D3.5 | Report on economic factors impacting individual long-term energy choices

Deliverable:	Report on economic factors impacting individual long-term energy choices
Author(s):	Andreas Löschel (WWU), Madeline Werthschulte (WWU), Raphaela Kotsch (LSE), Daire McCoy (LSE)
Version:	Final
Quality review:	Emilie Magdalinski (JDI), Stefano Proietti (ISINNOVA)
Work Package:	WP3 Technological and Economic Factors
Date of publication	28/02/2019

Grant Agreement N°:	727524
Starting Date:	01/11/2016
Duration:	36 months
Coordinators:	Silvia Gaggi and Stefano Proietti (ISINNOVA)
E-mail:	sgaggi@isinnova.org; sproietti@isinnova.org

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement number 727524.

Table of contents

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

The project in brief

The Energy Union Framework Strategy laid out on 25 February 2015 aims at fostering a cost-efficient energy transition able to deliver secure, sustainable and affordable energy to all European consumers. It has embraced a citizen-oriented energy transition based on a low-carbon transformation of the energy system. At the end of the day, the successful implementation of the Energy Union will materialise in a change in energy production and energy consumption choices. Such choices are heavily shaped by particular economic prerequisites, value systems, gender-based preferences, efficiency of governance and the maturity of civil society.

The ENABLE.EU project attempts to understand the key drivers of individual and collective energy choices, including in the shift to prosumption (when energy consumers start to become also energy producers). The project will develop participatory-driven scenarios for the development of energy choices until 2050 by including the findings from the comparative sociological research. As differences between European countries remain salient, ENABLE.EU will have a strong comparative component.

The final aim of this project is to contribute to more enlightened, evidence-based policy decisions, to make it easier to find the right incentives to reach the twin goals of successful implementation of the Energy Union and Europe's transition towards a decarbonised energy system. To reach this final aim, ENABLE.EU will seek to provide an excellent understanding of the social and economic drivers of individual and collective energy choices with a focus on understanding changes in energy choice patterns. Results will be disseminated to relevant national and EU-level actors as well as to the research community and a wider public.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

Executive summary

The European Union's 2020 strategy, which constitutes a set of binding legislation, aims to increase energy efficiency by 20% by 2020 and by 27% by 2030. Such an increase is possible through both households' short- and long-term changes in electricity consumption. In the short-term households can adopt behavioural energy saving measures (such as switching lights off when leaving a room, avoid using a dryer etc.). In a rather long-term perspective, households can invest in energy efficient durable goods. However, as indicated through literature on the "energy efficiency gap", there is significant unexploited potential to save energy. The aim of this report is to identify drivers behind households' long-term energy choices. By understanding the drivers, policy can implement corresponding strategies to decrease final energy consumption and accordingly contribute to lower carbon emissions from energy production. Therefore, the following report is split into two parts. The first part, belongs to subtask 3.2.1 of WP3 and is elaborated by WWU. The second part belongs to subtask 3.2.2 of WP3 and is elaborated by LSE.

The first part pays attention to the opaqueness of energy costs. The opaqueness manifests in two sorts of misperceptions: first, uncertainty in energy prices and second, present biased discounting of future energy costs. By extending the household survey of WP4[1] by an additional section only in Germany, we are able to gather incentivized measures of these two misperceptions. Therefore, the additional section was designed as an artefactual field experiment. Further, because the experiment was operated through face-to-face interviews, we observed participants' revealed electricity consumption and true electricity price. The measures of present biased discounting and price expectations are correlated with either electricity consumption, as a measure of short-term energy choices, or the share of energy efficient lightning and the age of electric appliances, as measures of low-cost and mid-cost long-term energy choices. The main result is the significant correlation between present bias and electricity consumption, which stays robust upon including covariates and across specifications. Participants with present bias are predicted to consume on average 8-9% more electricity than participants with time-consistent discounting. In absolute amounts, this is 22kWh per month. In contrast, we do not identify a significant relation between present bias and long-term energy choices. The results further suggest, that neither the true electricity price nor the expected electricity price can predict short-term and long-term energy choices. These results suggest to support policy in introducing commitment technologies, such as energy saving goals or particular contracts which help individuals to stick to their ex ante electricity consumption plans. Classical price based interventions, such as increasing electricity prices by taxes, could not be effective given our correlational results. In contrast, more research is needed to identify whether households have simply a nearly zero price elasticity or whether another price construct influences short-term and long-term energy choices.

The second part examines which factors influence enrolment into government-funded energy efficiency schemes in the UK and the resulting energy savings from these measures using the NEED database. Results indicate that household and dwelling characteristics significantly determine the uptake of measures and affect the returns to energy efficiency measures. The results suggest that the schemes examined have been quite successful in delivering energy efficiency measures to more deprived households in the UK. Given that this was a stated aim of many of the policies it is not too surprising to observe this. However, the analysis also demonstrates that while energy efficiency programmes have been successful in delivering measures to households from deprived areas, the savings are much less for these households. The analysis also revealed large regional differences

[1] ENABLE.EU conducted a nationally representative survey among the population in the 11 project's partner countries – Bulgaria, France, Germany, Hungary, Italy, Norway, Poland, Serbia, Spain, Ukraine and the United Kingdom. The survey methodology was designed to allow both in-depth analysis of country specifics and cross-country comparisons, putting a focus on three key consumption areas – heating and cooling, mobility and use of electricity, as well as governance and prosumers' issues related to the energy transition (see D 4.1 for more information).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

in the participation in government funded schemes. Clearly, colder winters and more heating degree-days will drive higher adoption of measures in more northern parts of the UK. Future policies will need to address the regional differences of barriers to uptakes and set incentives for households in and around London and the South of England.

The results also indicate that combinations of measures deliver higher savings than the combined sum of individual measures. This suggests that there may be efficiency gains in installing multiple measures simultaneously, and also that households may be installing additional measures that are not being reported. This suggests that policy support should target deep renovations, rather than individual measures. Relatedly, pay-as-you-save financing mechanisms are becoming increasingly popular for energy efficiency. Given the results we observe, low-income households would actually lose money by making these improvements unless energy prices rise significantly. Market-based interventions will only work for certain segments of the population and policy needs to take this into account.

To conclude, this report investigates drivers of households' long-term energy choices, i.e. households' energy efficiency investments. The first part concentrates on how behavioural biases and price misperceptions correlate with short-term and long-term energy choices in Germany, the second part focusses on the policy and regional dimensions of energy efficiency uptake in the UK and corresponding energy savings. While neither present bias nor price measures can predict energy efficiency investments in Germany, policy support is effective in delivering energy efficiency, particular to deprived households in the UK. Both reports support that single, market-based interventions, such as energy price increases might not be too effective in increasing energy efficiency, instead there may be efficiency gains in installing multiple measures simultaneously.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

1. Long-term energy choices and energy cost misperceptions in Germany

1.1 Introduction

Governmental policy aims at reducing energy consumption, due to greenhouse gas emissions associated with energy production. The German government set a target of 10% reductions in gross electricity consumption and 20% reductions in total primary energy consumption until 2020 (BMWi, 2018). Such reductions are possible through both households' short- and long-term changes in electricity consumption. In the short-term households can adopt behavioural energy saving measures (such as switching lights off when leaving a room, avoid using a dryer etc.). In a rather long-term perspective, households can invest in energy efficient durable goods. However, as indicated through literature on the "energy efficiency gap" (Jaffe and Stavins, 1994, Allcott and Greenstone, 2012, Gillingham and Palmer, 2014), there is significant unexploited potential to save energy. In accordance, in Germany the exiting reductions in electricity consumption are way behind the targets. Gross electricity consumption decreased by 3.6% and total primary energy consumption decreased by 6.5% in 2016 (BMWi, 2018, Löschel et al., 2018).

One reason for this energy efficiency gap might be the opaqueness of energy, which contributes both to information asymmetries and various behavioural anomalies. The consumption of energy services is associated with two sources of uncertainty. First, in the productivity with which energy is turned into energy service, and second, in the cost of using one kilowatt-hour due to complex energy pricing structures. Further, energy consumption is just intermittently billed, leading to dynamic trade-offs between consumption and payment as well as inattention towards consumption expenditures. The dynamic trade-off can cause discounting mistakes, such as hyperbolic discounting and naiveté towards such biased discounting. Similar concerns hold for energy efficiency investments. Costs are immediate for these investments, but the benefits lie in the future and are subject to uncertainty. As a result, households may optimize their long- and short-term energy decisions under various misperceptions. With respect to energy consumption, the future energy bill may be misperceived. Regarding energy efficiency investments, the future investment benefits may be misperceived. We concentrate in this work on two sources of misperceptions: quasi-hyperbolic discounting and uncertainty in energy prices.

Quasi-hyperbolic discounting describes a form of time-inconsistent discounting. The behavioural bias stemming from this time-inconsistent discounting is called present bias. Quasi-hyperbolic discounting is commonly operationalized through two discounting parameters, a time-consistent exponential discounting parameter δ and a time-inconsistent present bias parameter β (Laibson, 1997). The issue of present bias is that a household discounts utility in $t+1$ (i.e. future utility) by both β and δ when maximising utility in t (i.e. present utility). In contrast, when making decisions involving only future states, for example when making ex ante plans in $t-1$, the weighting difference between utility in t and $t+1$ is only given by δ. Due to this change in valuation of future utility, holding everything else constant, present bias can induce a reversal of preferences. Ex ante dominated decisions, such as smoking or eating fast food, become the optimal choice once its benefits are immediate.

One can distinguish two different consumption settings: first, with immediate costs and delayed benefits, and second, with immediate benefits and delayed costs (O'Donoghue and Rabin, 1999). Energy efficiency investments are an example of the first class: investments costs are immediate, whereas the benefits of energy efficiency investments are only realized in the form of lower future energy costs. Present bias induces an overvaluation of the immediate costs compared to the future benefits. Thus, the consequence is procrastination and underinvestment in energy efficiency. Contrary, energy consumption can be considered as an example of the second class: households

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

receive immediate utility from energy service consumption, but the corresponding payments are delayed and usually just occur on a yearly or monthly basis. In this case, the future costs of energy are quasi-hyperbolically discounted. The consequence is an overconsumption of energy from households' ex ante perspective.

Additional uncertainty in energy costs interacts with present bias. Literature demonstrated that households know neither their energy price nor how kilowatt-hour consumption maps into energy services (Blasch et al., 2017, Brounen, Kok and Quigley, 2013). Regardless of present bias, if the expected energy price deviates from the true energy price, households can invest too much or too few in energy efficiency as well as consume too much or too few, depending on the direction of deviation.

The question to be empirically analysed, is the extent to which both misperceptions relate to energy consumption and energy efficiency investments. Further, we will derive policy recommendation on how policy can target these misperceptions for both short- and long-term energy consumption. To answer the research question, we extended the cross-country household survey (D 4.1) by an additional section only in the German survey. This additional section was designed as an artefactual field experiment as a representative sample of 711 individuals participated in a non-framed experiment. In the experiment, each participant was asked to take multiple decisions, with each decision having a certain probability to be paid. From this incentivized within-subjects design, we are able to elicit each participant's revealed time preferences and energy price beliefs. Further, because the experiment was operated through face-to-face interviews, we are able to observe participants' revealed electricity consumption: each participant was asked to show their last electricity bill to the interviewer. This measurement of revealed preferences and consumption enables us to derive trustworthy, robust estimates. In contrast, studies based on stated electricity consumption rely on participants recalling their kilowatt-hour consumption correctly and might thus suffer from hypothetical bias. In line with existing research, we measure energy efficiency investments from stated behaviour (Fischbacher, Schudy and Teyssier, 2015, Schleich et al., 2017, Bradford et al., 2017).

This deliverable contributes to the literature on experiments eliciting households' preference parameters and correlating them to energy outcomes. Among this literature Fischbacher, Schudy and Teyssier (2015), Qiu, Colson and Grebitus (2014), Heutel (2017), Newell and Siikamäki (2015), Schleich et al. (2017), Bradford et al. (2017) need to be mentioned. These studies focus on household's energy efficiency investments and correlate them with individual risk preferences (Qiu, Colson and Grebitus, 2014), Heutel, 2017) and time preferences (Newell and Siikamäki, 2015, Bradford et al., 2017), elicited through incentivized experiments. Bradford et al. (2017) further consider stated short-term consumption measures, such as consuming more energy than average and summer temperature in home. Fischbacher, Schudy and Teyssier (2015) additionally elicit environmental and social preferences, and relate parameters not only to energy efficiency investments but also to stated heating and energy costs. Closest to the preference parameters elicited in this paper, is the study by Schleich et al. (2017). They analyse the influence of exponential discount rates, present bias, risk aversion parameters and loss aversion on energy efficiency investments using experimental data from a representative cross-country sample. To our knowledge, there is no experimental evidence on the correlation of revealed energy consumption with preference parameters. Only Harding and Hsiaw (2014) report quasi-experimental results in support of present biased energy consumption. Further, literature suggests a causal relationship between energy price uncertainty and revealed energy consumption (Blasch et al., 2017, Brounen, Kok and Quigley, 2013). In line with this research, Ito (2014) has shown that households do not react to marginal energy prices but to average energy prices. However, none of these studies elicit revealed own energy price beliefs.

The following section 2.2 describes the measurement and elicitation of energy consumption, energy efficiency investments, the explanatory variables, i.e. quasi-hyperbolic discounting and price

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

uncertainty, as well as various control variables. Section 2.3 outlines the empirical strategy and section 2.4 gives the results considering both households' long-term and short-term choices. Finally, section 2.5 concludes and derives policy recommendations.

1.2 Measurement and elicitation of experimental data

To elicit experimental data, 711 representative face-to-face interviews (CAPI) have been conducted in Germany within the ENABLE.EU cross-national household survey of D 4.1 between December 2017 and January 2018. The interviews were administered by the GMS GmbH and conducted by the ARIS GmbH, who used quota sampling to recruit participants. The participants were recruited to be representative for the German population given federal state, population size, age and gender. The preference parameters were elicited in an incentivized manner in a first part of the survey. This first part took about 10 minutes, the total interview took about 45 minutes. The participants answered the questions of the first part themselves on the computer. No interviewer conducted more than 25 interviews to avoid interviewer-effects.

