BRISKEE

Behavioural Response to Investment Risks in Energy Efficiency

D 2.3 DETERMINANTS OF HOUSEHOLD ADOPTION OF ENERGY EFFICIENT TECHNOLOGIES IN EUROPE: FOCUSSING ON PREFERENCES FOR TIME, RISK AND LOSSES

Authors: Joachim Schleich, Xavier Gassmann, Corinne Faure, Thomas Meissner

Grenoble Ecole de Management (GEM)

19.04.2018

This project has received funding from the *European Union's Horizon 2020 research and innovation programme* under grant agreement No 649875. This document only reflects the authors' views and EASME is not responsible for any use that may be made of the information it contains

Content

1 Introduction

Improving energy efficiency is commonly considered to be the cheapest short- to medium-term option for meeting energy and climate targets (e.g. IEA 2016), and it is a prime policy goal in many countries. For example, the European Union aims to reduce energy use by at least 30 percent compared to the projected use of energy in 2020. To address environmental externalities such as global warming or resource use, governments employ policies such as technology standards, information measures (e.g. labeling), rebates, tax credits, or subsidized loans. In addition, well-designed policies may also help overcome the so-called "energy efficiency paradox", according to which decision-makers may fail to invest in energy-efficient technologies even though these appear to pay off under prevailing market conditions (e.g. Jaffe and Stavins 1994, Sorrell et al. 2004, Allcott and Greenstone 2012, Gillingham and Palmer 2014).

For household technology choices, insights from the psychology and behavioral economics literatures suggest that both time and risk preferences may help explain the energy efficiency paradox (e.g. Allcott and Mullainathan 2010, Allcott 2011, Gerarden et al. 2015, Ramos et al. 2015, or Schleich et al. 2016). There is some growing body of evidence on the effects of time discounting and risk preferences on energy-efficient technology adoption; however, a comprehensive test of these effects is missing. Researchers have also used different methods to capture time and risk preferences. Some rely on multiple price list experiments, following Coller and Williams (1999) and Holt and Laury (2002), while others have used Likert scales, following Dohmen et al. (2010, 2011) and Falk et al. (2016). While producing internally consistent measures of preferences in a controlled and incentive-compatible manner, experiments are typically lengthy and involve high administrative and financial costs when employed in large sample surveys. In comparison, Dohmen et al. (2011) show that asking individuals for a global assessment of their willingness to take risks is a good predictor of behavior in several domains. While such scale-based measures lack internal consistency and self-reporting is not incentive-compatible, they are simpler, less time-consuming and cheaper than experiment-based measures. Dohmen et al. (2011, p. 543) argue that experiment-based risk measures are good predictors of individual behavior in the financial domain, but are less informative for risk taking in nonfinancial domains. Thus, empirical findings on the role of time and risk preferences for explaining individual behavior and corresponding implications may depend on the type of measure used to elicit these preferences.

Moreover, the effects of loss aversion, that can be expected to affect energy-efficient technology adoption remain largely unstudied. To our knowledge, only Heutel (2017) has – in a parallel effort - empirically investigated the effects of loss aversion on household adoption of EETs. Simultaneously considering the effects of risk aversion, standard time discounting, present bias, and loss aversion on EET adoption to avoids mistakenly conflating their effects. Methodologically, to get internally consistent parameter estimates, the parameters reflecting standard time discounting, risk aversion, loss aversion, and of present bias are calculated jointly at the individual level. Preferences for time discounting, present bias, risk and loss aversion were elicited via (partly incentivized) decontextualized multiple price list (MPL) lotteries. As an alternative, we compare findings when time and risk preferences are elicited via Likert scales. To address concerns with previous literature, adoption decisions were surveyed from decision-makers for low- (LED light bulbs), medium- (appliances) and high- (retrofit) –stake energy-efficient technologies. Further, the study includes many household control variables (such as intention to move, renting, socio-demographics and individual traits), as well as dwelling characteristics such as size or dwelling age. Finally, empirically, our study is the first to utilize representative samples in a cross-country comparison and with a final sample of about 13.500 respondents, our sample size is much larger than in previous studies, allowing for more generalizable results. Thus, our study contributes to the emerging literature that relate preference measures employed in laboratory experiments to actual behavior for representative samples (e.g. Dohmen et al. 2011).

The empirical analysis of EET adoption may also be linked to the conceptual framework of the factors underlying the implicit discount rates (IDRs) developed in BRISKEE deliverable D2.1 and further refined in Schleich et al. (2016). IDRs govern individual adoption of EET in energy-economic models. Since higher IDRs typically imply lower investments in energy efficiency, there is a direct link between EET adoption and the size of the IDR. Following this framework the size of the IDR generally depends on (i) preferences such as time preferences, risk preferences, reference-dependent preferences such as loss aversion, and pro-environmental preferences; (ii) predictable (ir)rational behavior, i.e. bounded rationality, rational inattention, and behavioral biases, such as present bias or status quo bias; and (iii) external barriers to energy efficiency such as split incentives, lack of information, or lack of capital. The empirical analyses employed in this paper include a fairly broad set of these factors, and hence allow for inference on their relation to EET adoption based on a large demographically representative sample. The findings of this report on the factors related to EET adoption also provide the basis for BRISKEE deliverable 2.4., which relates socio-economic factors such as income and age to the factors underlying the IDR, and hence provides guidance for energy-economic modelling.

The remainder of this report is organized as follows. Section 2 provides a discussion of the existing literature that links preferences to energy-efficient technology adoption. Section 3 briefly presents the theoretical model of individual preferences, describes the survey and the elicitation of time preferences, risk preferences, loss aversion, and present bias via multiple price lists, and outlines the variables used in the econometric analysis. Section 4 presents and discusses the findings of the econometric analysis. The final section summarizes the main findings and discusses their implications.

2 Literature on Preferences and Energy Efficient Technology Adoption

In this section, we review the empirical literature analyzing the role of preferences for time (i.e. standard time discounting and present bias), risk and losses. The section closes with a critical assessment of the literature.

2.1 Standard time discounting

The adoption of energy-efficient technologies typically involves an up-front investment followed by dispersed financial savings in the future. Individual time preferences are therefore expected to affect technology choice. Yet, the few empirical studies linking individual time discounting to energy-efficient technology adoption provide mixed evidence. For US households, Newell and Siikamäki (2015) find that the standard time discount rate is positively related to the adoption of energy-efficient water heaters; similarly, Allcott and Taubinsky (2015) conclude that standard time discounting helps explain the choice of compact fluorescent lightbulbs (CFLs) versus incandescent light bulbs in the USA. Also for the USA, Bradford et al. (2014) find a positive correlation for low cost technologies such as CFLs or thermostats, but not for higher cost measures such as thermal insulation. In comparison, Heutel (2017) does not find a statistically significant link between standard time discounting and several low and high cost measures for the USA. Fischbacher et al. (2015) conclude that standard time preferences play no role for the renovation decisions among Swiss homeowners. Finally, Bruderer Enzler et al. (2014) do not find consistent effects of time discounting on the adoption of a variety of high- and low-cost energy-efficient technologies for Swiss households.

2.2 Present bias

The traditional economic model of intertemporal decision-making presumes an exponential discounting function implying a constant rate of discounting (Samuelson 1937). Yet, the experimental psychology and experimental economics literatures (e.g. Laibson 1997, Loewenstein and Prelec 1992, or Thaler 1991) suggest that individuals tend to systematically overvalue the present compared to the future. As argued by O'Donoghue and Rabin (1999), this so-called present bias may cause naïve individuals to procrastinate when costs are immediate. Present bias may therefore help explain the energy efficiency paradox. Individuals with present bias may not account for future energy cost savings in the way that the traditional economic model of discounting presumes. In adoption studies, present bias is typically modelled with a (quasi) hyperbolic dis-counting function (Ainslie, 1974; Laibson, 1997). The body of work that has explored the effects of present bias on the adoption of energy efficient technologies is inconclusive. Bradford et al. (2014) find that present bias is statistically associated with self-reports of driving a fuel-efficient car, having a well-insulated home, and with the temperature setting the temperature on one's thermostat (but not with other energy efficiency measures). In comparison, Allcott and Taubinsky (2015) do not find present bias to be correlated with CFL adoption decisions in their choice experiment. Similarly, Heutel (2017) finds no relation between present bias and the take up of energy efficiency measures. Busse et al. (2013), Allcott and Wozny (2014) and Cohen et al. (2017) explore whether individuals behave myopically, i.e. whether they undervalue expected future energy costs relative to the up-front expenditures when making energy-related investment decisions. Thus, myopia captures both, present bias and high standard time preferences. For high mileage automobile purchases in the USA, Allcott and Wozny (2014) find evidence of myopia, while Busse et al. (2013) conclude that individuals do not act myopically. Cohen et al. (2017) find myopia to moderately impede the (observed) adoption of energy-efficient refrigerators in the United Kingdom.

