.5%	505 (test), 52 (control)	2.5-year study.	912.5
Arvola et al (1994) in Darby (2006).	Bills every 36 days; in the 2nd year, historic feedback was added to the bills. 3% against controls for feedback; 5% for feedback+ advice tips	Monthly	-3.0%	525 (test), 175 (control)		700
Wilhite and Ling (1995)	6 bills/year based on meter readings, with simplified text and a graphic showing each period compared with the previous year, temperature-corrected. 10% against control group	Monthly (every 2nd month)	-10.0%	209 (feedback); 211 (feedback+tips), 675 (control)	3 years	1095

Hydro One Networks of Ontario, Canada in Faruqui (2010b)	Real-time feedback on residential electricity. Over 400 participants. Consumption patterns were tracked for a period of over 2.5 years. During this time, the treatment period lasted approximately 12 months. Comparing IHD and control group customers in pre-treatment and treatment periods, real-time feedback from IHD reduced electricity consumption on average by 6.5% across the whole sample. The impacts for individual non-electric heating households ranged from 5.1% to 16.7%.	Daily (hourly)	-6.5%	382 (test) and 42 (control)	2,5 years, 12 month treatment	365
Abrahamse et al. (2007)	In this multidisciplinary study, an Internet-based tool was used to encourage households (n=189) to reduce energy use. A combination of tailored information, goal setting (5%), and tailored feedback was used. After 5 months, households exposed to the combination of interventions saved 5.1%, while households in the control group used 0.7% more energy.	Monthly	5.7%		189 group 1 (feedback)=71, group 2 (feedback+norms)=66 reference group =53.	