1.2.1 Dependent variables: electricity consumption and energy efficiency investments

To measure revealed energy consumption participants are asked to show their electricity bill of the last contracting year to the interviewer. When the participant was on monthly billing, they should provide the average monthly bill of the last contracting year. To avoid a large dropout rate when asking for the electricity bill, participants were informed on this requirement upon recruitment[2]. Energy consumption is coded as monthly consumption to be consistent with the time preference estimations, which are as well on a monthly basis.

As in Schleich et al. (2017), we categorize energy efficiency investments in low-cost and mid-cost investments. We abstract from high-cost investments as we cannot distinguish between tenants and homeowners in our sample. Due to tenants-homeowners conflicts high-cost investments are only relevant for homeowners. A categorical variable based on the average age category of refrigerator/freezer, of washing machine (if not community clothes washer) and of cooker is used as proxy for mid-cost energy efficiency investment. The available age categories are "Up to 3 years old", "4-10 years old", "Older than 10 years". We rely on this variable as an older age is supposed to indicate a lower energy efficiency level and because these electric appliances are not leisure related (such as a TV set), such that investment in new appliances has no extra benefits. Thus, a higher value means a higher average age category of these electric appliances, and lower degree of mid-costs energy efficiency investments. Asking for the age of the appliances instead of its energy efficiency level is easier for participants to answer as the labels changed over time and might have not been the focus of the buying decision, thus difficult to recall. Finally, low-cost energy efficiency investments are given by a categorical share of energy efficient light bulbs ("All"/"Most"/"About half"/"Some"/"None"), including LED, compact fluorescent bulbs or halogen bulbs. The higher the categorical value, the higher is the share of energy efficient light bulbs.

1.2.2 Explanatory variables

To estimate time preferences jointly the measure of time-inconsistent present bias is a function of participant's time-consistent exponential discounting parameter. We explain here both estimations,

[2] This might have biased the price belief estimations towards the true values but the participants were not aware of the incentivized price belief questions upon recruitment. Hence, there was no visible necessity to the respondents to check and remember their marginal electricity price.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

although only the present bias estimate will be considered as explanatory variable and the exponential discounting estimate will be considered as control variable. Both parameters are measured in two Multiple Price Lists (MPLs) (Andersen et al., 2008)). The first MPL elicits the present bias parameter β and the second MPL elicits the exponential discounting parameter δ. The β-MPL models 31 decisions of either receiving 100 Euro today or of receiving a larger amount in four weeks. The later payment varied from 100 Euro to 175 Euro in increments of 2.50 Euro. The δ-MPL used the same 31 monetary amounts, but the payment dates were between four weeks or eight weeks.

Estimations build on the assumption that participants directly consume the experimental payment on receipt. That is, there is no consumption smoothing of the experimental payments. We hence use a variant of the consumption-on-receipt model, as described by Cohen et al. (2016). In particular, to get parameter estimates, we employ the DMPL-method by Andersen et al. (2008) and Andreoni, Kuhn and Sprenger (2015). Thus, we use a third MPL, to control for each individuals risk preferences, as described in section 2.2.3. Consumption utility is then given by the constant relative risk aversion (CRRA) specification $u(x) = x^{\alpha}$, where the α-parameter measures risk aversion[3] and is parametrized through the third MPL.

In all three MPLs, we assume indifference to be indicated by the midpoint $\bar{x}$ between the two monetary decisions at which we observe a switch in options. Thus, the β- and δ-parameters are estimated from

$$100^{\alpha} = \beta\delta(\bar{x}_1)^{\alpha}$$
$$\beta\delta(100)^{\alpha} = \beta\delta^2(\bar{x}_2)^{\alpha}.$$

The first line gives the indifference equation of the first β-MPL. As this MPL involves a trade-off between an immediate payment of 100 Euro and a future payment, future payments are quasi-hyperbolically discounted. The second line gives the indifference equation of the second δ-MPL. The trade-off is now between two future payments. Thus, the present bias parameter cancels out here and only the exponential discounting parameter is relevant. With the α-Parameter given, the two equations can be solved for β and δ. Importantly, if the participant switches in both time MPLs at the same monetary amount, that is $\bar{x}_1$ is equal to $\bar{x}_2$, we measure a β=1, i.e. no present bias[4].

We present the MPLs with the staircase or bisection method[5], such that participants only had to answer five consecutive questions. Due to this method, we do not allow for multiple switching points. There are 11 participants who never switched in the β-MPL and 2 additional participants who never switched in the δ-MPL. Because these 13 participants were not willing to forgo 100 Euro a month earlier to get 175 Euro a month later, we exclude these participants[6].

To measure price uncertainty, we elicit participants' electricity price beliefs by using the incentivized quadratic scoring rule (Trautmann and van de Kuilen, 2014). First, we explained the energy pricing system to the participants, containing a marginal energy price, paid per kilowatt-hour, and a base price. Then, for five price intervals, participants are asked to estimate the probability that their marginal electricity price of the last contracting year was inside that interval. The five price intervals, in Eurocent, are [8-14], [15-21], [22-28], [29-35], [36-42]. Price intervals are chosen such that price

[3] A value of α<1 implies risk aversion, α=1 means risk neutrality and α>1 indicates risk seeking behaviour.

[4] In addition to the parametric specification, we also calculate present bias non-parametrically by just analysing the switching points of both MPLs.

[5] Falk et al. (2016) introduce this method as "staircase method", whereas Abdellaoui, Bleichrodt and L'Haridon (2008) employ the same method and call it "bisection method".

[6] These participants either did not understand the MPLs or did not trust in payments, as the resulting annual discounting rates are not corresponding to other rates reported in the literature.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

estimations measured by Blasch et al. (2017) in a survey of 2000 households in Switzerland are largely covered. The estimations in these five intervals are required to add to 100%. In addition, participants could state a 100%-probability that their electricity price is either lower than 8 Eurocent or higher than 42 Eurocent. Participants were informed that their payment depends on the precision of their estimations. With q_i being the stated probability for interval i, the participant received $20\ \text{Euro} - 20\ \text{Euro} * q_i^2$, if her true price was not inside the interval and $20\ \text{Euro} - 20\ \text{Euro} * (1 - q_i)^2$, if her true price was within the interval. The true electricity price paid was observed through the electricity bill which was shown to the interviewer after this question. The degree of uncertainty is then given by the deviation between the expected electricity price and the true electricity price and the variance in price beliefs.

To gather the expected electricity price and the variance in price beliefs, we assume price beliefs to follow a discrete uniform distribution. That is, with q_i being the probability for interval i, the cumulative distribution function of electricity price p is given by

$$F(p) = \begin{cases} 0 \text{ for } p < 8 \\ q_1\left(\frac{p-8}{7}\right) \text{ for } 8 \le p \le 14 \\ q_1 + q_2\left(\frac{p-15}{7}\right) \text{ for } 15 \le p \le 21 \\ q_1 + q_2 + q_3\left(\frac{p-22}{7}\right) \text{ for } 22 \le p \le 28 \\ q_1 + q_2 + q_3 + q_4\left(\frac{p-29}{7}\right) \text{ for } 29 \le p \le 35 \\ q_1 + q_2 + q_3 + q_4 + q_5\left(\frac{p-36}{7}\right) \text{ for } 36 \le p \le 42 \\ 1 \text{ for } p > 42. \end{cases}$$

As a second measure of the expected electricity price, we include a question asking participants for a point estimate of their electricity price paid in the last contracting year. The estimation is again incentivized with the quadratic scoring rule. Therefore, the payment is higher the closer the estimated electricity price is to the true electricity price. The maximum payment is 20 Euro.

If the participant states a 100%-probability that her price is lower than 8ct or higher than 42ct in the price intervals, we use the point estimate as expected energy price, if it fits to that statement. In two observations it was stated that there is a 100%-probability that the price is lower than 8ct but the point estimate was higher than 8ct. We exclude these two observations. Further, if there is no answer to the point estimate but a 100%-probability is given to having a price lower than 8ct, we use 4ct as expected energy price[7].

Of the 711 conducted interviews, 554 participants were able to show their last electricity bill to the interviewer. To avoid hypothetical bias, we restrict the sample to the 554 participants as the true energy price was only observed for them.

1.2.3 Control variables

The risk preference parameter α is measured by using a MPL similar to Koch and Nafziger (2017) and Falk et al. (2016). Participants are asked to decide between a lottery with equal chances of winning 300 Euro or 0 Euro, and a safe payment. The safe payment varied in 31 decisions from 0 to

[7] There were no equivalent observations in the "higher than 42ct"-interval.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

300 Euro in increments of 10 Euros. The α-MPL is presented as well with the staircase method (Falk et al., 2016, Abdellaoui, Bleichrodt and L'Haridon, 2008). The risk aversion parameter α is measured under the assumption of CRRA utility: $u(x) = x^{\alpha}$. Again we assume indifference to be indicated by the midpoint $\bar{x}$ between the two monetary decisions at which we observe a switch from the lottery to the safe payment. The α-Parameter is thus estimated from the indifference equation

$$0.5 * 300^{\alpha} + 0.5 * 0^{\alpha} = \bar{x}^{\alpha}.$$

We observe every participant switching once. However, we exclude 29 participants, who were just indifferent between the lottery and a safe payment of 295 Euro, i.e. had an α-value equal to 41[8].

The estimation of the δ-value is described above. Further control variables are asked in the second part of the survey. In addition to risk preferences and the exponential discounting parameter, we also control for environmental preferences. Environmental preferences are measured as a categorical variable, giving the average agreement on a four-point-scale to seven statements based on the OECD Greening Household Behaviour classification (OECD, 2014). These three preference measures on risk, long-term discounting and environmental behaviour serve as a first set of control variables.

In a second step, we control for characteristics of the house and the household by including the number of persons living in the household (for at least six months of the year), the number of persons younger than eighteen living in the household and a categorical variable on the size of the dwelling ("Up to 42m²", "43-65m²", "66-90m²", "91-120m²", "121-200m²", "More than 200m²"). A third set of covariates controls for sociodemographic characteristics of the participant. We observe age, gender, a categorical education variable ("No formal education or below primary", "Primary education", "Certificate of Secondary Education (Hauptschulabschluss)", "General Certificate of Secondary Education (Mittlere Reife)", "General qualification for university entrance (Abitur)", "Tertiary education first stage, i.e. bachelor or master", "Tertiary education second stage (PhD)"), a dummy on whether the participant is employed ("Employed full-time", "Employed part-time") or not ("Long time not employed (more than 3 months)", "Retired/pensioner", "Student", "Other economically inactive person") and a categorical variable describing the participant's income status ("Living comfortably on present income", "Coping on present income", "Finding it difficult on present income", "Finding it very difficult on present income")[9].

1.2.4 Incentives

All explanatory variables plus the risk aversion and exponential discounting elicitation are incentivized (Becker, Degroot and Marschak, 1964), Grether and Plott, 1979). In particular, each participant had a 3.5% chance that one of their decisions in the three MPLs plus one price interval question plus the price point estimate question is chosen to be paid. The MPLs include high stake incentives. For the price beliefs, we work with rather low stakes (maximum 20 Euros) to ensure the necessary assumption of risk neutrality for incentive compatibility of the quadratic scoring rule.

After each interview, a computerized random mechanism decided whether the participant was selected for payment and which decision was selected. Payment logistics included a check. The check was directly given to the participant after the interview if the β-MPL was chosen and if the

[8] When offered either a lottery with equal chances of 300 Euro and 0 Euro or a safe payment of 290 Euro, these participants preferred the lottery. Such estimates of risk-seeking behaviour are not in line with other estimates in the literature. We believe that these participants did not understand the MPLs or did not trust the payments.

[9] Income was also asked through a scale with brackets representing the income deciles. However, 183 participants refused to answer this question, which is why we rely on the categorical income status.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

participant chose the 'today' option. If the participant chose a delayed payment in either the β- or δ-MPL, she received a check via mail on the chosen date. This payment method ensures constant transaction costs across time as the check needed to be refunded at all dates. If the α-MPL was selected for payment, the interviewer gave a check on the monetary amount to the participant directly after the interview. In case that the participant chose the lottery in the selected decision, a computer determined the lottery outcome. Since the interviewers and the interviewing company are certified in terms of quality research[10] and the checks were registered, we believe in low payment uncertainty.

In total 25 participants were paid an average amount of 188.76 euro, the minimum payment was 0 euro, the maximum payment was 339.60 euro.

1.2.5 Summary statistics

With respect to the dependent variables, the average monthly energy consumption is 276.81 kWh, the standard deviation is 104.31. The smallest monthly consumption is 83.50 kWh and the largest is 676.25kWh. The average age category of energy consuming appliances is “4-10 years old” and the average category of share of energy efficient lightning is “Most”.

Parameter	Average [Std. Dev.]	Percentile 10th	25th	50th	75th	90th	N
β	1.12 [0.88]	0.96	1.00	1.00	1.04	1.15	537
Price intervalls: E(p)-p	-0.08 [9.33]	-9.18	-3.00	0.10	3.96	10.31	525
Point estimate: E(p)-p	-8.50 [7.05]	-16.76	-13.17	-9.51	-4.23	1.28	460
Variance σ^2	19.73 [24.44]	4.00	4.00	15.76	21.64	45.16	497

[10] They are certified as ESOMAR member (https://www.esomar.org/what-we-do/code-guidelines).

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 727524.

TABLE 1: AVERAGES, PERCENTILES, NUMBER OF OBSERVATIONS OF EXPLANATORY VARIABLES. STANDARD ERRORS IN PARENTHESES.

Concerning the explanatory variables, Table 1 shows that the average present bias estimate is 1.12, suggesting a rather future biased sample. The median of observations are time-consistent discounters. 15% of our sample can be classified as present biased and 51% are future biased. However, our data seems to include some extreme future bias values (such as a β=12.31), which also biases the average estimate upwards. These statistics only change slightly when considering the non-parametric estimates. Non-parametrically 14% of the sample demand a higher compensation when the present is involved and 46% demand a lower compensation.