2.3 Risk aversion

Because the profitability of EET adoption depends on several uncertain factors such as future energy prices and energy use, technology performance, and regulation (e.g. energy tax rates, CO_2-prices), EET investments are risky. Therefore, risk preferences are also expected to affect energy efficiency adoption. When faced with two investments with a similar expected return (but different risks), a risk-averse investor will prefer the lower risk option. Since adoption of EETs also lowers household energy expenditures and thus reduces the financial risks of uncertainty about future energy prices or consumption levels, the relationship between risk aversion and technology adoption remains ambiguous. Scant empirical literature on risk aversion and EET adoption suggests that more risk-averse households are less likely to adopt energy-efficient ventilation and insulation systems in Switzerland (Farsi, 2010; Fischbacher et al. 2015) and also less likely to adopt various retrofit measures and appliances (excluding air conditioners) (Qiu et al., 2014), or high efficient light bulbs and thermostats (but not appliances or vehicles) in the USA (Heutel (2017).

2.4 Loss aversion

Loss aversion is another type of individual preference that has received substantial attention in the experimental psychology and economics literatures. Individuals have been shown to evaluate losses relative to a reference point more strongly than gains of equal size, i.e. "losses loom larger than gains" (Kahneman and Tversky 1979). Because decision-makers often evaluate the initial EET investment costs as a loss, loss aversion may affect EET adoption and therefore help explain the energy efficiency paradox (Greene et al. 2009; Greene 2011). Yet empirical research exploring the impact of loss aversion on EET adoption is generally lacking (Greene 2011). To our knowledge, only Heutel (2017) has empirically investigated these effects; he finds loss aversion to impede adoption for three (high efficient light bulbs, replacement of air conditioners, alternative fuel vehicles) of the ten measures considered. Heutel (2017) calls for future analyses to consider larger samples than his sample of about 2000 observations.

2.5 Critical assessment of extant literature

As can be seen from the literature reviewed above, there is little empirical evidence on the effects of time and risk preferences and loss aversion on energy-efficient adoption. Few studies include both time and risk preferences, and the evidence is scant and often inconsistent. To allow for a comprehensive understanding of these effects, we evaluated extant studies, identified important differences, and designed an empirical study that accounts for these differences. We identified differences across studies on the following issues 1) different approaches to study time and risk preferences (inclusion of parameters, methods of elicitation, estimation methods), and 2) different approaches to assess adoption (technologies considered, methods of elicitation, sampling strategy).

So far, only few empirical studies have looked at the effects of time or risk preferences on energy efficient technology adoption simultaneously (Bradford et al. 2014, Heutel 2017). Andersen et al. (2008) stress the importance of a joint identification of risk and time preferences: they show that not accounting for the curvature of the utility function (typically described by the parameter of risk aversion) leads to biased estimates of individual discount rates ("curvature bias"). Similarly, not accounting for loss aversion may result in biased estimates of risk parameters (e.g. Abdellaoui et al. 2007). More generally, failure to simultaneously include loss aversion and time and risk preferences may lead to an omitted variable bias of parameter estimates in econometric analyses of adoption behavior. Identifying the distinct effects of standard time discounting, present bias, and risk preferences on EET adoption is particularly relevant to best identify policy measures to improve EET adoption. For example, policies aimed at accelerating the adoption of EETs by reducing risks of EET investments, typically differ from policies aiming to mitigate the effects of present bias. Thus, for a better understanding of different preference types and energy-efficient adoption behavior overall, risk and time preferences may have to be jointly and simultaneously estimated.

Furthermore, differences across studies can also be noted regarding the methods used to elicit preferences. While some studies rely on self-reported qualitative measures using Likert scales (Dohmen et al. 2011), other studies have used on multiple price lists (MPLs) (Coller and Wil-liams 1999, Holt and Laury 2002), which allow for parametric estimations of preferences.[1] Even among the studies using MPLs for the elicitation of preferences, some have used contextualized price lists (e.g., Qiu et al 2014) while only a few relied on the more widely accepted context-free MPLs (e.g.,

1 This is important, for instance, when assessing risk preferences: A response to a Likert scale question on risk aversion does not allow to distinguish between risk averse, neutral or loving people.

Bradford et al. 2014, Fischbacher et al. 2015, Heutel 2017)[2]. Although contextualized MPLs have been shown to be better at predicting targeted behaviors, these higher correlations are somewhat confounded because contextualized MPLs confound preferences with the behaviors of focus (here energy technology adoption). Finally, the experimental economics literature stresses the importance of using incentivization (paying respondents as a function of their responses) to enable incentive-compatible choices. So far, incentivization has only been used in a few demographically representative studies including Bradford et al. (2014) through gift cards and in Fischbacher et al. (2015) through bank transfers. To conclude, the literature on time and risk preferences stresses the importance of assessing and estimating all parameters (standard time preferences, present bias, risk aversion, and loss aversion) simultaneously; furthermore, these preferences should be elicited through decontextualized and incentivized experiments such as multiple price lists.

Previous researchers have also differed in their operationalization of EET adoption. A variety of technologies (e.g. light bulbs or cars) and indicative behaviors (e.g. power usage or driving habits) have been studied, making it difficult to establish comparisons across studies. Clearly, the investments involved in different adoption decisions range from a few euros for light bulbs to large sums of money for cars or retrofit measures. These differences should affect perceived risk, for instance; therefore, the stakes involved should be systematically accounted for. The method of elicitation of adoption also differs sharply across studies: while Newell and Siikamäki (2015) and Allcott and Taubinsky (2015) infer technology adoption from revealed preference experiments, Bradford et al. (2014), Heutel (2017) and Fischbacher et al. (2015) rely on stated adoption behavior; Bruderer Enzler et al. (2014) utilize a mix of simple choice tasks and stated adoption behaviors. One frequent concern is that studies may at times confound adoption and ownership (for instance, asking respondents whether they own an energy-efficient refrigerator, rather than about the adoption decision of the last purchased refrigerator-tor) and at times may include respondents who are not "in the market"

2 Fischbacher et al. (2015) use incentivized MPLs to elicit standard time preferences and the Likert scales proposed by Dohmen et al. (2011) to capture risk preferences.

(for instance, applying hypothetical stated choice experiments to all respondents, including those who are not normally involved in such decisions). Studies also typically include very few control variables on household or dwelling characteristics; to the extent that such variables affect adoption decisions their impact has not been assessed, thereby also raising omitted variables concerns. Finally, while many adoption studies have used representative samples of the population, they were single-country studies almost exclusively conducted in the USA or in Switzerland.

In summary, different ways of operationalizing EET adoption in previous studies underscore the importance of considering investment stakes, focusing on adoption and not just owning, including relevant household and dwelling characteristics as controls, and using representative samples of actual decision-makers across outcomes.

Building upon our critical evaluation of the literature, we empirically analyze the effects of standard time preferences, risk aversion, loss aversion, and present bias on household adoption of low-, medium- and high-cost EETs. We field a demographically representative survey in eight EU countries.

3 Methods

This section first describes the theoretical framework underlying our estimation of parameters that reflect standard time preferences, present bias, risk aversion, and loss aversion. Then, a sub-section on empirical methods describes the survey, displays the multiple price lists (MPLs) that are employed to elicit and calculate these preference parameters, and presents the econometric model together with the dependent variables and control variables used.

3.1 Theory

3.1.1 Modelling risk preferences and loss aversion

To model individual preferences for risk and loss aversion we rely on a standard simplified version of the utility function derived from Prospect Theory (Kahneman and Tversky 1979):

$$(1) \qquad u(x) = \begin{cases} x^{\alpha} & if\ x \geq 0 \\ -\lambda(-x)^{\alpha} & if\ x < 0 \end{cases}$$

where x reflects wealth, α (≥0) is the parameter reflecting risk aversion and λ is the parameter capturing loss aversion[3]. The utility specification in equation (1) implies that relative risk aversion is constant (CRRA) and identical for losses and gains. Compared to the original cumulative Prospect Theory (Tversky and Kahneman, 1992 or Prelec 1998) we abstract from probability distortion since in our MPL experiments, all lotteries are symmetric in terms of probability. We also assume a reference wealth of zero.

3 □=1 / 0<□<1 / □>1 means the participant is risk neutral / risk averse / risk loving; □=1 / 0<□<1 / □>1 means the participant is loss neutral / loss seeking / loss averse.

3.1.2 Modelling time preferences

To capture individual preferences for wealth at different points in time, we use the standard model of quasi-hyperbolic discounting, proposed by (Laibson 1997)

$$\boldsymbol{U_t}(x_t, \dots, x_T) = E[u(x_t) + \beta \textstyle\sum_{k=1}^{T-t} \delta^k u(x_{t+k})] \tag{2}$$

where $\boldsymbol{U_t}(x_t, \dots, x_T)$ is the expected utility of a stream of wealth gains $x_0, \dots, x_T$ at different points in time from 0 (now) to T. $u(x_t)$ is the utility of the wealth x at the date t, δ is the standard time discount factor, and β is the parameter reflecting present bias. In our model t is expressed in years and δ is the annual time discounting factor.[4]

3.1.3 Need to jointly estimate preferences parameters

Equations (1) and (2) illustrate the need to jointly estimate the parameters reflecting preferences for time, risk and losses. For example, if individuals are loss averse and perceive the outcomes of a project as a loss, failure to account for loss aversion when estimating α results in overestimating α (e.g. Abdellaoui et al. 2007). Likewise, if individuals are assumed to be risk neutral when in fact they are risk averse, the estimated time discount factors are biased downward (e.g. Andersen et al. 2008). Similarly, if individuals are assumed to be loss-neutral when in fact they are loss-averse, the estimated time discount factors are biased upward for projects involving an up-front loss followed by a later gain. Obviously, identification of specific estimates of the parameters reflecting risk aversion, standard time preferences, present bias and loss aversion rely on assuming particular functional forms such as equations (1) and (2).

4 δ=1 / 0<δ<1 means the participant is not discounting future outcomes / discounting future outcomes. β=1 / 0<β<1 / β>1 means the participant is neither present nor future biased / present biased / future biased.

3.2 Empirical methods

An online survey was implemented by Ipsos GmbH via computer-assisted web interviews (CAWI) using existing household panels. About 15,000 participants from eight EU countries (France, Germany, Italy, Poland, Romania, Spain, Sweden, and the United Kingdom) completed the survey. These countries account for about 80 percent of the EU population, energy use, and greenhouse gas emissions. Participants were selected via quota sampling to be representative of each country in terms of gender, age (between 18 and 65 years), and regional population dispersion; only participants who reported being involved in their household's investment decisions for utilities, heating, and household appliances were qualified for the survey. Interviews were carried out between July and August 2016. All surveys were professionally translated from the original language (English) to the target language of each country, and subsequently back translated to test for and eliminate any differences that could be attributed to language.

The survey contained non-contextualized MPL questions to elicit time preferences, risk preferences, and loss aversion. Additional questions addressed EET adoption, dwelling characteristics, and also assessed personality traits and attitudes via established scales. Socio-demographic information was gathered both at the beginning of the questionnaire (to ensure that quota requirements were met), and at the end of the questionnaire.

3.2.1 Elicitation of preferences via MPL experiments

The MPLs employed to elicit time and risk preferences and loss aversion were adapted from Coller and Williams (1999) for time preferences and by Holt and Laury (2002) for risk preferences. Participants faced a list of choices between two options, A and B, and were asked for each choice to indicate their preferred option.[5] Since the survey was conducted in countries with different currencies, the monetary amounts displayed to participants were adjusted to keep the relative value similar between countries in terms of purchasing power. To this end, the following rates were applied: Poland: 1€ = 3 PLN; Romania: 1€ = 3 RON; Sweden: 1€ = 10 SEK; UK: 1€ = 1£. In all Euro-zone countries, the monetary amounts shown to participants were identical; for Sweden, the UK, Poland, and Romania, monetary amounts were multiplied by their respective factors. Similar to Bradford et al. (2014), but in contrast to Qiu et al. (2014), the MPLs in our study were not contextualized.

3.2.1.1 Elicitation of time preferences

The first price lists (MPL1) primarily identified individual time preferences, i.e. standard time discounting and present bias. MPL1 consisted of two series of seven choices with different upfront time delays. In the first set (MPL1.1), Option A specified a monetary gain to be paid in one week, and Option B specified a monetary gain to be paid in 6 months. In the second set (MPL1.2), Option A specified a monetary gain to be paid in six months and one week and Option B a monetary gain to be paid in 12 months. In general, the more often Option A is chosen, the greater the respective participant discounts future gains (thus reflecting impatience). Further, the difference between MPL1.1 and MPL1.2 allows assessing present bias: the MPLs are identical, except for the additional

5 Since decisions may be influenced by the order in which the choices are presented (order bias), we randomized the order in which the decisions were presented to participants. Across all MPLs, participants had a 50% percent chance to see AB and a 50% chance to see BA. The order used remained constant for each participant across all MPLs (i.e. either AB or BA for all decisions). All analyses rely on pooled data of AB and BA options.

6-month delay imposed on both options in MPL1.2. A participant's differences in responses between these two tables therefore reflect inconsistencies in time preferences (present bias).[6]

Table 1: Multiple price list for eliciting time preferences (MPL 1.1).

Line	Option A	Option B
1	Receive 98€ in one week	Receive 100€ in 6 months
2	Receive 94€ in one week	Receive 100€ in 6 months
3	Receive 90€ in one week	Receive 100€ in 6 months
4	Receive 86€ in one week	Receive 100€ in 6 months
5	Receive 80€ in one week	Receive 100€ in 6 months
6	Receive 70€ in one week	Receive 100€ in 6 months
7	Receive 55€ in one week	Receive 100€ in 6 months

Table 2: Multiple price list for eliciting time preferences with 6-month additional delay (MPL 1.2).

Line	Option A	Option B
1	Receive 98€ in 6 months and one week	Receive 100€ in 12 months
2	Receive 94€ in 6 months and one week	Receive 100€ in 12 months
3	Receive 90€ in 6 months and one week	Receive 100€ in 12 months
4	Receive 86€ in 6 months and one week	Receive 100€ in 12 months
5	Receive 80€ in 6 months and one week	Receive 100€ in 12 months
6	Receive 70€ in 6 months and one week	Receive 100€ in 12 months
7	Receive 55€ in 6 months and one week	Receive 100€ in 12 months

3.2.1.2 Elicitation of risk preferences

MPL 2 was adapted from Holt and Laury (2012) to elicit individuals' risk preferences. Participants selected among a series of 14 choices between two options A and B.

In both options, respondents faced a lottery that paid either a high or a low monetary gain with equal probability of 0.5 (this probability was presented as a coin flip). Note that Option A had a lower

6 Note that there is some debate in the literature whether time preferences can be elicited experimentally, using time-dated monetary payments as incentives. One argument against using monetary incentives, is that subjects may borrow against the experimenter, in which case the elicited time preferences may simply reflect participants outside borrowing opportunities. A preferable solution would be to incentivize subjects by use of time-dated consumption/real effort (as for instance in Augenblick et al. 2015). This would require, however, that participants actually solve real effort work tasks in different points of time, which is practically infeasible in large-scale studies such as ours. We therefore opted to use time-dated monetary rewards to elicit time preferences.

variance compared to Option B, but a higher expected value in Lines 1 to 7; after Line 7, Option B had a higher expected value.

Table 3: Multiple price list for eliciting risk preferences (MPL 2).