Comparing estimates across studies is difficult because of different methodologies, samples, framing or stakes. One major difference is that the staircase method only allows for one switching point, such that our participants were forced to make consistent choices. Other studies report fewer outlier values because they exclude participants with multiple switching points (Schleich et al., 2017, Bradford et al., 2017). Overall, our β-estimate seems to be in line with other estimates. Schleich et al. (2017) estimates an average value of β=1, with also a large share of participants being future biased. Bradford et al. (2017) estimates an average β=1.02. Andreoni, Kuhn and Sprenger (2015) estimates an average β=0.99 when employing the DMPL method. Burks et al. (2012) finds 15% being present biased.

Because we do not want to restrict our sample by some self-imposed rule about what could be outliers and the empirical magnitudes are not the point of this study, the further analysis pools the continuous present bias measure into three groups: individuals with present bias (β<1), with future bias (β>1) and with time-consistent discounting (β=1).

When considering price misperceptions there are large differences between both elicitation methods. The price intervals exhibit more conservative estimates with no misperception on average. The reason might be the design of the price intervals with the middle interval containing most true energy prices. The distribution is however quite symmetric around zero, showing both over- and underestimation of energy prices. For the point estimates these intervals where not given. This contributes to an increase in the misperception towards an underestimation of around 9 Eurocent on average. The distribution shows a strong tendency to underestimate the price of energy. The number of observations also decreases, probably because it was much more difficult for participants to give an answer without the guidance of the intervals. We are not aware of other studies which have elicited incentivized own energy price beliefs. Blasch et al. (2017) reports that 27% of their sample were able to correctly estimate the average price of electricity paid in Switzerland.

The average variance in price beliefs is 19.73, where a variance of 4 means that the participant chooses one interval with certainty and a variance of 102 means that the participant puts equal probabilities on all five intervals. Hence, participants have believed to have some idea about possible magnitudes of their energy price.

Variable	**Average [Std. Dev.]**
δ	0.80 [0.20]
α	0.90 [1.04]

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

Environmental preferences	2.08 [0.41]
Number of persons in household	2.40 [1.25]
Number of children	0.40 [0.75]
Size of dwelling	3.70 [1.27]
Age	49.12 [18.79]
Female	0.51 [0.50]
Education	3.16 [1.28]
Employed	0.53 [0.50]
Income status	2.78 [0.80]

TABLE 2: AVERAGES OF CONTROL VARIABLES. STANDARD ERRORS IN PARENTHESES.

Table 2 reports the average estimates of control variables. The average participant exhibits an exponential discount factor of 0.80, which is comparable to the estimate by Bradford et al. (2017). The α-parameter is in line with the estimates by Schleich et al. (2017), which are also slightly higher than the values found in the literature. However, we confirm the common result of risk aversion. Environmental preferences are on average weakly pro-environmentalist ("Agree" to pro-environmental statements).

The average participant in our sample lives in a household with two persons and no children. The average size of dwelling category is "91-120m²". Regarding sociodemographic characteristics, the average participant is 49 years old, the sample has an about equal split of male and female participants, the average participants has a "General Certificate of Secondary Education (Mittlere Reife)" as highest educational degree, about 50% of the sample is either full- or part-time employed and the average income category is "Coping on present income".

1.3 Empirical strategy

Going back to our research question, we are interested in the extent to which cost misperceptions relate to energy consumption and energy efficiency investments. Cost misperceptions encompass time and price misperceptions. For a closer examination of time misperceptions, we define as in Meier and Sprenger (2010) two indicator variables based on the parametric estimations described above, indicating either *Present Bias* (i.e. $\beta<1$) or *Future Bias* (i.e. $\beta>1$). Time-consistent discounting (i.e. $\beta=1$) will be the omitted category. As robustness check, we will use two alternative non-

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

parametric indicator variables for present and future bias. The non-parametric estimations rely on either a switching point higher (*SP_higher*=1) or lower (*SP_lower*=1) in the β-MPL than in the δ-MPL. A higher switching point means that a larger amount is needed to forgo an amount received today, i.e. the participant is present biased. Having the same switching point in both MPLs as evidence of time-consistent discounting is again omitted.

If participants are uncertain in their energy price, then energy consumption will be influenced by the expected energy price rather than the true energy price. If numeraire utility is non-linear also the variance in price beliefs is relevant. Similar to Ito (2014), we run a regression including the expected energy price *E(p)*, the true energy price *p* and the variance σ^2 in price beliefs. This allows us to test a model of energy price uncertainty against a model of full information. If the coefficient of the true energy price is insignificant, whereas the coefficient of the expected energy price is significant, this would be evidence against a model of full information. An alternative measure of price uncertainty will be the expected energy price given from the point estimation question[11]. All measures of *E(p)* and *p* will be in logarithms, to interpret them as (expected) price elasticities. The variance σ^2 is standardized for interpretive reasons.

To analyse the relationship between cost misperceptions and energy outcomes, we estimate the following equation:

$$outcome_i = \gamma_0 + \gamma_1 PresentBias_i + \gamma_2 FutureBias_i + \gamma_3 log(p_i) + \gamma_4 log(E(p)_i) + \gamma_5 \sigma_i^2 + \boldsymbol{\gamma_6 X_i} + \varepsilon_i$$

The coefficients are given by the γ-values, i is the index for each participant, **X** is a vector of all control variables described in 2.2.3 and ε is the error term.

When the dependent variable is energy consumption, the outcome is the logarithm of each participant's kilowatt-hour consumption $log(kWh_i)$, such that the coefficients will be interpreted in percentage terms and estimate the equation above using OLS. Because both the age of electric appliances and the share of energy efficient lightning are categorical variables with underdispersion, we estimate a zero-truncated poisson regression model with either age_i or $share\_LED_i$ as outcome variable.

1.4 Results on households' short-term energy choices

[11] To distinguish between both expected price estimations, we will use the index 2 whenever we refer to the expected price from the point estimation question.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

The OLS regressions on households' short-term energy choices are displayed in Table 3 and Table A6-A8 in the appendix. Table 3 uses the parametric estimations of PresentBias and FutureBias as well as the expected price and variance from the price intervals. As a first robustness check, Table A6 uses the expected price from the point estimation question. Table A6 does not include the variance in price beliefs as this was not covered in the point estimation question. Table A7 again uses the price intervals as price misperception indicator, but relies on the non-parametric estimations of time misperceptions, *SP_higher* and *SP_lower*. By just comparing the switching points, Table A7 serves as robustness check for the time misperception estimations. Finally, Table A8 covers both robustness estimations, the non-parametric time misperceptions and the price misperceptions from the point estimate question. In all regressions, the control variables are subsequently added. The first set of control variables encompasses other preference parameters, particularly risk, environmental and time-consistent preferences. The second set covers household and dwelling characteristics. Sociodemographic variables of the participant are included in the third set of controls.

FIGURE 1: AVERAGE KWH CONSUMED OVER PRESENTBIAS GROUPS. THE VERTICAL LINES INDICATE 95% CONFIDENCE INTERVALS OF THE MEANS.

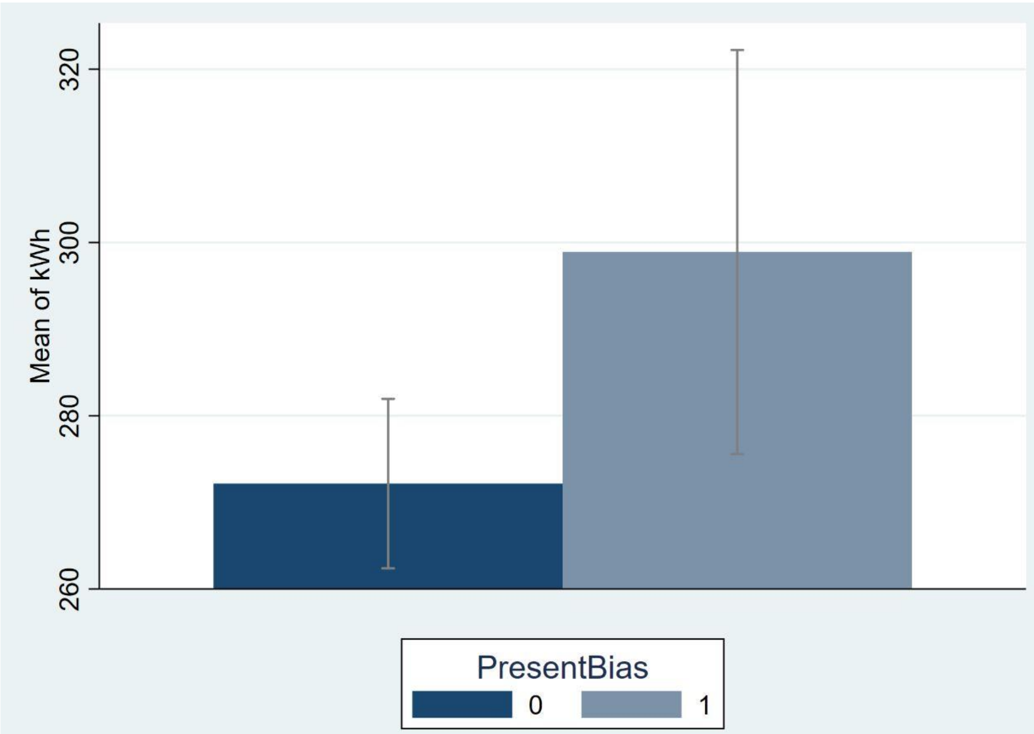


Table 3 presents that present bias significantly positively correlates with electricity consumption. According to regressions (1) and (2), participants with present bias consume on average around 16% more electricity than individuals with time-consistent discounting. This result is visualized in Figure 1. The average electricity consumption in the group with present biased participants is higher than the average electricity consumption in the group with either future bias or time-consistent discounting. The confidence intervals of the average kWh in the respective groups only slightly overlap. Accordingly, a t-test on equal means in both groups can be rejected at the 5%-level[12]. This is robust towards the first set of controls, but not to the second set. As Table 3 (3) shows, the estimate decreases when including household and dwelling characteristics. However, present biased participants are predicted to consume on average about 8% more electricity than time-consistent discounting participants. The estimates are significant at the 5%-level. The drop in the estimate is caused by the relationship between present bias and the household characteristics, which have

[12] Similarly, a non-parametric Mann-Whitney test rejects the hypothesis of equal medians at the 5%-level.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

biased the present bias estimate upwards in the first two regressions. In contrast, Bradford et al. (2017) do not report a significant correlation between present bias and stated energy consumption (summer temperature in home and less energy than average). The difference could stem either from differences in measuring present bias (as discussed above) or from differences in stated and revealed energy consumption.

None of the other explanatory variables has a significant relation to electricity consumption. Noteworthy is that neither the true electricity price nor the expected electricity price can explain electricity consumption. This supports both a nearly zero short-term price elasticity and a different misperception in energy prices than the one studied here. This compares to the results by Ito (2014), who conclude that the average electricity price influences electricity consumption. The results are robust towards including all control variables. Among the controls only the household characteristics, included in regression (3) are highly significantly correlated with electricity consumption. In particular, a greater size of the dwelling and a larger number of people living in the household are positively correlated with electricity consumption. Which is also why the adjusted R^2 jumps to 66%, when including the household characteristics.

These results are remarkably robust across specifications as can be seen from Tables A6-A8 in the appendix. Both the parametric and non-parametric estimate of present bias is significant at the 5%-level. Also the size of the estimate remains constant, varying between 8% and 9% in specifications (3) and (4) of all tables. The same holds for the other explanatory variables. They remain insignificant through all regressions. These results support the hypotheses that present bias positively relates to short-term electricity consumption. Present biased participants discount the future electricity bill to a greater extent than non-present biased participants, which leads to an overconsumption of electricity. However, we cannot support the hypothesis of price misperceptions relating to electricity consumption. Interestingly, also the true electricity price cannot explain consumption behaviour. A reason might be the argument put forward by Ito (2014). The author concludes that price misperceptions in the form of average electricity prices explain electricity consumption. An alternative explanation is that participants have a nearly zero short-term (expected) price elasticity.

	(1) **log(kWh)**	**(2)** **log(kWh)**	**(3)** **log(kWh)**	**(4)** **log(kWh)**
PresentBias	0.17*** (0.05)	0.16*** (0.06)	0.08** (0.03)	0.09** (0.04)
FutureBias	0.05 (0.04)	0.06 (0.04)	0.00 (0.03)	0.00 (0.03)
log(p)	-0.20 (0.28)	-0.05 (0.30)	-0.11 (0.25)	0.03 (0.27)
log(E(p))	0.10 (0.10)	0.02 (0.11)	-0.06 (0.07)	-0.06 (0.07)
σ^2	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.01)	-0.00 (0.01)
Control 1		X	X	X
Control 2			X	X
Control 3				X

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

N	436	378	367	316
Adj. R^2	0.02	0.03	0.67	0.66

TABLE 3: RESULTS OF AN OLS REGRESSION OF ELECTRICITY CONSUMPTION ON TIME AND PRICE MISPERCEPTIONS. TIME MISPERCEPTIONS ARE ESTIMATED PARAMETRICALLY, PRICE MISPERCEPTIONS ARE ESTIMATED FROM PRICE INTERVALS. ROBUST STANDARD ERRORS ARE IN PARENTHESES. SIGNIFICANCE LEVELS: *: P-VALUE<0.10, **: P-VALUE<0.05, ***: P-VALUE<0.01.

1.5 Results on households' long-term energy choices

1.5.1 Age of electric appliances

The results on the relation between the age of electric appliances and energy cost misperceptions are displayed in Table 4. The various robustness checks are in the appendix in tables A9-A11. From specification (1) to (4) the different sets of control variables are added. Across specifications in Table 4, none of the main explanatory variables is significantly correlated to the age of electric appliances. However, the non-parametric measure of present bias, SP_higher, is significant at the 10%-level in specification (4) in Table A10 and A11. This means that present biased individuals have on average older electric appliances. Similarly, the alternative measure of price misperceptions based on the point estimation is highly significant at the 1%-level in specification (4) of Tables A9 and A11. According to this specification a higher expected electricity prices decreases the average age of electric appliances. These findings on long-term energy choices are losing significance in other specifications and will thus not further be discussed.