Line	Option A		Option B	
	Coin shows **Heads**	Coin shows **Tails**	Coin shows **Heads**	Coin shows **Tails**
1	50€	40€	54€	10€
2	50€	40€	58€	10€
3	50€	40€	62€	10€
4	50€	40€	66€	10€
5	50€	40€	70€	10€
6	50€	40€	74€	10€
7	50€	40€	78€	10€
8	50€	40€	82€	10€
9	50€	40€	87€	10€
10	50€	40€	97€	10€
11	50€	40€	112€	10€
12	50€	40€	132€	10€
13	50€	40€	167€	10€
14	50€	40€	222€	10€

3.2.1.3 Elicitation of loss aversion

In MPL3, which was designed to identify loss aversion, participants faced a series of seven choices between two options A and B. In both options, participants had an equal chance of winning or losing some money. Option A offered lower gains and losses whereas option B offered greater gains but also greater losses.

Table 4: Multiple price list for eliciting loss aversion (MPL 3).

Line	Option A		Option B	
	Coin shows **Heads**	Coin shows **Tails**	Coin shows **Heads**	Coin shows **Tails**
1	+100€	-20€	+150€	-100€
2	+55€	-20€	+150€	-100€
3	+15€	-20€	+150€	-100€
4	+5€	-20€	+150€	-90€
5	+5€	-30€	+150€	-90€
6	+5€	-40€	+150€	-90€
7	+5€	-40€	+150€	-70€

3.2.2 Different stakes

We also varied the monetary amounts shown to participants in each of the decisions. The MPL design otherwise remained the same, except for the magnitudes of the monetary amounts. We implemented two manipulations. For about 10% of the total sample, all values shown in the MPLs were multiplied by 10, relative to the baseline treatment. For about 7% of the sample, all values shown in the MPL were divided by 10, relative to the baseline treatment.

3.2.3 Incentivization

To mitigate hypothetical bias, more than half the sample were incentivized (54%). Of those, we paid a random subset (1%) of the participants based on their actual choices to the MPL questions. Incentivization was only implemented for baseline and low stakes. For each selected participant, one question was randomly chosen as the payout question. Note that although only a small percentage of respondents actually received money, more than half the sample was incentivized - the drawing was done at the end of the survey, with one in 100 chances to win. Participants were informed that if a question from Table 4 (loss aversion) was chosen as the pay-out question, the participant would receive an additional 100 euros (or equivalent sum in Poland, Romania or Sweden), regardless of the choice and regardless of the result of the coin flip. Any losses would then be subtracted from these 100 euros, and gains would be added[7]. For participants who were not incentivized, the instructions stated that these were hypothetical choices. In all countries, the selected participants received a prepaid credit card (MasterCard) by postal mail. A separate letter stated the amount, provided the PIN code and included the terms and conditions for credit card use. The stated amount could be spent in any online or offline shop accepting MasterCard (due to processing time, a one-week delay was added to the MPLs). The stated amount could be spent in any online or offline shop accepting MasterCard. Processing and shipping of these payments took one week time, which is why the

[7] In contrast, Heutel (2017) incentivized gains only.

earliest payment date in all MPLs was one week from the date participants completed the survey. The stated amount could be spent in any online or offline shop accepting MasterCard (due to processing time, a one-week delay was added to the MPLs). Perceived payment reliability is an issue that may confound the elicitation of preferences, especially when a sooner payment may be deemed more reliable, or involves less transfer costs. In our survey, payment modalities were kept constant across all time horizons. Additionally, the instructions informed participants that the market research company would guarantee payments as specified in the survey, and provided an email address that participants could contact in case of questions regarding the payment modalities. The sur-vey drew from an existing panel, consisting mostly of participants who had have experience with the market research company and their payment modalities, which should further alleviate issues of perceived payment reliability. Payments to the 75 winning participants averaged 54.43 euros and ranged from 0 to 250 euros (including the 100 euros the winner received if a line in the loss aversion experiment was selected).

3.2.4 Calculation of preference parameters

We calculated preference parameters individually for each respondent by use of their switch-points, i.e. the points at which a given respondent started to prefer Option B over Option A in each of the MPLs. Subjects with monotonous preferences should have had at most one switch-point in each of the MPLs. Generally, the switch-points in our four MPLs spanned a four-dimensional interval of permissible parameter values, which described the observed switching behavior. Rather than calculate this complex interval, we assumed that respondents were indifferent at the mean values of the lines between which they switched: A participant who chose Option A in Line 1 of MPL1.2 and Option B in the remaining lines was assumed to be indifferent between 96€ in six months and one week and 100€ in twelve months. Participants who never (immediately) switched, i.e. always choose A (B) in one MPL, were assumed to be indifferent at the last (first) line of this MPL. The switch-points thus provided four equations (one for each MPL) that could be solved for the four unknown preference parameters. Participants with multiple switch-points were dropped, resulting in a loss of

10.75% of the sample. Compared to most other studies, this share is relatively low and comparable to Harrison et al. (2005). Results of these calculations are presented in Table 5.[8]

Table 5: Means of estimated parameters of risk aversion, standard time discounting, present bias and loss aversion (standard deviations in parentheses).

	All countries	*France*	*Germany*	*Italy*	*Poland*	*Romania*	*Spain*	*Sweden*	*United Kingdom*
Risk aversion: α	0.883 (1.203)	0.849 (1.124)	0.901 (1.209)	0.903 (1.160)	0.786 (1.194)	1.032 (1.468)	0.932 (1.246)	0.998 (1.254)	0.744 (0.999)
Standard time discounting: δ (annual rate)	0.781 (0.254)	0.809 (0.225)	0.789 (0.253)	0.763 (0.250)	0.769 (0.270)	0.739 (0.303)	0.771 (0.257)	0.792 (0.234)	0.801 (0.237)
Present bias: β	1.007 (0.445)	0.991 (0.180)	1.019 (0.543)	0.980 (0.285)	1.005 (0.396)	1.053 (0.746)	1.001 (0.409)	1.014 (0.449)	1.007 (0.443)
Loss aversion: λ	3.414 (3.883)	3.451 (3.732)	3.455 (4.091)	3.432 (3.981)	3.374 (4.005)	3.460 (3.952)	3.237 (3.601)	3.534 (4.028)	3.408 (3.709)
Number of observations	13,436	1,895	1,807	1,728	1,761	1,274	1,756	1,368	1,847

Table 5 suggests that the average standard annual time discount rate across the entire sample was about 28% ((1/0.78-1)*100%), with little differences across countries. In general, comparing our estimates of standard time preferences (or present bias, risk aversion and loss aversion) across studies is difficult because of differences in participants, stakes, framing, elicitation method, incentivization, and/or methodologies. The later include assumptions about the underlying preferences (i.e. utility function), or estimation procedures. In any case, our estimates of the annual discount factors are in the range of those found in previous studies employing MPLs to elicit standard time preferences (Frederick et al. 2002). On average, participants were risk averse. Our mean value for $\alpha = 0.883$ is similar to the mean value found by Heutel (2017, 0.809) or university students by Kahneman and Tversky (1979, 0.88), but higher than those among participants in Denmark (Harrison et al. 2007, 0.67), among others (Tanaka et al. 2010, 0.60; Liu 2013, 0.52). The average participant in our sample

8 Incentivized participants were found to exhibit a lower standard time discount rate, to be less risk averse and to be less loss averse. No difference was found for present bias between incentivized and non-incentivized participants.

did not exhibit present bias. Thus, our mean value for β= 1.007 is higher than the values for present bias typically found in the literature (Tanaka, Camerer, and Nguyen 2010, 0.64 for villages in Vietnam; Bradford et al. (2014, 0.94)). We also note that a large share of participants in our sample appeared to be future biased, like in Takeuchi (2011). Note that this lack of evidence for present bias may in part be explained by the fact that the soonest subjects could receive their incentivization was one week away. Nevertheless, as documented in later parts of this paper, we did find that our measure of present bias played a role in efficient adoption behavior. The average participant in each of the surveyed countries was loss averse. Our mean value for λ = 3.414 in similar to the values found by Liu (2013, 3.47 for farmers) or Heutel (1997, 4.508), but higher than the values elicited in Tanaka et al. (2010, 2.63), or in Kahneman and Tversky (1979, 2.25). We further found that country averages of our parameter estimates of standard time preferences, loss aversion, and present bias (and to a lesser extent for risk aversion), varied little across countries. Table 6 displays the correlation of the estimated preference parameters.

Table 6: Correlation of preference parameters.