Among the control variables, the exponential discounting parameter is in some specifications negatively correlated to the age of electric appliances at the 10%-level. A stronger discounting of future investment benefits is thus associated with older, probably more inefficient, appliances. Only Schleich et al. (2017) and Newell and Siikamäki (2015) consider the relation between energy efficient appliances and time preferences as well. Newell and Siikamäki (2015), who report a significant negative relation between time discounting and stated willingness to pay for an energy efficient water heater, support our marginally significant results. In contrast, Schleich et al. (2017) do not find a significant relation between exponential time discounting and energy efficient appliance adoption but of present bias and appliance adoption. However, as discussed by Schleich et al. (2017), their measure of present bias included a front-end delay such that results are difficult to compare.

	(1) **Age**	**(2)** **Age**	**(3)** **Age**	**(4)** **Age**
PresentBias	-0.02 (0.09)	0.06 (0.10)	0.07 (0.11)	0.15 (0.11)
FutureBias	-0.09 (0.07)	0.03 (0.08)	0.03 (0.09)	0.03 (0.09)
log(p)	-0.17 (0.44)	-0.21 (0.46)	-0.20 (0.46)	-0.18 (0.50)
log(E(p))	0.13 (0.17)	0.01 (0.19)	-0.03 (0.19)	-0.24 (0.20)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

σ^2	0.02 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)
Control 1		X	X	X
Control 2			X	X
Control 3				X
N	426	363	354	308
Pseudo R^2	0.06	0.06	0.07	0.08

TABLE 4: RESULTS OF A ZERO-TRUNCATED POISSON REGRESSION OF CATEGORICAL AGE OF ELECTRIC APPLIANCES ON TIME AND PRICE MISPERCEPTIONS. TIME MISPERCEPTIONS ARE ESTIMATED PARAMETRICALLY, PRICE MISPERCEPTIONS ARE ESTIMATED FROM PRICE INTERVALS. ROBUST STANDARD ERRORS ARE IN PARENTHESES. SIGNIFICANCE LEVELS: *: P-VALUE<0.10, **: P-VALUE<0.05, ***: P-VALUE<0.01.

Further, a higher education, employment and a higher income are negatively related to the age of electric appliances. These result support the distributional concerns in buying new, energy efficient appliances.

1.5.2 Share of energy efficient lightning

The results on the share of energy efficient lightning are provided in Table 5 and Tables A12-A14 in the appendix. From specification (1) to (4) the different control variables are added. All specifications across all tables report insignificant parameter estimates of our explanatory variables at conventional levels. The same holds for the control variables. Slightly above the 10% significance level are only the estimates on employment and a having a large apartment (more than 200m^2, with 43-65m^2 being the reference category), which are both positively correlated with the share of energy efficient lightning. Likewise, the pseudo R^2 is low and shows no increase upon including the control variables.

Bradford et al. (2017), Allcott and Taubinsky (2015) and Schleich et al. (2017) find a significant correlation between exponential discounting and having installed a CFL or LED. Further, Schleich et al. (2017) report present bias influencing the adoption of LEDs. Differences in results could be related to the stated nature of adoption of energy efficient lightning in Bradford et al. (2017), Schleich et al. (2017) and our study. In addition, “energy efficient lightning” has different definitions across studies. Schleich et al. (2017) distinguish between LED as energy efficient and compact fluorescent light bulbs, halogen bulbs and incandescent light bulbs as energy inefficient. Our analysis in contrast defines compact fluorescent light bulbs and halogen bulbs as energy efficient, and only incandescent light bulbs as inefficient. Further, Bradford et al. (2017) ask for the adoption of any CFL, Schleich et al. (2017) for the most recent purchase and we for the share in the household.

	(1) Share_LED	**(2) Share_LED**	**(3) Share_LED**	**(4) Share_LED**
PresentBias	-0.02 (0.04)	-0.03 (0.04)	-0.03 (0.05)	-0.04 (0.05)
FutureBias	0.01 (0.03)	0.01 (0.03)	0.02 (0.03)	0.01 (0.03)
log(p)	-0.13 (0.18)	-0.08 (0.20)	-0.11 (0.20)	-0.11 (0.19)

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 727524.

log(E(p))	0.09 (0.07)	0.04 (0.07)	0.04 (0.07)	0.02 (0.08)
σ^2	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.00 (0.02)
Control 1		X	X	X
Control 2			X	X
Control 3				X
N	442	381	370	318
Pseudo R^2	0.00	0.00	0.00	0.00

TABLE 5: RESULTS OF A ZERO-TRUNCATED POISSON REGRESSION OF CATEGORICAL SHARE OF ENERGY EFFICIENT LIGHTNING ON TIME AND PRICE MISPERCEPTIONS. TIME MISPERCEPTIONS ARE ESTIMATED PARAMETRICALLY, PRICE MISPERCEPTIONS ARE ESTIMATED FROM PRICE INTERVALS. ROBUST STANDARD ERRORS ARE IN PARENTHESES. SIGNIFICANCE LEVELS: *: P-VALUE<0.10, **: P-VALUE<0.05, ***: P-VALUE<0.01.

1.6 Conclusions and policy recommendations

The aim of this report is to identify drivers behind households' short-term and long-term energy choices. By understanding the drivers, policy can implement corresponding strategies to decrease final energy consumption and accordingly contribute to lower carbon emissions from energy production. Particular attention is given to the opaqueness of energy costs. The opaqueness manifests in two sorts of misperceptions: first, uncertainty in energy prices and second, present biased discounting of future energy costs. By extending the household survey by an additional section only in Germany, we are able to gather incentivized measures of these two misperceptions.

Therefore, the additional section was designed as an artefactual field experiment. By each participants making a series of decisions between earlier and later payments, some of them involving the present, we elicit individual present bias parameters. By asking for the probability with which each participant's electricity price lies in certain price intervals, we elicit individual price expectations. Further, because the experiment was operated through face-to-face interviews, we observe participants' revealed electricity consumption and true electricity price. Relying on revealed and incentivized measures enables us to derive robust, trustworthy estimates. The measures of present biased discounting and price expectations are correlated with either electricity consumption, as a measure of short-term energy choices, or the share of energy efficient lightning and the age of electric appliances, as measures of low-cost and mid-cost long-term energy choices. To our knowledge, this is the first study correlating preference parameters to revealed electricity consumption. Further, this is the first study eliciting participants' price beliefs in an incentivized manner and correlating the beliefs to energy outcomes.

Our main result is the significant correlation between present bias and electricity consumption, which stays robust upon including covariates and across specifications. Participants with present bias are predicted to consume on average 8% more electricity than participants with time-consistent discounting. In absolute amounts, this is 22kWh per month. In contrast, we do not identify a significant relation between present bias and long-term energy choices. This could be because the assumption of immediate investments costs compared to delayed investment benefits is in practice often violated. At the time of deciding whether to buy an energy efficient appliance, investments costs occur as well in the future. Partly because credit card payments are more common and partly because payment by instalments is becoming more popular. As a consequence, decisions on energy

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

efficiency investments might involve only future states: future costs and future benefits.

Our results further suggest, that neither the true electricity price nor the expected electricity price can predict short-term and long-term energy choices. That result hints to either an almost zero price elasticity in short-term and long-term choices, or to households optimizing their energy choices with respect to another energy price misperception, such as their average energy price.

Because our analysis is correlational and restricted to a German sample, we are careful with deriving general policy recommendations. An important avenue for future research is in the relation between present bias and electricity consumption. In particular, experimental research identifying causal relations is needed. Until now this report suggests to support policy in introducing commitment technologies, such as energy saving goals or particular contracts which help individuals to stick to their ex ante electricity consumption plans. Further, policy should test alternative billing schemes, such as more frequent billing or pre-paid billing, to target the dynamic nature of consuming and paying for electricity as being the source for such present bias. As we do not find a significant correlation between (expected) energy prices and energy consumption, classical price based interventions might not be effective in reducing energy consumption. In contrast, more research is needed to identify whether households have a nearly zero price elasticity or whether another price construct influences short-term and long-term energy choices.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

1.7 References

Abdellaoui, Mohammed, Han Bleichrodt, and Oliver L'Haridon. "A tractable method to measure utility and loss aversion under prospect theory." *Journal of Risk and Uncertainty*, 2008: 245-266.

Allcott, Hunt, and Dmitry Taubinsky. "Evaluating Behaviorally Motivated Policy: Experimental Evidence from the Lightbulb Market." *American Economic Review*, 2015: 2501-2538.

Allcott, Hunt, and Michael Greenstone. "Is there an energy efficiency gap?" *Journal of Economic Perspectives*, 2012: 3-28.

Andersen, Steffen, Glenn W Harrison, Morten I Lau, and E. Elisabet Rutström. "Eliciting Risk and Time Preferences." *Econometrica*, 2008: 583-618.

Andreoni, James, Michael A Kuhn, and Charles Sprenger. "Measuring Time Preferences: A Comparison of Experimental Methods." *Journal of Economic Behaviour and Organization*, 2015: 451-464.

Becker, Gordon M, Morris H Degroot, and Jacob Marschak. "Measuring Utility by a Single-Response Sequential Method." *Behavioral Science*, 1964: 226-232.

Blasch, Julia, Nina Boogen, Massimo Filippini, and Nilkanth Kumar. "Explaining electricity demand and the role of energy and investment literacy on end-use efficiency of Swiss households." *Energy Economics*, 2017: 89-102.

BMWi. "Die Energie der Zukunft - Berichtsjahr 2016." *Sechster Monitoring-Bericht zur Energiewende*, 2018.

Bradford, David, Charles Courtemanche, Garth Heutel, Patrick McAlvanah, and Christopher Ruhm. "Time preferences and consumer behavior." *Journal of Risk and Uncertainty*, 2017: 119-145.

Brounen, Dirk, Nils Kok, and John M Quigley. "Energy literacy, awarness and conservation behavior of residential households." *Energy Economics*, 2013: 42-50.

Burks, Stephen, Jeffrey Carpenter, Lorenz Götte, and Aldo Rustichini. "Which measures of time preference best predict outcomes: Evidence from a large-scale field experiment." *Jouranl of Economic Behavior & Organization*, 2012: 308-320.

Cohen, Jonathan D, Keith Marzilli Ericson, David Laibson, and John Myles White. "Measrung Time Preferences." *NBER Working Paper 22455*, 2016.

Falk, Armin, Anke Becker, Thomas Dohmen, David Huffman, and Uwe Sunde. "The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences." *Working Paper*, 2016.

Fischbacher, Urs, Simeon Schudy, and Sabrina Teyssier. "Heterogeneous preferences and investments in energy saving measures." *Munich Discussion Paper No. 2015-11*, 2015.

Gillingham, Kenneth, and Karen Palmer. "Briging the energy efficiency gap: Policy insights from economic theory and empirical evidence." *Review of Environmental Economics and Policy*, 2014: 18-38.

Grether, David M, and Charles R Plott. "Economic Theory of Choice and the Preference Reversal Phenomenon." *American Economic Review*, 1979: 623-638.

Harding, Matthew, and Alice Hsiaw. "Goal setting and energy conservation." *Journal of Economic Behavior & Organzation*, 2014: 209-227.

Heutel, Garth. "Prospect Theory and Energy Efficiency." *NBER Working Paper 23692*, 2017.

Ito, Koichiro. "Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing." *American Economic Review*, 2014: 537-563.

Jaffe, Adam B, and Robert N Stavins. "The energy paradox and the diffusion of conservation technology." *Resource and Energy Economics*, 1994: 91-122.

Koch, Alexander, and Julia Nafziger. "Correlates of Narrow Bracketing." *The Scandinavian Journal of Economics*, 2017.

Laibson, David. "Golden Eggs and Hyperbolic Discounting." *Quarterly Journal of Economics*, 1997: 443-478.

Löschel, Andreas, Georg Erdmann, Frithjof Staiß, and Hans-Joachim Ziesing. *Stellungnahme zum sechsten Monitoring-Bericht der Bundesregierung für das Berichtsjahr 2016.* Berlin, Münster, Stuttgart: Expertenkommission zum Monitoring-Prozess "Energie der Zukunft", 2018.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

Meier, Stephan, and Charles Sprenger. "Present-biased preferences and credit card borrowing." *American Economic Journal: Applied Economics*, 2010: 193-210.

Newell, Richard G, and Juha Siikamäki. "Individual time preferences and energy efficiency." *American Economic Revieew*, 2015: 196-200.

O'Donoghue, Ted, and Matthew Rabin. "Doing it now or later." *American Economic Review*, 1999: 103-124.

OECD. "Greening Household Behaviour: Overview from the 2011 Survey - Revised edition." *OECD Studies on Environmental Policy and Household Behaviour*, 2014.

Qiu, Yueming, Gregory Colson, and Carola Grebitus. "Risk preferences and purchase of energy-efficient technologies in the residential sector." *Ecological Economics*, 2014: 216-229.

Schleich, Joachim, Xavier Gassmann, Corinne Faure, and Thomas Meissner. "Determinants of household adoption of energy efficient technologies in Europe: Focussing on preferences for risk, time and losses." *BRISKEE, Behavioural Response to Investment Risks in Energy Efficiency, D 3.3*, 2017.