	α	δ	β	λ
Risk aversion: α	1.000			
Standard time discounting: δ (annual rate)	-0.522*** (0.000)	1.000		
Present bias: β	0.100*** (0.000)	-0.155*** (0.000)	1.000	
Loss aversion: λ	0.357*** (0.000)	-0.174*** (0.000)	0.123*** (0.000)	1.000

*** p<0.01

In our sample, each parameter is correlated with the other three parameters (p<0.01). In particular, risk aversion is correlated with standard time discounting and with loss aversion. For example, individuals who are more risk averse (lower α) are more likely to be patient (lower δ), more likely to be present biased (lower β) and less likely to be loss averse (lower λ).

3.2.5 Elicitation of preferences via scales

As an alternative to the MPL-based parameters, we also measure time and risk preferences on one-item scales validated by Falk et al. (2016) and Dohmen et al. (2010, 2011). Participants were asked to rate the following items on a scale: from 1 ("Not at all willing") to 5 ("Very willing").

1. How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?

2. In general, how willing are you to take risks?

To facilitate the interpretation of the coefficients obtained from the econometric analyses, these items were entered in the regressions as z-scores. To construct *WillRisk* and *WillGiveup* we calculated the z-score on each scale. Participants were further asked to rate the following six items on a scale from: 5 ("Almost never") to 1 ("Almost always"):

1. I plan tasks carefully
2. I am self-controlled
3. I am a careful thinker
4. I save regularly
5. I like to think about complex problems
6. I am more interested in the present than the future

To construct *Impulsiveness* we calculated the unweighted average of the z-scores of each item. For this calculation the sixth item was reversed. Thus, more impulsive participants are believed to have a higher *Impulsiveness* score.

In sum, *WillRisk* is supposed to capture risk preferences, *WillGiveup* standard time preferences, and *Impulsiveness* present bias. No Likert scale measure reflecting loss aversion was available.

3.2.6 Dependent variables

We used three types of dependent variables derived from participants' stated adoption decisions on light bulbs, appliances, and retrofit measures, representing low-cost, medium-cost, and high-cost technologies, respectively. First, participants who had purchased a new light bulb within the last two years were asked to identify the type of bulb they had most recently purchased among pictures of a light emitting diode (LED), a compact fluorescent light bulb, a halogen bulb, and an incandescent light bulb. The purchase of an LED was retained as the energy-efficient decision. Second, participants who had bought a new appliance (refrigerator or fridge/freezer combination, freezer, dishwasher, washing machine) within the last five years were asked whether their most recent purchase (to minimize recall bias) was, to the best of their knowledge, a top-rated energy-efficient appliance. To further limit the effects of recall bias, we only included in our analyses appliance adoption decisions that were made from 2014 forward (that is, in the two years preceding the study). Third, if participants had implemented a retrofit measure within the last ten years (insulation of roof or ceiling, insulation of exterior walls, insulation of basement, installation of double-glazed windows, or installation of triple-glazed windows), this was considered an energy-efficient decision. This question was only shown to participants who stated that they (or any other household member) had actively decided or taken part in a decision to make their residence more energy efficient (to limit hypothetical bias). Participants who indicated that their landlord or property management would decide on retrofit measures were excluded.

Compared to previous literature, our methods of eliciting technology adoption focused only on adoption and additionally compared adoption of energy-efficient and non-EET for one specific decision; furthermore, respondents indicated the adoption decision date, which al-lowed us to control for recall bias.

(3) $$y_{ik} = \begin{cases} 1 & if \quad y_{ik}^* > 0 \\ 0 & otherwise \end{cases}$$

(4) $$y_{ik}^* = \gamma_{0k} + \gamma_{1k}\alpha_k + \gamma_{2k}\delta_k + \gamma_{3k}\beta_k + \gamma_{4k}\lambda_k + \sum_{j=5}\gamma_k X_{ijk} + \varepsilon_{ik} \quad ,$$

where i denotes the individual household, k stands for the technology type, α, δ, β and λ are the parameters reflecting risk preferences, standard time preferences, present bias and loss aversion, respectively; y_{ik}^{*} is the latent variable, X_{ijk} are control variables, and ε_{ik} is the error term. In a probit model, ε_{ik} is assumed to be normally distributed.

3.2.7 Control variables

We included information on demographic characteristics, dwelling characteristics, and participant attitudes to control for their potential to confound relationships between preferences over time, risk and losses and EET adoption decisions. The set of control variables also contained country dummies and product category dummies (for appliances). Descriptive statistics appear in Table A1 in the Appendix.

While this rich set of covariates should help explain EET adoption and mitigate a potential omitted variable bias, it also bears the risk of including bad controls (Angrist and Pischke 2009, pp. 64). That is, some of the control variables may themselves be outcome variables. Given our interest in the role of preferences over time, risk and losses, control variables such as *income*, *education*, likelymove, *renting*, or *capitalaccess* could be driven by these preference parameters.[9] In this case, the effects of the preference parameters on the adoption of EET may be mainly through these bad control variables, potentially leading to erroneous inferences.

To assess the impact of bad controls on our findings, we included estimated three types of models, which differ by the sets of control variables employed. Model 1 (M1) only includes the four parameters representing preferences over risk, time and losses, together with country dummies and product category dummies (for appliances). Model 2 (M2) also contains socio-demographic characteristics and hence is similar to the specifications in Heutel (2017) or Bradford et al. (2014), for example. Finally, Model 3 (M3) includes the most comprehensive set of covariates and is expected to

9 For example, educational outcomes were found to be higher for more patient children (Castillo et al. 2011) and more risk-averse children (Castillo et al. 2018).

predict EET adoption particularly well, but may also be prone to bad controls and has lower degrees of freedom. The control variables included in Models 2 and 3 are described in detail in Table 7.

Table 7: Description of control variables.

Label	Description
M2 and M3	
Age	Respondent age in years.
Gender	Dummy = 1, if respondent is male.
Income	Household annual income (after taxes) in 1000 euro per year (using midpoint of eleven income categories, and the lower level of the highest category).
Education	Dummy = 1 if level equal to or higher than country median. Considered levels: no degree or certificate/trade or vocational certificate /high school or equivalent/higher education.
Household size	Number of household members.
M3	
Likelymove	Dummy = 0, if household would likely not change its primary residence in the following 10 years, = 1 if it would likely change within the next 5 to 10 years, and = 2 if it would likely change within the next 5 years.
Renting	Dummy = 1, if the household is renting the current dwelling.
individual_meter	Dummy = 1 if the household has its own electricity meter.
Homesize	Residence space used for living (excluding garage, cellar, attic, etc.) in 100 square meters (using midpoint of four categories, and the lower level of the highest category).
Buildage	Age of the building calculated by subtracting the midpoint year (of the selected category describing when the dwelling was built) from the year of the survey (i.e. 2016). These categories are < 1920, 1921-1944, 1945-1959, 1960-1969, 1970-1979, 1980-1989, 1990-1999, 2000-2009, > 2009; for the first and last category, we used the upper and lower limit respectively.
Detached housing	Dummy = 1 if house was detached.
Main bulb	Dummy = 1, if the new bulb was a main bulb (or part of the main fixture) in the living/dining room.
Env_ID	Score reflecting environmental identity (adapted from Whitmarsh and O'Neill 2010). Constructed using the equally weighted responses to the subsequent scale items (1= strongly disagree to 5= strongly agree): "Please rate how much you agree with the following statements (i) To save energy is an important part of who I am. (ii) I think of myself as an energy conscious person. (iii) I think of myself as someone who is very concerned with environmental issues. (iv) Being environmentally friendly is an important part of who I am."
Socialnorm	Score reflecting social norms. Constructed using the responses to the following scale item (1= very unfavorable to 5= very favorable: "In general, what do you think your family's, friends' or colleagues' views would be of you purchasing energy efficient products?"
Capitalaccess	Subjective assessment of a household's access to capital. Constructed using the responses to the following question (1= very poor access to 5= very good access): "How would you categorize your access to loans/credits/capital?"
Incentivized	Dummy = 1, if respondent was incentivized.

4 Results

We estimated three individual probit models for the EET-adoption decisions on LEDs, appliances and retrofit measures. For all measures, we estimated an all-countries model, where observations from all eight countries were pooled, and eight individual country models. To save space, we subsequently present and discuss in detail the findings for the all-countries model, and refer to the Annex for the presentation of the country-specific models. For comparison, we also report findings, where preferences for time and risk were elicited via Likert scales rather than via MPL experiments. Finally, we report results on whether failing to include all parameters reflecting preferences for time, risk and losses in the econometric analysis will result in an omitted variable bias, and hence lead to erroneous policy implications.

4.1 Results on adoption of energy-efficient technologies

We present and discuss the findings for the specification where preferences for time, risk and losses were elicited via MPLs. Subsequently we briefly discuss the findings where these preferences are captured via Likert scales.

4.1.1 Results on experiment-based elicitation of preferences

Estimation results for the three models appear in Table 8. We first present and discuss the findings for M1 and then move on to M2 and M3.

Results for M1

The findings for α suggest that less risk-averse respondents (i.e. a higher α) were more likely to have adopted an energy efficient appliances. For LEDs and retrofit, however, the associated coefficient is just shy of being statistically significant. Individuals with high standard time discount factors (δ) were also more likely to have selected an LED as their most recent light bulb purchase. In comparison, the associated coefficient is slightly shy of being statistically significant at conventional levels for retrofit measures, and non-significant for appliances. The preference parameter reflecting present bias β is positively and significantly correlated with the adoption of all three EETs. Thus, individuals with a higher present bias (i.e. a lower β) were less likely to have adopted LEDs, energy- efficient appliances, and retrofit measures. For example, an increase in the present bias discount factor by one standard deviation is associated with a 1.5 percentage-point increase in the propensity to adopt an LED, which corresponds to an increase in LED adoption of about 3.5 percent for a sample adoption rate of 41% (see Table A3). These findings for low cost, medium cost, and high cost EETs are consistent with O'Donoghue and Rabin (1999) who argue that present-biased individuals exhibit a higher tendency to procrastinate when costs are immediate. Finally, respondents with higher loss aversion (i.e. a higher λ) were less likely to have adopted LEDs and energy-efficient appliances. Yet, loss aversion appears to be unrelated to the adoption of LEDs, appliances, and retrofit measures.

Our findings on risk aversion are in line with Qiu et al. (2014), who found risk aversion to be correlated with the adoption of energy efficient appliances and retrofit measures, even though the MPLs to elicit risk preferences in Qiu et al. (2014) were context-specific, i.e. payments were expressed as "receiving life-time energy cost savings". In this case, the effect of risk (or time) preferences cannot be distinguished from context-specific factors (here: environmental benefits). The findings for standard time discounting (but not for present bias) for energy efficient light bulb adoption are consistent with Allcott and Taubinsky (2015) and Bradford et al. (2014). Our findings that present bias also matters for this choice may be explained by the fact that our analysis focused on LEDs, which are substantially more expensive than the CFLs considered in Allcott and Taubinsky (2015) or Bradford et al. (2014). In addition, since the experiment in Allcott and Taubinsky (2015) forced participants to make a choice, present bias as related to procrastination played no role in their study. In general, our findings for present bias are consistent with O'Donoghue and Rabin (1999) who argue that present-biased individuals exhibit a higher tendency to procrastinate when costs are immediate. Finally, our results on loss aversion are similar to Heutel (2017) who finds higher loss aversion to be associated with lower adoption of three of the ten measures considered in his study, i.e. with high efficient lights, AC replacement and alternative fuel vehicles.

Results for M2

Turning to M2, we observe that most of the findings for the four preference parameters are rather similar to M1, but, as expected, the P-values tend to be higher. The increase in the P-value (and decline in the marginal effect) is particularly large for the coefficient of risk aversion in the retrofit equation. Arguably, this may be due to bad controls. The findings for the additional covariates in M2 suggest that age was negatively related with LED adoption and positively related with energy efficient appliance adoption, but the effect for LEDs is just shy of being statistically significant. Gender is only found to be correlated with LED adoption. In contrast, higher income households were more likely to have adopted LEDs, energy efficient appliances, and retrofit measures. Education appears positively related to the adoption of LEDs and energy-efficient appliances, but – somewhat unexpectedly – negatively to retrofit measures. However, Bruderer Enzler et al. (2014) also found education to be negatively related to the adoption of retrofit measures. Possibly, better educated households live in better insulated dwellings, ceteris paribus. Household size was significantly correlated with the adoption of LEDs and retrofit measures, arguably because the related financial incentives--i.e. energy costs savings--are higher for larger households.

Results for M3

Looking a the results for M3, we first note that the findings for present bias appear to be robust across the three models. However, the marginal effects associated with α, and λ (and to a lesser extend also for δ)), tend to be smaller in magnitude and associated with (much) higher P-values compared to M1 and M2. This outcome is consistent with the interpretation that some of the additional covariates included such as *renting*, *likelymove* or *capitalaccess* are driven by these parameters. While the additional co-variates are generally able to predict adoption of EET, they may be bad controls, in particular for preferences for risk and losses. For example, and in line with the OECD cross-country study by Krishnamurthy and Kriström (2015), the coefficients associated with variables reflecting split incentives (*likelymove*, *renting*, *individual metering*) exhibit the expected signs and are statistically significant for the adoption of all three technologies. *Home size* (but compared to M2 no longer *household size*) is positively related to EET adoption and statistically significant for appliances and retrofits. Similarly, retrofit measures were more likely to have been implemented in detached housing. As expected, the propensity to have purchased an LED was larger if the new bulb was for a high-usage location (main bulb in the dining room / living room), reflecting greater financial savings incentives. Households living in newer buildings were more likely to have adopted both an LED and an energy efficient appliance. In contrast, newer buildings were correlated with a lower retrofit rate, arguably because they tend to already be equipped with good insulation and windows. As intuitively expected, households with better access to capital, higher environmental identity, or higher social norms were more likely to have adopted all three types of energy efficiency technologies. Finally, regardless of whether the MPLs to elicit time, risk, and loss aversion preferences, or present bias were incentivized, there were no significant effects on the relationships between these factors and the adoption of any of the three energy efficiency technologies.[10,11,12]

Finally, Table 8 also reflects differences in EET adoption across countries. For example, compared to the base country Germany, adoption of LEDs and energy-efficient appliances is lower in most countries, up to ca. 25 percentage points lower for LEDs in Romania. In comparison, retrofit adoption is higher in all countries compared to Germany, most likely because the home ownership rate is much lower in Germany than in the other countries.

For completeness, Tables A2 to A4 report the findings for the individual country models. Those are generally consistent with the findings presented in Table 8. Most likely because of the lower degrees

---

10 Including dummies reflecting the different stakes in the MPLs only marginally affects the findings presented in Table 8.

11 We also asked participants to report the EU energy label (A++ or A+++, A or A+, B or C, D or E) of the appliance they last purchased. In an alternative specification, purchase of an appliance with a label of A++ or better was considered an energy-efficient decision. To limit the effects of recall bias we only used appliance adoption decisions for 2016. Findings for this alternative are consistent with those reported in Table 8, but P-values were generally higher, arguably because of a lower sample size (1550 compared to 5465).

12 As an additional robustness check, we interact country dummies with the four parameters reflecting preferences for time, risk and losses. Based on the findings from a likelihood-ratio test between this interaction model and the (nested) non-interaction model we conclude that interaction terms have no explanatory power, i.e. unobservable variables (likely to take on different values across countries) are not affecting our findings.

of freedom, however, the P-values are generally higher, leading to fewer coefficients being statistically significant, in particular for the parameters reflecting individual preferences for time, risk and losses.

Table 8: Results (average marginal effects) of probit models for energy efficiency technology adoption decisions for the all-countries model and experiment-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis).