Trautmann, Stefan T, and Gijs van de Kuilen. "Belief Elicitation: A Horce Race Among Truth Serums." *The Economic Journal*, 2014: 2116-2135.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

1.8 Appendix

	(1) log(kWh)	(2) log(kWh)	(3) log(kWh)	(4) log(kWh)
PresentBias	0.17*** (0.05)	0.17*** (0.06)	0.08** (0.03)	0.09** (0.04)
FutureBias	0.04 (0.04)	0.07 (0.04)	0.00 (0.03)	0.01 (0.03)
log(p)	-0.24 (0.28)	-0.05 (0.30)	-0.12 (0.25)	0.03 (0.28)
$\log(E(p)_2)$	0.07* (0.04)	0.02 (0.04)	-0.03 (0.03)	-0.04 (0.03)
Control 1		X	X	X
Control 2			X	X
Control 3				X
N	427	372	361	309
Adj. R^2	0.03	0.03	0.66	0.66

TABLE A6: RESULTS OF AN OLS REGRESSION OF ELECTRICITY CONSUMPTION ON TIME AND PRICE MISPERCEPTIONS. TIME MISPERCEPTIONS ARE ESTIMATED PARAMETRICALLY, PRICE MISPERCEPTIONS ARE ESTIMATED FROM POINT ESTIMATE QUESTION. ROBUST STANDARD ERRORS ARE IN PARENTHESES. SIGNIFICANCE LEVELS: *: P-VALUE<0.10, **: P-VALUE<0.05, ***: P-VALUE<0.01.

	(1) log(kWh)	(2) log(kWh)	(3) log(kWh)	(4) log(kWh)
SP_higher	0.15*** (0.05)	0.15*** (0.06)	0.08** (0.03)	0.09** (0.04)
SP_lower	0.04 (0.04)	0.06 (0.04)	0.00 (0.03)	0.00 (0.03)
log(p)	-0.17 (0.28)	-0.05 (0.30)	-0.11 (0.25)	0.03 (0.27)
log(E(p))	0.12 (0.10)	0.03 (0.11)	-0.06 (0.07)	-0.06 (0.07)
σ^2	-0.01 (0.02)	-0.01 (0.02)	-0.00 (0.01)	-0.00 (0.01)
Control 1		X	X	X
Control 2			X	X

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

Control 3				X
N	439	378	367	316
Adj. R^2	0.02	0.02	0.67	0.66

Table A7: Results of an OLS regression of electricity consumption on time and price misperceptions. Time misperceptions are estimated non-parametrically, price misperceptions are estimated from price intervals. Robust standard errors are in parentheses. Significance levels: *: p-value<0.10, **: p-value<0.05, ***: p-value<0.01.

	(1) log(kWh)	(2) log(kWh)	(3) log(kWh)	(4) log(kWh)
SP_higher	0.16*** (0.05)	0.16*** (0.06)	0.08** (0.03)	0.09** (0.04)
SP_lower	0.04 (0.04)	0.07 (0.04)	0.00 (0.03)	0.01 (0.03)
log(p)	-0.22 (0.28)	-0.05 (0.30)	-0.12 (0.25)	0.03 (0.28)
log($E(p)_2$)	0.07* (0.04)	0.03 (0.04)	-0.03 (0.03)	-0.04 (0.03)
Control 1		X	X	X
Control 2			X	X
Control 3				X
N	430	372	361	309
Adj. R^2	0.02	0.03	0.66	0.66

Table A8: Results of an OLS regression of electricity consumption on time and price misperceptions. Time misperceptions are estimated non-parametrically, price misperceptions are estimated from point estimate question. Robust standard errors are in parentheses. Significance levels: *: p-value<0.10, **: p-value<0.05, ***: p-value<0.01.

	(1) Age	(2) Age	(3) Age	(4) Age
PresentBias	-0.00 (0.09)	0.07 (0.10)	0.08 (0.11)	0.17 (0.11)
FutureBias	-0.06 (0.07)	0.06 (0.08)	0.06 (0.09)	0.07 (0.09)
log(p)	-0.18 (0.42)	-0.10 (0.45)	-0.10 (0.45)	-0.18 (0.48)
log($E(p)_2$)	-0.02	-0.08	-0.09	-0.18***

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

	(0.06)	(0.07)	(0.07)	(0.07)
Control 1		X	X	X
Control 2			X	X
Control 3				X
N	418	358	349	302
Pseudo R^2	0.06	0.06	0.07	0.09

TABLE A9: RESULTS OF A ZERO-TRUNCATED POISSON REGRESSION OF CATEGORICAL AGE OF ELECTRIC APPLIANCES ON TIME AND PRICE MISPERCEPTIONS. TIME MISPERCEPTIONS ARE ESTIMATED PARAMETRICALLY, PRICE MISPERCEPTIONS ARE ESTIMATED FROM POINT ESTIMATE QUESTION. ROBUST STANDARD ERRORS ARE IN PARENTHESES. SIGNIFICANCE LEVELS: *: P-VALUE<0.10, **: P-VALUE<0.05, ***: P-VALUE<0.01.

	(1) Age	(2) Age	(3) Age	(4) Age
SP_higher	0.03 (0.08)	0.12 (0.10)	0.13 (0.10)	0.19* (0.11)
SP_lower	-0.06 (0.07)	0.04 (0.08)	0.05 (0.09)	0.04 (0.09)
log(p)	-0.19 (0.44)	-0.23 (0.46)	-0.21 (0.46)	-0.18 (0.50)
log(E(p))	0.14 (0.17)	0.01 (0.19)	-0.03 (0.19)	-0.24 (0.20)
σ^2	0.02 (0.03)	0.01 (0.03)	0.01 (0.03)	0.00 (0.03)
Control 1		X	X	X
Control 2			X	X
Control 3				X
N	429	363	354	308
Pseudo R^2	0.06	0.06	0.07	0.08

TABLE A10: RESULTS OF A ZERO-TRUNCATED POISSON REGRESSION OF CATEGORICAL AGE OF ELECTRIC APPLIANCES ON TIME AND PRICE MISPERCEPTIONS. TIME MISPERCEPTIONS ARE ESTIMATED NON-PARAMETRICALLY, PRICE MISPERCEPTIONS ARE ESTIMATED FROM PRICE INTERVALS. ROBUST STANDARD ERRORS ARE IN PARENTHESES. SIGNIFICANCE LEVELS: *: P-VALUE<0.10, **: P-VALUE<0.05, ***: P-VALUE<0.01.

	(1) Age	(2) Age	(3) Age	(4) Age
SP_higher	0.03 (0.09)	0.11 (0.10)	0.13 (0.11)	0.19* (0.11)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

SP_lower	-0.03 (0.07)	0.07 (0.08)	0.07 (0.09)	0.07 (0.09)
log(p)	-0.21 (0.42)	-0.11 (0.45)	-0.11 (0.45)	-0.17 (0.48)
log(E(p)$_2$)	-0.01 (0.06)	-0.08 (0.07)	-0.09 (0.07)	-0.18*** (0.07)
Control 1		X	X	X
Control 2			X	X
Control 3				X
N	421	358	349	302
Pseudo R^2	0.06	0.06	0.07	0.09

Table A11: Results of a zero-truncated Poisson regression of categorical age of electric appliances on time and price misperceptions. Time misperceptions are estimated non-parametrically, price misperceptions are estimated from point estimate question. Robust standard errors are in parentheses. Significance levels: *: p-value<0.10, **: p-value<0.05, ***: p-value<0.01.

	(1) **Share_LED**	**(2)** **Share_LED**	**(3)** **Share_LED**	**(4)** **Share_LED**
PresentBias	-0.02 (0.04)	-0.03 (0.05)	-0.03 (0.05)	-0.04 (0.05)
FutureBias	0.02 (0.03)	0.02 (0.03)	0.03 (0.03)	0.02 (0.04)
log(p)	-0.09 (0.19)	-0.07 (0.21)	-0.10 (0.21)	-0.09 (0.20)
log(E(p)$_2$)	0.04 (0.04)	0.01 (0.04)	0.01 (0.04)	-0.02 (0.04)
Control 1		X	X	X
Control 2			X	X
Control 3				X
N	432	374	363	311
Pseudo R^2	0.00	0.00	0.00	0.01

Table A12: Results of a zero-truncated Poisson regression of categorical share of energy efficient lightning on time and price misperceptions. Time misperceptions are estimated parametrically, price misperceptions are estimated from point estimate question. Robust standard errors are in parentheses. Significance levels: *: p-value<0.10, **: p-value<0.05, ***: p-value<0.01.

	(1) **Share_LED**	**(2)** **Share_LED**	**(3)** **Share_LED**	**(4)** **Share_LED**

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

SP_higher	-0.01 (0.04)	-0.02 (0.04)	-0.02 (0.05)	-0.04 (0.05)
SP_lower	0.02 (0.03)	0.02 (0.03)	0.02 (0.03)	0.01 (0.03)
log(p)	-0.14 (0.18)	-0.08 (0.20)	-0.11 (0.20)	-0.11 (0.19)
log(E(p))	0.09 (0.07)	0.04 (0.07)	0.04 (0.07)	0.01 (0.08)
σ^2	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.00 (0.02)
Control 1		X	X	X
Control 2			X	X
Control 3				X
N	445	381	370	318
Pseudo R^2	0.00	0.00	0.00	0.00

TABLE A13: RESULTS OF A ZERO-TRUNCATED POISSON REGRESSION OF CATEGORICAL SHARE OF ENERGY EFFICIENT LIGHTNING ON TIME AND PRICE MISPERCEPTIONS. TIME MISPERCEPTIONS ARE ESTIMATED NON-PARAMETRICALLY, PRICE MISPERCEPTIONS ARE ESTIMATED FROM PRICE INTERVALS. ROBUST STANDARD ERRORS ARE IN PARENTHESES. SIGNIFICANCE LEVELS: *: P-VALUE<0.10, **: P-VALUE<0.05, ***: P-VALUE<0.01.

	(1) Share_LED	**(2) Share_LED**	**(3) Share_LED**	**(4) Share_LED**
SP_higher	-0.00 (0.04)	-0.01 (0.05)	-0.01 (0.05)	-0.03 (0.05)
SP_lower	0.02 (0.03)	0.02 (0.03)	0.03 (0.03)	0.02 (0.03)
log(p)	-0.09 (0.18)	-0.07 (0.20)	-0.10 (0.21)	-0.09 (0.20)
$\log(E(p)_2)$	0.04 (0.04)	0.01 (0.04)	0.01 (0.04)	-0.02 (0.04)
Control 1		X	X	X
Control 2			X	X
Control 3				X
N	435	374	363	311
Pseudo R^2	0.00	0.00	0.00	0.01

TABLE A14: RESULTS OF A ZERO-TRUNCATED POISSON REGRESSION OF CATEGORICAL SHARE OF ENERGY EFFICIENT LIGHTNING ON TIME AND PRICE MISPERCEPTIONS. TIME MISPERCEPTIONS ARE ESTIMATED NON-PARAMETRICALLY, PRICE

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

MISPERCEPTIONS ARE ESTIMATED FROM POINT ESTIMATE QUESTION. ROBUST STANDARD ERRORS ARE IN PARENTHESES. SIGNIFICANCE LEVELS: *: P-VALUE<0.10, **: P-VALUE<0.05, ***: P-VALUE<0.01.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

2. Long-term energy choices and enrolment into government-funded energy efficiency schemes in the UK

2.1 Introduction

The European Union Third Energy Package, which constitutes a set of binding legislation, aims to cut greenhouse gas (GHG) emissions by 20% by 2020 compared to 1990 levels. To lead by example, the United Kingdom (UK) committed to the ambitious target of an 80% reduction in GHG emissions by 2050 relative to 1990 levels13. Energy efficiency plays a crucial role in reaching this goal. The UK's domestic sector was responsible for around 17% of GHG emissions in 2015 and accounts for around 30% of total final energy consumption, mainly from gas and electricity consumption (ONS 2016).

A key element in reducing residential energy consumption is encouraging consumers to install energy efficiency measures, through either policy or market-based instruments. For policy-makers faced with the task of designing the right mix of instruments to promote energy efficiency measures, it is particularly important to know which factors determine the selection of households into government-funded energy efficiency schemes and the impact the savings generated through installation of these measures.

In the following study, we examine the drivers of enrolment into energy efficiency schemes and analyse the variation in uptake according to household and dwelling characteristics. Our analysis then sheds light on the gas and electricity savings realised through the primary energy efficiency upgrades installed through UK policies. Our findings have implications for the design of future government programmes and allow us to draw conclusions on the benefit of energy efficiency measures to particular household groups and property types. The results of our analysis of the UK's residential sector also provides important recommendations for policy-makers in other European countries14.

[13] UK Government Climate Change Act. See http://www.legislation.gov.uk/ukpga/2008/27/contents (accessed 21/11/2018) (2008).

[14] The UK data used in the study covers England and Wales.

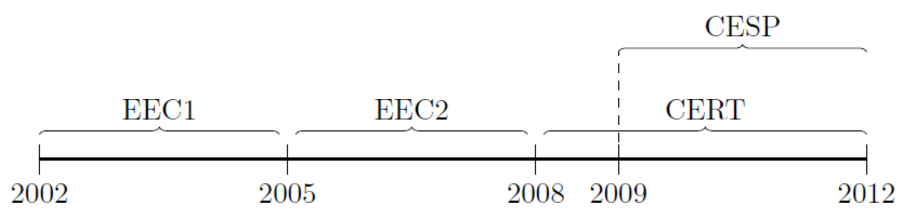
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

2.2 Background

The UK has a long history of government intervention in energy efficiency for industries and households. The UK was the first European country to introduce a market-based approach to encourage energy efficiency upgrades. The Supplier Obligation (SO), introduced in 1994, has become the principal policy instrument for implementing energy efficiency improvements in the residential sector. Suppliers are obliged to deliver a quantified target of energy savings through energy efficiency measures. Energy suppliers have various options to achieve their targets such as contracting installers, subsidising energy efficiency products, cooperating with local authorities, delivery agents or supermarkets or directly working with home occupants (Rosenow, 2012). This flexibility ideally allows suppliers to choose the most cost-effective way to reach their target. While suppliers bear the cost of installations in the first instance, they pass on the bill to the whole population through increases in the energy price (Chawla and Pollitt, 2013).

Figure 1 gives an overview of SOs from 2002 to 2012. The first Energy Efficiency Commitment (EEC1) ran from 2002 to 2005, followed by EEC2 in 2005. In 2008, EEC2 was renamed the Carbon Emissions Reduction Target (CERT) which then ran until 2012. In parallel with CERT, the Community Energy Saving Programme (CESP) was introduced in 2009 and ran until 2012. Even though the main architecture of SOs did not change, the savings targets and the costs of the programmes increased significantly over time.