	LED			Appliances			Retrofit		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
$\alpha^{\dagger}$	0.00878	0.0065	0.0036	0.0143**	0.0126*	0.0083	0.0087	0.0052	-0.0008
	(0.196)	(0.277)	(0.542)	(0.045)	(0.072)	(0.216)	(0.169)	(0.403)	(0.899)
$\delta^{\dagger}$	0.0123**	0.0131**	0.0119**	-0.0002	-0.0012	-0.0032	0.0093	0.0068	0.0037
	(0.033)	(0.022)	(0.036)	(0.979)	(0.852)	(0.610)	(0.125)	(0.253)	(0.510)
$\beta^{\dagger}$	0.0147***	0.0160***	0.0160***	0.0126***	0.0121***	0.0115***	0.0107**	0.0105**	0.0123***
	(0.003)	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)	(0.028)	(0.027)	(0.009)
$\lambda^{\dagger}$	-0.0121**	-0.0080	-0.0063	-0.0102*	-0.0089	-0.0047	-0.0048	-0.0027	0.0002
	(0.024)	(0.135)	(0.224)	(0.077)	(0.123)	(0.405)	(0.378)	(0.611)	(0.969)
Age		-0.0006	-0.0021***		0.0018***	0.0003		0.0037***	0.0002
		(0.119)	(0.000)		(0.000)	(0.563)		(0.000)	(0.677)
Gender		0.0749***	0.0711***		-0.0013	0.0022		-0.0020	0.0072
		(0.000)	(0.000)		(0.902)	(0.826)		(0.841)	(0.445)
Income		0.0020***	0.0010***		0.0012***	0.0006**		0.0027***	0.0007***
		(0.000)	(0.000)		(0.000)	(0.041)		(0.000)	(0.007)
Education		0.0310***	0.0247**		0.0288**	0.0140		-0.0079	-0.0205**
		(0.005)	(0.024)		(0.012)	(0.206)		(0.478)	(0.049)
Hhsize		0.0057*	0.0011		0.0041	-0.0006		0.0187***	0.0037
		(0.089)	(0.757)		(0.353)	(0.869)		(0.000)	(0.261)
Likelymove			-0.0247***			-0.0233***			-0.0121**
			(0.000)			(0.000)			(0.037)
Renting			-0.0701***			-0.0397***			-0.2794***
			(0.000)			(0.002)			(0.000)
Individual_meter			0.0298*			0.0515***			0.0535***
			(0.070)			(0.001)			(0.001)
HomeSize			0.0134			0.0280**			0.0436***
			(0.269)			(0.026)			(0.001)
BuildAge			-0.0006***			-0.0004**			0.0007***
			(0.003)			(0.033)			(0.001)
Detached housing									0.0706***
									(0.000)
Main bulb			0.0686***						
			(0.000)						
Capitalaccess†			0.0316***			0.0213***			0.0264***
			(0.000)			(0.000)			(0.000)
Env_ID†			0.0331***			0.0656***			0.0645***
			(0.000)			(0.000)			(0.000)
Socialnorm†			0.0134**			0.0215***			0.0121**

			(0.011)			(0.000)			(0.018)
Incentivized			-0.0098			-0.0069			0.0008
			(0.324)			(0.509)			(0.935)
FR	-0.1094***	-0.1001***	-0.1123***	-0.2015***	-0.1935***	-0.1937***	0.2295***	0.2395***	0.1563***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IT	-0.0763***	-0.0728***	-0.1167***	0.0717***	0.0691***	0.0314	0.1307***	0.1360***	0.0282
	(0.000)	(0.000)	(0.000)	(0.003)	(0.005)	(0.208)	(0.000)	(0.000)	(0.153)
PL	0.0028	0.0399**	-0.0206	-0.1004***	-0.0706***	-0.1072***	0.3309***	0.3888***	0.2350***
	(0.881)	(0.043)	(0.326)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
RO	-0.2492***	-0.2083***	-0.2684***	-0.0293	0.0083	-0.0361	0.5201***	0.5977***	0.4375***
	(0.000)	(0.000)	(0.000)	(0.204)	(0.734)	(0.159)	(0.000)	(0.000)	(0.000)
ES	0.0313	0.0420**	-0.0045	-0.0635***	-0.0572***	-0.0879***	0.0796***	0.0937***	0.0039
	(0.101)	(0.028)	(0.821)	(0.004)	(0.009)	(0.000)	(0.000)	(0.000)	(0.849)
SE	-0.1277***	-0.1504***	-0.1114***	-0.1990***	-0.2223***	-0.1860***	0.0020	-0.0165	-0.0188
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.927)	(0.443)	(0.365)
UK	-0.1710***	-0.2014***	-0.1929***	-0.1098***	-0.1256***	-0.1089***	0.1733***	0.1401***	0.1040***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Appliance dummies				YES	YES	YES			
N	9630	9630	9630	5645	5645	5645	8430	8430	8430

*** p<0.01, ** p<0.05, * p<0.1; †z-score of the variable was used

4.1.2 Results on scale-based elicitation of preferences

Table 9 presents the findings for the all-country model when time and risk preferences are elicited via the one-item scales validated by Falk et al. (2016) and Dohmen et al. (2010, 2011). That is, *WillRisk* is assumed to reflect risk preferences, *WillGiveup* standard time preferences, and *Impulsiveness* present bias. Accordingly, the findings for M1 suggest that respondents who perceive themselves as less risk averse, more patient, and less impulsive, are more likely to have adopted all three EET measures considered. Only the coefficient associated with *WillRisk* in the appliance equation is not statistically significant. The results for M2 are quite similar to those for M1, yet P-values tend to be higher, as expected. For M3, P-values tend to be higher, and the coefficient levels smaller than in M1 and M2. Thus, in addition to the loss of degrees of freedom, bad controls are likely to explain this finding, similar to the findings in Table 8, where the parameters reflecting risk and time preferences were elicited via MPLs. We also note that, while the findings for the experiment and scale based measures are generally consistent (i.e. there is no statistically significant countervailing evidence) we also observe differences, in particular for risk (appliances and retrofit) and standard time preferences (appliances). Our results are also consistent with Fischbacher et al. (2015), who found risk preferences (as captured by scales) to be related with insulation measures, but not standard time preferences (as captured by MPL-based parameters). Finally, we note that for the remaining covariates, the results presented in Table 8 and Table 9 are very similar.

Table 9: Results (average marginal effects) of probit models for energy efficiency technology adoption decisions for the all-countries model and scale-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis).

	LED			Appliances			Retrofit		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
WillRisk†	0.0159***	0.0089*	0.0052	0.0011	0.0013	-0.0020	0.0126**	0.0116**	0.0116**
	(0.003)	(0.098)	(0.329)	(0.845)	(0.817)	(0.724)	(0.021)	(0.034)	(0.027)
WillGiveup†	0.0175***	0.0154***	0.0063	0.0214***	0.0209***	0.0071	0.0250***	0.0269***	0.0120**
	(0.001)	(0.005)	(0.254)	(0.000)	(0.000)	(0.223)	(0.000)	(0.000)	(0.025)
Impulsiveness†	-0.0279***	-0.0229***	-0.0019	-0.0450***	-0.0414***	-0.0106*	-0.0525***	-0.0472***	-0.0134**
	(0.000)	(0.000)	(0.733)	(0.000)	(0.000)	(0.057)	(0.000)	(0.000)	(0.013)
Age		-0.0005	-0.0020***		0.0019***	0.0003		0.0039***	0.0004
		(0.257)	(0.000)		(0.000)	(0.435)		(0.000)	(0.330)
Gender		0.0715***	0.0695***		-0.0025	0.0024		-0.0036	0.0045
		(0.000)	(0.000)		(0.807)	(0.813)		(0.721)	(0.634)
Income		0.0018***	0.0010***		0.0010***	0.0005*		0.0024***	0.0006**
		(0.000)	(0.000)		(0.001)	(0.060)		(0.000)	(0.013)
Education		0.0245**	0.0239**		0.0145	0.0109		-0.0195*	-0.0233**
		(0.026)	(0.029)		(0.203)	(0.325)		(0.078)	(0.026)
Hhsize		0.0050	0.0006		0.0048	-0.0001		0.0185***	0.0032
		(0.130)	(0.864)		(0.250)	(0.984)		(0.000)	(0.321)
Likelymove			-0.0259***			-0.0235***			-0.0141**
			(0.000)			(0.000)			(0.015)
Renting			-0.0701***			-0.0378***			-0.2781***
			(0.000)			(0.003)			(0.000)
Individual_meter			0.0292*			0.0493***			0.0493***
			(0.077)			(0.002)			(0.002)
HomeSize			0.0135			0.0280**			0.0423***
			(0.264)			(0.026)			(0.001)
BuildAge			-0.0006***			-0.0004**			0.0007***
			(0.003)			(0.031)			(0.000)
Detached housing									0.0710***
									(0.000)
Main bulb			0.0672***						
			(0.000)						
Capitalaccess†			0.0305***			0.0192***			0.0218***
			(0.000)			(0.001)			(0.000)
Env_ID†			0.0309***			0.0612***			0.0562***
			(0.000)			(0.000)			(0.000)
Socialnorm†			0.0120**			0.0205***			0.0096*
			(0.023)			(0.000)			(0.063)