FIGURE 2: SUPPLIER OBLIGATIONS 2002-2012



Recent literature on the determinants of the uptake of energy efficiency measures find that participation in government funded schemes is largely driven by dwelling and household characteristics. Research by Tovar (2012) and Brechling and Smith (1994) show that income, age and type of household are drivers of energy efficiency upgrades in England. More recent studies by Hamilton (2014) and Mallaburn and Eyre (2013) support this observation. Using the Home Energy Efficiency Database (HEED), Hamilton (2014) found that there is a strong relationship between uptake levels of energy efficiency measures and neighbourhood income levels. According to their study, the highest number of installations of fabric measures, such as insulation, were more likely found in areas with high proportions of low-income households. This finding suggests that a big share of energy efficiency uptakes was enabled by government-funded schemes targeting low-income households.

Collecting pre- and post-treatment data from 1372 households, Hong (2006) provides the first estimates for the effect of government-funded energy efficiency measures on domestic space heating fuel consumption in the UK. They show that loft and cavity wall insulation reduce energy consumption by 10-17% and reveal that actual savings are much smaller than the predicted savings of 49%. This is supported by Wyatt (2013) and Fowlie (2018). Wyatt (2013) finds that reductions in gas consumption varies between property types with the highest savings achieved for detached

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

dwellings with a reduction of 19%.

2.3 Data

The National Energy Efficiency Database (NEED) Dataset contains dwelling-level data on four million UK households, over an eight-year period. It provides information on energy efficiency measures from Homes Energy Efficiency Database (HEED), gas and electricity consumption data from energy suppliers, Valuation Office Agency (VOA) property attribute data, as well as household characteristics modelled from Experian. Table 15 provides a summary of the various data sources contained in NEED.

Type of variable	Source
Energy efficiency measures	HEED/Ofgem/DECC
Energy consumption	Energy Supplier
Property attributes	VOA
Household characteristics	Experian

TABLE 15: DATA SOURCES CONTAINED IN NEED

2.3.1 Energy consumption

Figure 2 demonstrates that both gas and electricity consumption decreased in England and Wales over the period from 2005 to 2012. This change in energy demand could be partly due to the increase in retail energy prices during the same period but also suggests that policies in place over the period were effective in delivering energy savings.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

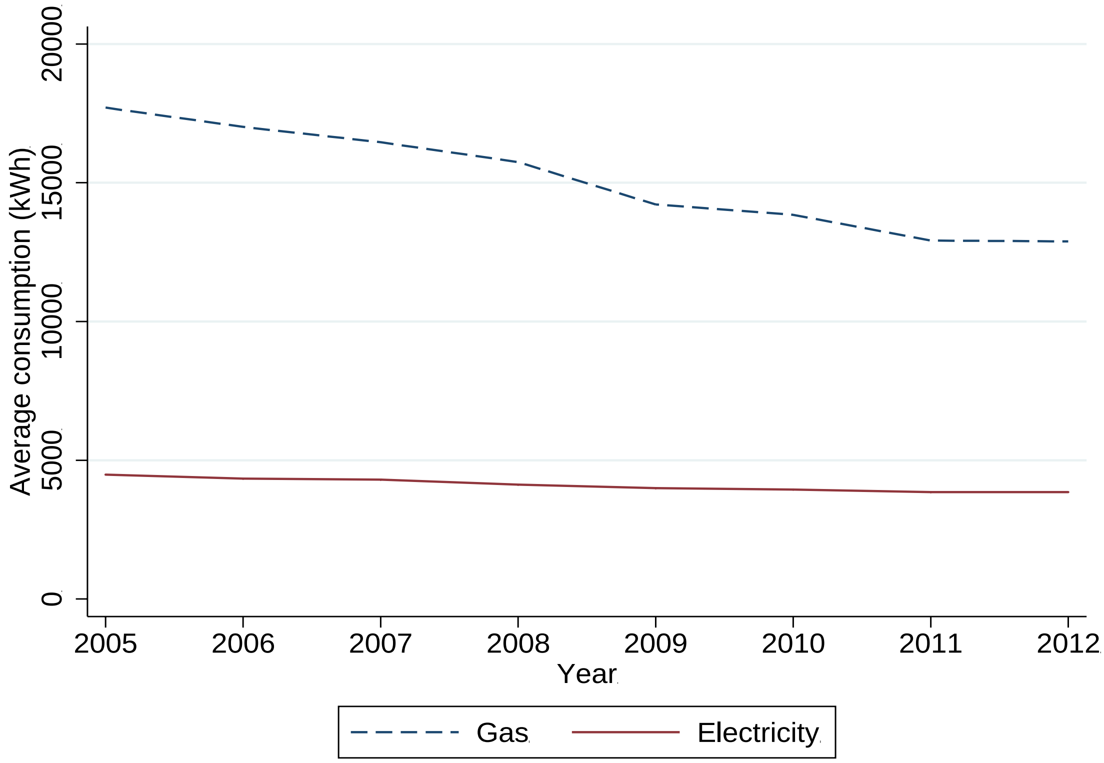


Figure 3: Gas And Electricity Consumption From 2005 To 2012. Average domestic energy consumption UK, 2005-2012. Source: author's calculation based on NEED data

2.3.2 Household characteristics

The NEED dataset comprises information on household characteristics modelled by Experian and matched with indicators based on the geographic location of the property (DECC, 2016). For reasons of data protection, the dataset was anonymised and household-level information on variables such as income and tenure-type are not available. However, the dataset does include two composite indicators of the socio-economic background of the households. NEED contains two variables describing the Index of Multiple Deprivation (IMD): IMD 2010 for England and IMD 2011 for Wales. Both indicators classify Lower Layer Super Output Areas (LSOAs) according to a quintile ranking that is based on eight different domains that are incorporated using a weighting scheme. The first quintile (IMD=1) indicates the most deprived areas. Table 16 shows the composition of domains that are incorporated in the indicators and their weight in percent (Payne and Abel, 2012; National Statistics, 2011).

	England 2010	Wales 2011
Income	22.5	23.5
Employment	22.5	23.5
Health	13.5	14
Education	13.5	14
Access/ barriers to services	9.3	10
Living environment	9.3	5
Physical environment	0	5
Crime	9.3	5

Table 16: Composition of IMD in Percent

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

2.3.3 Measures installed

The NEED database includes measures installed through EEC2, CERT and CESP schemes. These schemes were by far the most prevalent mechanisms for delivering energy savings in residential dwellings in the UK over this period. The database does not include an exhaustive list of measures installed as part of the various schemes, appliances and lighting also featured but are not included. However, insulation and heating comprised the vast majority of estimated energy savings across various schemes over this period. In total over two million measures were installed over the period within our sample, this is graphically represented in Figure 4.

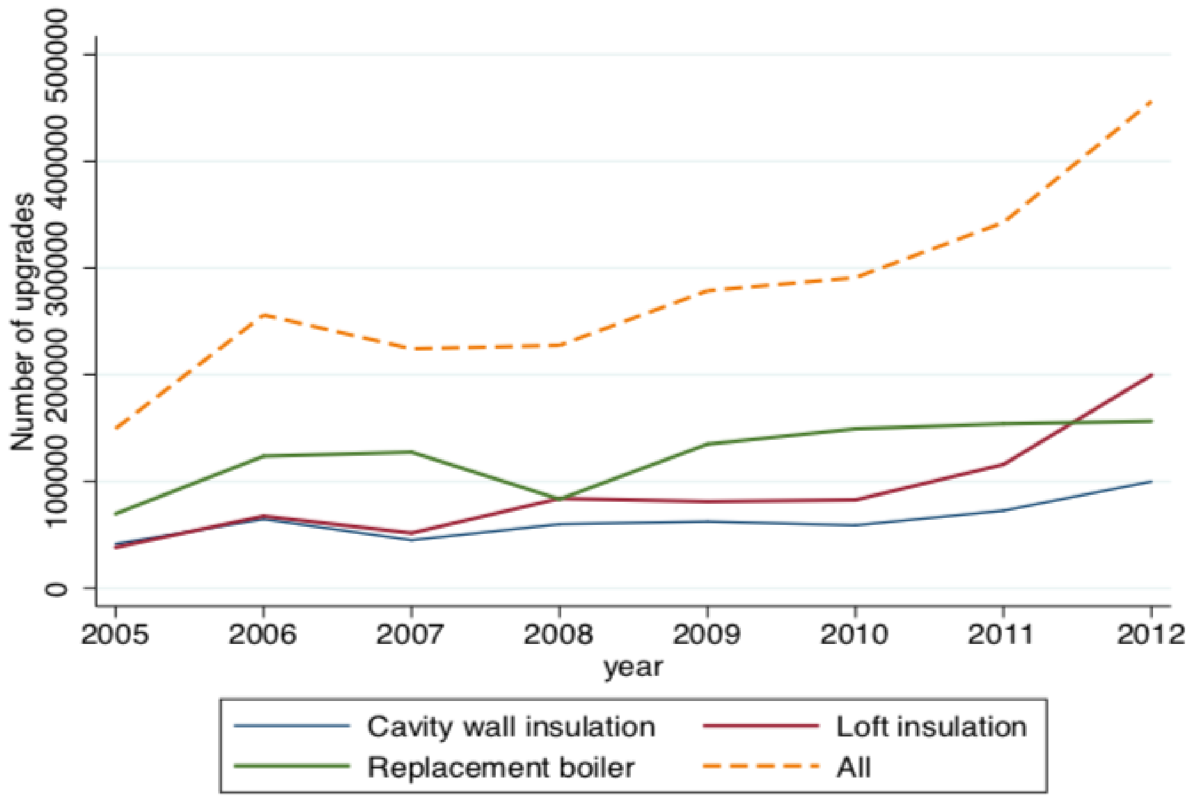


FIGURE 4: ENERGY EFFICIENCY MEASURES INSTALLED, 2005-2012. SOURCE: AUTHOR'S CALCULATION BASED ON NEED DATA

2.4 Determinants of enrolment into government schemes

2.4.1 Methodological approach

In order to estimate the likelihood of enrolment into energy efficiency schemes, we employ a logistic regression estimation strategy. All relevant variables are regressed on the binary dependent variable, which takes on the value 1 if any energy efficiency measure was installed through a government scheme and the value 0 otherwise. In an analogous manner, we do separate

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

regressions for cavity wall insulation, loft insulation, and boiler replacement.

The generated odds ratios (ORs) describe the association of household and dwelling characteristics and the likelihood of the uptake of energy efficiency measures. The OR represents the odds of an outcome (e.g. uptake of energy efficiency measure) given a particular characteristic (e.g. IMD group 1) over the odds of not having the outcome (e.g. no energy efficiency uptake) compared to the reference group (in Table 17 the reference category is highlighted in bold in each case), holding all other variables constant. If the OR > 1, then the odds of the outcome for the particular group are higher than the odds of the outcome in the reference group.

Example: The OR of installing any energy efficiency measure for IMD group 1 is 1.419 (Table 17). This means that for group IMD 1 the odds of installing any energy efficiency measures are 41.9% higher than for the reference group IMD 5. To make interpretation easier, the OR are displayed in Figures 5-7.

2.4.2 Results

Our analysis shows that the selection into government funded energy efficiency schemes depends on a range of factors. The decision of a household to take up either a cavity wall insulation, loft insulation or boiler upgrade depends on both the household and dwelling characteristics.

The results presented in Table 17 demonstrate that the income level of households plays an important role in the likelihood of energy efficiency uptakes. The more deprived the neighbourhood, the higher the odds ratio. Households living in the most deprived neighbourhoods (IMD 1) are more than 40% more likely to avail of measures supported by government schemes compared to households in least deprived neighbourhoods. This is true for all energy efficiency upgrades under consideration.

Uptake of energy efficiency measures is generally more likely in the northern regions of England. Compared to households in the South East of England, the odds of installing any energy efficiency upgrade is 60% higher in North East England. Chances of cavity wall insulation were highest in North East and North West with odds of over 1.6. The most striking finding is that for all categories of energy efficiency measures London had the lowest levels of uptake.

Our analysis also shows that dwelling type significantly influences the uptake of measures. Households living in bungalows have the highest likelihood of energy efficiency uptakes (38% more likely compared to semi-detached dwellings). Uptakes are also more likely in detached houses. In contrast, upgrades in flats are very unlikely. The odds of any upgrade, and in particular loft insulation, are 50% - 80% lower in flats. This is likely explained by a combination of factors. Most obviously the fact that many flats may not have lofts. In addition, split incentives are likely also a factor as flats are often rented out in the UK (Pelenur 2012), resulting in reduced incentives for owners to install measures (Rehdanz 2007).

The age of the property constitutes an important determinant of energy efficiency uptake. In general, modern houses built since 1983 are less likely to have any kind of government funded measures installed. The odds of installing measures is highest for dwellings built between 1950 and 1966. This is especially true for cavity wall insulations where the odds of uptakes are more than 100% higher

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

for dwellings built in this period compared to dwellings built before 1930. Further, boiler replacements are more likely in small dwellings with a floor band smaller than 50m2. For dwellings larger than 151 m2, the chances of cavity wall insulation are the lowest, followed by the smallest dwelling with a floor band smaller than 50m2.

From Table 17, it can be seen that both electricity and gas consumption in previous years do not have an impact on the likelihood of energy efficiency upgrades.

	(1) upgrade		(2) CWI		(3) Loft		(4) Boiler	
2005 Gas	1.000***	(42.76)	1.000***	(56.90)	1.000***	(41.23)	1.000***	(30.83)
2005 Electricity	1.000***	(-98.06)	1.000***	(-55.11)	1.000***	(-135.35)	1.000***	(-47.74)
Cavity wall								
Other	0.609***	(-309.03)	0.0803***	(-768.14)	0.900***	(-55.33)	0.965***	(-21.02)
East Midlands	1.340***	(124.14)	1.218***	(66.46)	1.705***	(196.42)	1.058***	(23.17)
East of London	1.023***	(10.40)	0.991**	(-3.08)	1.207***	(69.68)	0.949***	(-22.73)
London	0.857***	(-69.62)	0.744***	(-80.88)	0.807***	(-69.86)	0.859***	(-64.14)
North East	1.651***	(176.19)	1.821***	(189.36)	2.011***	(226.76)	0.999	(-0.18)
North West	1.356***	(144.76)	1.613***	(190.29)	1.749***	(227.91)	0.869***	(-63.21)
South East								
South West	1.185***	(72.74)	1.224***	(70.24)	1.371***	(112.73)	0.997	(-1.36)
Wales	1.233***	(75.22)	1.312***	(76.33)	1.847***	(193.99)	0.791***	(-77.21)
West Midlands	1.217***	(86.33)	1.288***	(88.61)	1.473***	(143.83)	0.948***	(-22.08)
Yorkshire and The Humber	1.355***	(135.04)	1.347***	(108.04)	1.644***	(190.57)	1.039***	(16.31)
Detached house	1.096***	(45.98)	1.078***	(30.98)	1.155***	(62.89)	1.025***	(11.39)
Semi-detached house								
End terrace house	0.908***	(-46.86)	0.846***	(-63.12)	0.949***	(-22.47)	1.000	(0.04)
Mid terrace house	0.802***	(-132.53)	0.672***	(-173.20)	0.875***	(-69.42)	0.949***	(-29.32)
Bungalow	1.377***	(152.38)	1.042***	(18.28)	1.440***	(170.69)	1.252***	(108.91)
Flat (inc. maisonette)	0.528***	(-238.47)	0.495***	(-186.13)	0.233***	(-346.98)	0.943***	(-20.79)
before 1930								
1930-1949	1.277***	(130.30)	1.692***	(172.76)	1.272***	(108.41)	1.136***	(63.82)
1950-1966	1.477***	(191.43)	2.058***	(242.61)	1.265***	(99.21)	1.212***	(90.21)
1967-1982	1.338***	(141.94)	1.920***	(217.25)	1.289***	(105.47)	1.116***	(50.71)
1983-1995	0.835***	(-74.96)	0.861***	(-42.74)	0.966***	(-11.83)	0.995	(-1.85)
1996 onwards	0.301***	(-408.43)	0.406***	(-199.58)	0.247***	(-303.11)	0.459***	(-229.73)
imd_both=1	1.419***	(181.23)	1.278***	(101.05)	1.401***	(152.28)	1.214***	(96.65)
imd_both=2	1.169***	(84.90)	1.166***	(65.69)	1.236***	(98.95)	1.010***	(5.20)
imd_both=3	1.073***	(39.47)	1.099***	(42.26)	1.134***	(60.41)	0.972***	(-15.08)
imd_both=4	1.014***	(7.95)	1.034***	(15.64)	1.038***	(18.29)	0.971***	(-15.76)
imd_both=5								
Gas								
Other	0.976***	(-5.19)	1.234***	(32.54)	1.224***	(36.82)	0.831***	(-36.59)
1 to 50 m2	0.976***	(-8.51)	0.836***	(-44.00)	0.768***	(-58.45)	1.075***	(24.62)
51-100 m2								

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

101-150 m2	0.938***	(-45.24)	0.879***	(-71.14)	0.958***	(-27.12)	0.969***	(-21.06)
Over 151 m2	0.867***	(-53.86)	0.630***	(-123.82)	0.836***	(-56.28)	1.049***	(16.87)
Observations	2527182		2527182		2527182		2527182	

t statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001

TABLE 17: ODDS RATIOS

Figures 5-7 further illustrate these results by presenting them graphically. In each case the reference category of each variable is indicated in red and all other categories are presented in relative terms.

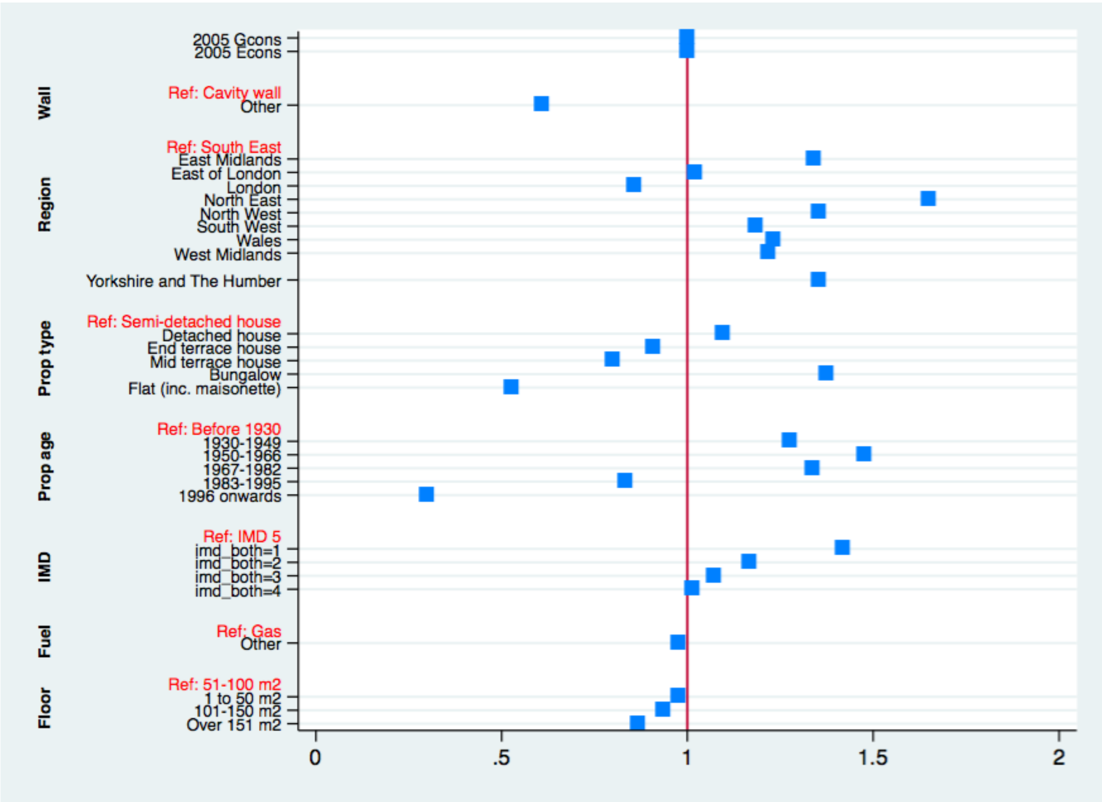


FIGURE 5: ODDS RATIO OF CWI UPGRADES

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 727524.

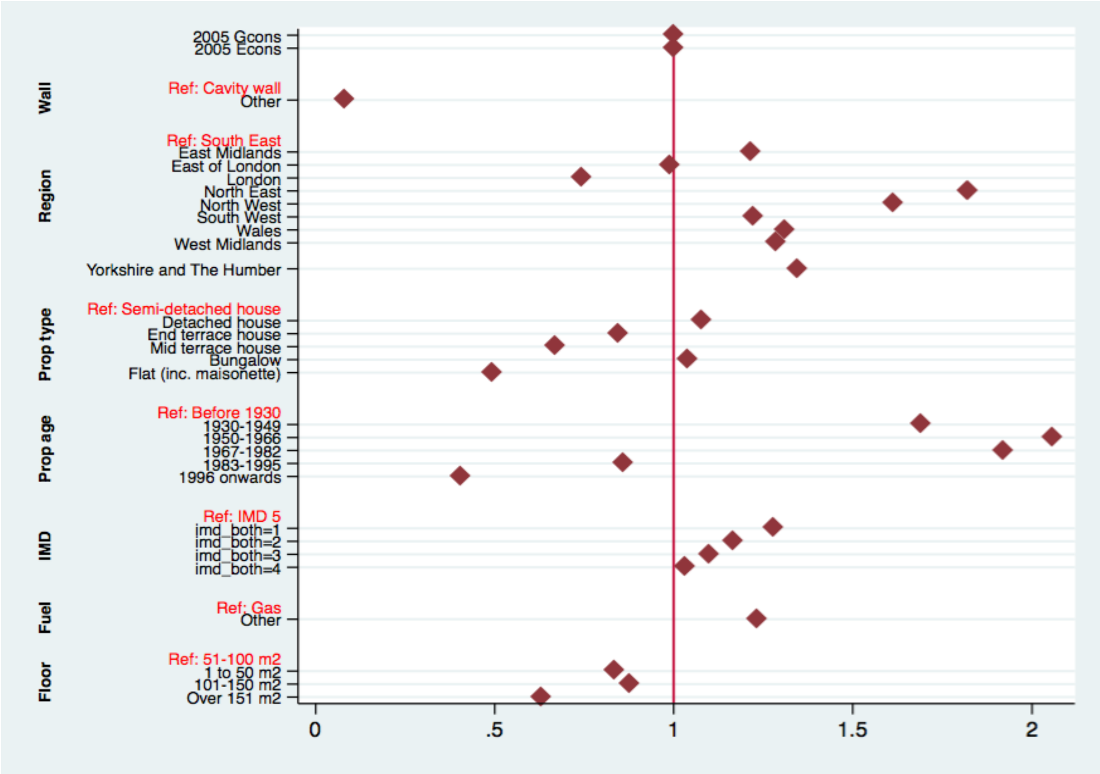


FIGURE 6: ODDS RATIO OF LOFT INSULATION

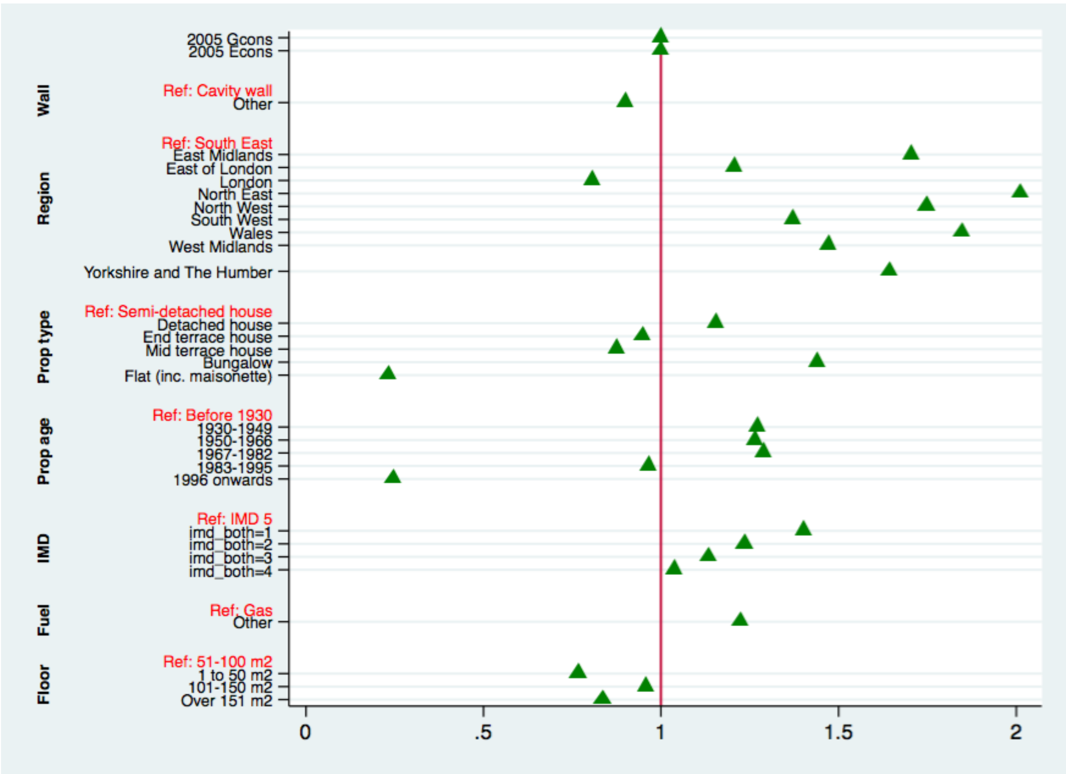


FIGURE 7: ODDS RATIO OF BOILER UPGRADES

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

2.5 The impact of measures on energy consumption

2.5.1 Methodological approach

To understand the impact of upgrades on energy consumption we build on our initial analysis to estimate how much energy the measures we have examined actually save. To estimate the effect we combine two techniques, statistical matching and panel econometric estimation. Statistical matching allows us to create (i) an upgrade group of households who received measures and (ii) a control group of households who did not receive upgrades but are otherwise identical to the upgrade group. Matching is necessary, as households who install measures may be different from those who do not, and by matching, we ensure both comparison groups are as similar as possible. The matching covariates used are predictors of household energy consumption and selection into energy efficiency programmes. These variables include neighbourhood IMD level, region, dwelling characteristics (property age and type, floor band) and energy consumption in previous years. Performing balancing tests, we ensure a good quality of matching and also ensure the treatment and control group follow a parallel path, which allows us to isolate the effect of the upgrade on energy consumption. Testing for different matching methods, kernel matching methods delivers the best result. Considering pre-treatment energy consumption, Figure 8 demonstrates both electricity and gas consumption for the year 2005 before and after matching. By comparing the right-hand figures with those on the left we illustrate how matching reduces imbalance in upgrade and control group.

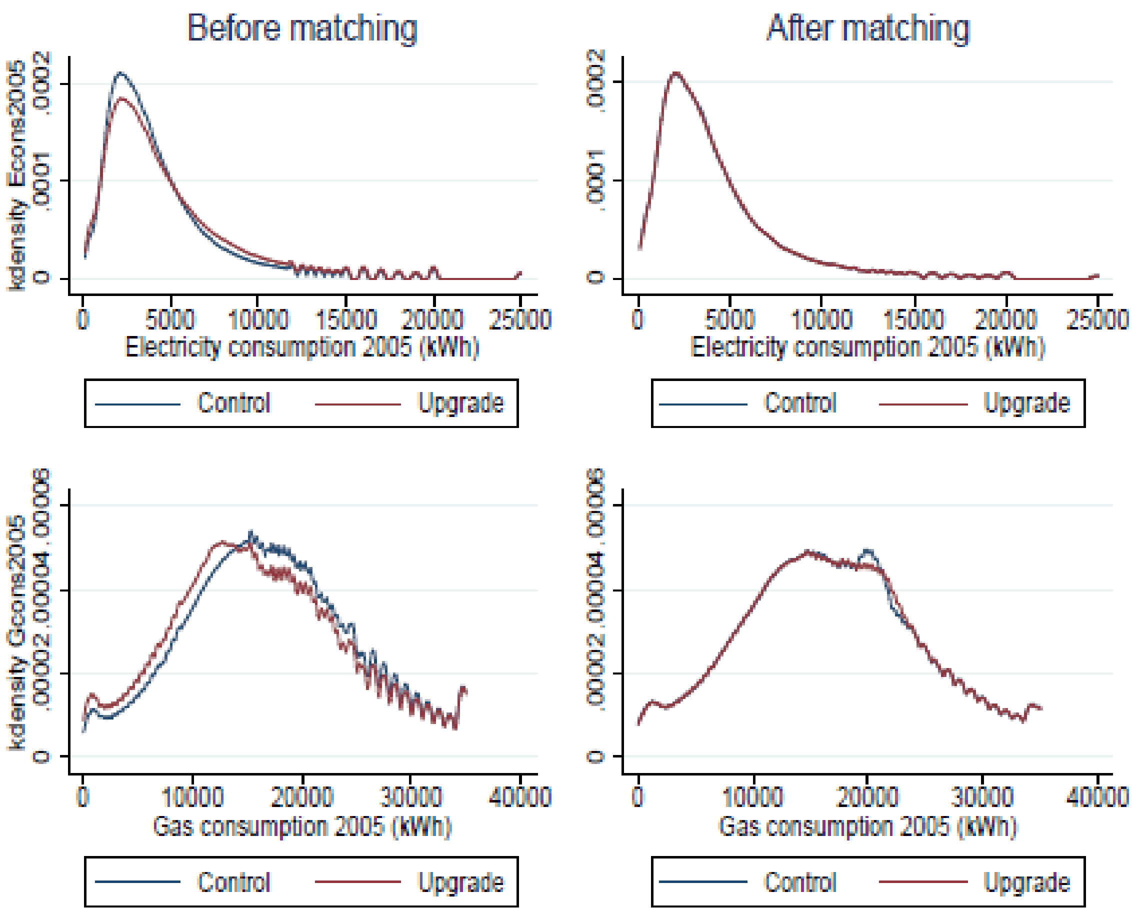


FIGURE 8: DISTRIBUTION ENERGY CONSUMPTION FOR THE TREATMENT AND CONTROL GROUP BEFORE AND AFTER KERNEL MATCHING

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

After matching the data, we employ a fixed effects panel econometric framework. This allows us to control for unobserved factors, which vary by household, with time and at a regional level. The baseline specification is estimated as follows:

$$Y_{it} = \alpha_i + \gamma_i + X_{it}\beta + \delta D_{it} + \epsilon_{it}$$

Where Y_{it} denotes energy consumption by household i in year t, αi is a household fixed-effect, γ_i is a year fixed-effect which controls for unobserved factors which vary at an annual level such as broader macroeconomic conditions and weather patterns. With X_{it}, we control for time-varying factors, such as heating and cooling degree days (HDD and CDD)[15], D_{it} is the treatment dummy. The key parameter of interest is δ the average treatment effect on the treated (ATT).

2.5.2 Results

The effect of energy efficiency upgrades on energy consumption

Table 18 shows the effect of individual, as well as combinations of energy efficiency measures. In general, the regression outputs suggest that energy efficiency measures installed through SOs have been successful in reducing energy consumption. All coefficients are significant at a 1 % significance level. Regarding annual gas consumption, cavity wall insulation is clearly the most effective energy efficiency measure with an average reduction of around 1310.8 kWh (or 7%)[16] compared to households which did not install any measure. This is almost double the gas savings for the second most effective measure, boiler replacements, which are 679.1 kWh (3.8%). In contrast, the installation of a new boiler is the single most effective measure in reducing annual electricity consumption with savings of around 73 kWh (1.8%). The least effective measure for both fuel types is loft insulation with around 389 kWh (2.1%) savings of gas and 16 kWH (0.04%) of electricity consumption.

Interestingly, combinations of measures deliver higher savings than the combined sum of individual measures. The suggests that there are there may be efficiency gains in installing multiple measures simultaneously, and also that households may be installing additional measures that are not being reported.

[15] Temperature data for the period from 2005 to 2012 comes from Met office, UK's national meteorological service. It provides the maximal and minimal air temperature at 9am and 9pm for more than 330 stations across England and Wales. After computing the average daily temperature for each station, it is possible to calculate the number of heating degree days (HDD) and number of cooling degree days (CDD).

[16] Compared to the average annual energy consumption of the control group in 2005 (Gas: 17878.77 kWh, Electricity: 3982.16 kWh.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

	(1)		(2)	
	Gas consumption		Electricity consumption	
loftin	-389.1***	(10.52)	-16.16***	(3.622)
boiler	-679.1***	(8.179)	-72.98***	(3.033)
cwi	-1310.8***	(11.81)	-67.93***	(4.208)
loftin & boiler	-1296.7***	(18.61)	-40.33***	(6.460)
loftin & cwi	-1974.1***	(15.14)	-79.16***	(5.143)
boiler & cwi	-2367.5***	(23.26)	-98.64***	(8.291)
loftin & boiler & cwi	-3059.1***	(27.02)	-73.05***	(9.417)
year dummies	yes		yes	
HDD	9.419***	(0.304)	-0.808***	(0.107)
CDD	-46.95***	(1.023)	-3.942***	(0.364)
cons	15966.2***	(84.08)	4205.9***	(29.68)
N	20701171		20626094	
adj. R^2	0.198		0.016	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors in parentheses

TABLE 18: THE EFFECT OF ENERGY EFFICIENCY UPGRADES ON ENERGY CONSUMPTION

	(7)		(8)	
	Gas consumption		Electricity consumption	
loftin	-318.7***	(17.78)	43.26***	(5.794)
boiler	-488.7***	(15.09)	-74.50***	(5.265)
cwi	-926.7***	(22.25)	-37.04***	(7.307)
2.IMD & loftin	-125.3***	(25.61)	-22.14**	(8.471)
3.IMD & loftin	-156.1***	(26.11)	-49.35***	(8.767)
4.IMD & loftin	-287.5***	(26.23)	-82.06***	(8.965)
5.IMD & loftin	-440.8***	(25.71)	-86.92***	(8.873)
2.IMD & boiler	-66.77**	(21.94)	-23.67**	(7.764)
3.IMD & boiler	-252.6***	(22.69)	-14.82	(8.124)
4.IMD & boiler	-473.7***	(22.88)	28.69***	(8.311)
5.IMD & boiler	-658.7***	(22.35)	91.93***	(8.183)
2.IMD & cwi	-300.3***	(31.33)	-17.14	(10.51)
3.IMD & cwi	-580.8***	(31.17)	-15.16	(10.55)
4.IMD & cwi	-732.2***	(30.47)	-29.69**	(10.44)
5.IMD & cwi	-882.6***	(29.17)	-24.31*	(10.09)
Year	Yes		Yes	
HDD	10.61***	(0.303)	-0.804***	(0.107)
CDD	-47.88***	(1.022)	-4.076***	(0.363)
_cons	15638.1***	(84.02)	4191.2	(13076.9)
N	20701171		20626094	
adj. R^2	0.198		0.016	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 19: THE EFFECT OF ENERGY EFFICIENCY UPGRADES ON ENERGY CONSUMPTION FOR DIFFERENT IMD GROUPS. SOURCE: AUTHOR'S CALCULATION BASED ON NEED DATA

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

Variation in savings from energy efficiency measures

The next set of results, presented in Table 19, show the interaction of the treatment variable with the IMD variable indicating the socioeconomic characteristics of the area in which the household resides. This allows us to estimate the effect of installing various measures for different household types. Energy savings are much greater for households living in more affluent areas (IMD = 5), compared to those in lower income areas (IMD = 1). This is true for both gas and electricity savings and applies to all types of measures.

This result raises concerns over distributional issues as the costs of these policies were likely applied as a flat-rate tariff on energy bills (Chawla and Pollitt, 2013). If savings are concentrated in the higher income groups, this suggest a further loading of policy costs onto those least able to afford it, particularly as a flat-rate charge is already regressive, disproportionately affecting those on lower incomes.

2.6 Conclusion and policy implication

This study examines which factors influence enrolment into government-funded energy efficiency schemes in the UK and the resulting energy savings from these measures. Results indicate that household and dwelling characteristics significantly determine the uptake of measures and affect the returns to energy efficiency measures.

The results suggest that the schemes examined have been quite successful in delivering energy efficiency measures to more deprived households in the UK. Given that this was a stated aim of many of the policies it is not too surprising to observe this. However, the analysis also demonstrates that while energy efficiency programmes have been successful in delivering measures to households from deprived areas, the energy savings are much higher for households living in more affluent areas.

The analysis also revealed large regional differences in the participation in government funded schemes. Clearly, colder winters and more heating degree-days will drive higher adoption of measures in more northern parts of the UK. Future policies will need to address the regional differences of barriers to uptakes and set incentives for households in and around London and the South of England.

Of particular note is the fact that combinations of measures deliver higher savings than the combined sum of individual measures. This suggests that there may be efficiency gains in installing multiple measures simultaneously, and also that households may be installing additional measures that are not being reported. This could be the result of households making additional private investments to complement the policy support they are receiving. Unfortunately the data do not allow us to fully disentangle this result, but it does suggest that policy support should target deep renovations, rather than individual measures.

While the focus of this research was on Supplier Obligations, or subsidised energy efficiency

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

measures, the results also provide important insights for other type of policy. Pay-as-you-save financing mechanisms are becoming increasingly popular for energy efficiency. For example, the Green Deal was a recent policy initiative in the UK (2011-2015) which provided households with loans in order to finance energy efficiency measures at interest rates of approximately eight percent. This was widely considered to have been a failure. The National Audit Office conducted an independent audit of the Green Deal scheme, finding that during its lifespan the scheme only funded one percent of energy efficient measures installed nationally (NAO, 2016). It also found that the scheme avoided negligible amounts of CO_2 emissions and that households did not see the loans as an attractive proposition. Concerns were raised prior to the Green Deal policy that it would not have sufficient appeal for householders. These relate to a range of factors, including uncertainty regarding energy savings, limited financial appeal, and limited awareness of the scheme (Dowson et al, 2012). A key factor in limiting its appeal were the high rates of interest charged on loans (Rosenow and Eyre, 2016). Given the results we observe, it is clear that this rate is not sufficiently low to provide incentives for many households to partake in this scheme. In particular, low-income households would actually lose money by making these improvements unless energy prices rise significantly.

Market-based interventions will only work for certain segments of the population and policy needs to take this into account.

Future work will focus on examining the cost-effectiveness of various measures and how this ultimately impacts the cost-effectiveness of policies and optimal policy mix for energy efficiency.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727524.

2.7 References

Brechling, V., & Smith, S. (1994). Household energy efficiency in the UK. Fiscal Studies, 15(2), 44–56.

Chawla, M., Pollitt, M. G., et al. (2013). Energy-efficiency and environmental policies & income supplements in the uk: evolution and distributional impacts on domestic energy bills. Economics of Energy & Environmental Policy, 2(1).

Dowson, M., Poole, A., Harrison, D., & Susman, G. (2012). Domestic UK retrofit challenge: Barriers, incentives and current performance leading into the Green Deal. Energy Policy, 50, 294-305.

Fowlie, M., Greenstone, M., and Wolfram, C. (2015). Do energy efficiency investments deliver? evidence from the weatherization assistance program. Technical report, National Bureau of Economic Research.

Giraudet, L.-G., Bodineau, L., and Finon, D. (2012). The costs and benefits of white certificates schemes. Energy Efficiency, 5(2):179–199.

Hamilton, I. G., Shipworth, D., Summerfield, A. J., Steadman, P., Oreszczyn, T., and Lowe, R. (2014). Uptake of energy efficiency interventions in english dwellings. Building Research & Information, 42(3):255–275.

Hong, S. H., Oreszczyn, T., Ridley I. (2006). “The impact of energy efficient refurbishment on the space heating fuel consumption in English dwellings.” Energy and Buildings 38(10), pp.1171-1181.

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

Mallaburn, Peter S., and Nick Eyre. "Lessons from energy efficiency policy and programmes in the UK from 1973 to 2013." Energy Efficiency 7, no. 1 (2014): 23-41.

NAO, G. D. Energy Company Obligation, National Audit Office (NAO), London, UK, 2016.

Office for National Statistics (2016). UK Perspectives 2016: Energy and emissions in the UK. [https://www.ons.gov.uk/economy/environmentalaccounts/articles/ukperspectives2016energyandemissionsintheuk/2016-05-26]

Pelenur, M., Cruickshank, H. (2012). Closing the Energy Efficiency Gap: A study linking demographics with barriers to adopting energy efficiency measures in the home. Energy 47:348-357.

Rehdanz, K. (2007). Determinants of residential space heating expenditures in Germany. Energy Economics 29: 167–182.

Rosenow, J. (2012). Energy savings obligations in the UK. A history of change. Energy Policy, 49:373–382.

Rosenow, J., & Eyre, N. (2016). A post mortem of the Green Deal: Austerity, energy efficiency, and failure in British energy policy. Energy Research & Social Science, 21, 141-144.

Tovar, M. A. (2012). The structure of energy efficiency investment in the UK households and its average monetary and environmental savings. Energy Policy, 50, 723 – 735.

Wyatt, Peter (2013). “A dwelling-level investigation into the physical and socio-economic drivers of domestic energy consumption in England”. Energy Policy 60, pp. 540– 549.

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 727524.