Incentivized			-0.0090			-0.0055			0.0008
			(0.365)			(0.597)			(0.931)
FR	-0.1028***	-0.0943***	-0.1129***	-0.1864***	-0.1805***	-0.1906***	0.2413***	0.2496***	0.1581***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IT	-0.0863***	-0.0803***	-0.1204***	0.0657***	0.0653***	0.0323	0.1150***	0.1231***	0.0240
	(0.000)	(0.000)	(0.000)	(0.006)	(0.007)	(0.195)	(0.000)	(0.000)	(0.224)
PL	-0.0048	0.0321	-0.0243	-0.1054***	-0.0815***	-0.1078***	0.3214***	0.3739***	0.2301***
	(0.801)	(0.104)	(0.248)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RO	-0.2711***	-0.2265***	-0.2747***	-0.0496**	-0.0161	-0.0379	0.4871***	0.5616***	0.4239***
	(0.000)	(0.000)	(0.000)	(0.031)	(0.510)	(0.140)	(0.000)	(0.000)	(0.000)
ES	0.0247	0.0374*	-0.0076	-0.0638***	-0.0588***	-0.0860***	0.0728***	0.0851***	-0.0004
	(0.195)	(0.052)	(0.706)	(0.003)	(0.007)	(0.000)	(0.000)	(0.000)	(0.983)
SE	-0.1241***	-0.1433***	-0.1128***	-0.1874***	-0.2028***	-0.1812***	0.0077	-0.0046	-0.0190
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.718)	(0.829)	(0.360)
UK	-0.1749***	-0.2012***	-0.1936***	-0.1136***	-0.1244***	-0.1091***	0.1639***	0.1365***	0.1015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Appliance dummies				YES	YES	YES			
N	9630	9630	9630	5645	5645	5645	8430	8430	8430

*** p<0.01, ** p<0.05, * p<0.1; † z-score of the variable was used

4.1.3 Results on omitted variable bias

In principle, failure to include any of the four variables reflecting individual preferences for time, risk and losses when modelling EET adoption results in an omitted variable bias and hence to misguided policy recommendations. We therefore estimated probit models with only one of these preference variables included as a covariate in the adoption regression equation. The findings presented in Table 10 for M1 does not provide convincing empirical evidence that omitting one or several of the time and risk or loss-aversion parameters when estimating any of the three EET adoption equations leads to an omitted variable bias. A similar result holds for the specifications M2 and M3 (see Annex Table A5 and Table A6).

Table 10: Results (average marginal effects) of probit models for energy efficiency technology adoption decisions for the all-countries model and experiment-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis). Specification M1.

			LED		
$\alpha^{\dagger}$	0.0078	-0.0011			
	(0.196)	(0.822)			
$\delta^{\dagger}$	0.0123**		0.0082*		
	(0.033)		(0.098)		
$\beta^{\dagger}$	0.0147***			0.0117**	
	(0.003)			(0.019)	
$\lambda^{\dagger}$	-0.0121**				-0.0091*
	(0.024)				(0.067)
N	9630	9630	9630	9630	9630
			Appliances		
$\alpha^{\dagger}$	0.0143**	0.0115**			
	(0.044)	(0.039)			
$\delta^{\dagger}$	-0.0002		-0.0070		
	(0.975)		(0.193)		
$\beta^{\dagger}$	0.0123***			0.0119***	
	(0.006)			(0.004)	
$\lambda^{\dagger}$	-0.0102*				-0.0038
	(0.078)				(0.469)
N	5465	5465	5465	5465	5465
			Retrofit		
$\alpha^{\dagger}$	0.0087	0.0032			
	(0.169)	(0.538)			
$\delta^{\dagger}$	0.0093		0.0041		
	(0.125)		(0.417)		
$\beta^{\dagger}$	0.0107**			0.0095**	
	(0.028)			(0.046)	
$\lambda^{\dagger}$	-0.0048				-0.0020
	(0.378)				(0.691)
N	8430	8430	8430	8430	8430

*** p<0.01, ** p<0.05, * p<0.1; †z-score of the variable was used

5 Conclusion

This report empirically studies factors related to the adoption of three types of EET measures, which differ by costs: LEDs, energy efficient appliances and retrofit measures. In contrast to previous studies, we focus on the role of risk aversion, standard time preferences, present bias, and loss aversion. The analysis relies on a large representative sample drawn from eight EU countries. Time, risk, and loss aversion preferences were elicited and jointly estimated from participant choices in context-free MPLs, more than half of which were incentivized. In an alternative specification of the econometric models we instead include scale-based measures of time and risk preferences, which are easier to obtain than through experimental measures. In addition to these preference parameters, our econometric analysis included covariates for socio-demographic characteristics, individual attitudes, and dwelling characteristics, thus controlling for a broad set of confounding factors, some of which may themselves be the outcome of preferences for time, risk and losses, and hence be so-called bad controls. To explore the robustness of findings, we therefore estimated three types of models, which differed by the set of covariates included. The findings on the relation of socio-demographic characteristics, individual attitudes (notably environmental identity and social norms) and dwelling characteristics are consistent with the extant empirical literature.

5.1 Findings on preferences for time, risk and losses

The results based on the MPL-based preference measures suggest that more present-biased individuals are less likely to adopt LEDs, energy efficient appliances and retrofit measures. Our findings further provide (weak) evidence that more risk-averse individuals, more loss-averse individuals and individuals exhibiting a lower time discount factor are less likely to have adopted EETs. Of the three measures considered, this evidence is strongest for LEDs and weakest for retrofit measures.

5.2 Findings on experiment- versus scale-based measures

While the findings when using experiment- and scale-based measures to elicit time and risk preferences are generally consistent, we also observe some differences, mostly for risk and standard time preferences. Thus, empirical findings on the role of time and risk preferences for explaining individual behavior and corresponding policy implications may depend on the type of measure used to elicit these preferences. Our findings on differences in finding when using experiment- versus scale based measures support the view that experiment- and scale-based measures capture different aspects of preferences. Experiment-based measures better reflect the financial domain, while scale based measures reflect more general aspects of risk and time preferences. Future analyses may include both types of measures, or, as recently suggested by Falk et al. (2017), employ an aggregate of both measures.

5.3 Findings on omitted variable bias

Interestingly, our findings do not provide convincing empirical evidence that omitting one or several of the time and risk or loss-aversion parameters when estimating any of the three EET adoption equations is likely to lead to an omitted variable bias or to erroneous policy recommendations. This finding should be reassuring when assessing previous research (which typically only includes one or two of these parameters). It also indicates that it might not be necessary to include all four parameters in future research

5.4 Relating findings to factors underlying the IDR

Our findings may also be tied to the framework of the factors underlying the implicit discount rates (IDRs) developed in BRISKEE deliverable D2.1. This framework distinguishes three broad categories, i.e. (i) preferences, (ii) predictable (ir)rational behavior, and (iii) external barriers to energy efficiency. Our results provide empirical evidence that EET adoption is related to preferences such as standard time discounting, preferences for risk and losses, environmental identity and social norms. In particular, the results suggest that present-biased individuals were less likely to adopt LEDs, energy efficient appliances and retrofit measures. Thus, we find present bias, which exemplifies a behavioral bias (and therefore has some welfare implications), to help explain the energy efficiency paradox. Last but not least, the variables reflecting split-incentives, that is ownership status (i.e. renters versus owners), the likelihood of the household moving in the near future, as well as whether household electricity use was measured individually) were found to have significant effects on energy-efficiency adoption, thus confirming and extending previous findings in the literature. Similarly, for all EET measures considered, lack of capital was found to inhibit adoption.

5.5 Implications for policymaking

Finally, our results also offer insights for policymaking. Specifically, the findings on present bias provide a rationale for policy interventions that alter the temporal association of financial implications and technology adoption. For present-biased individuals, such policies may include immediate rebates or low-interest loans for energy efficiency measures rather than tax breaks, which generate financial benefits in the future only. The findings on split-incentives support current measures addressing information asymmetries (e.g. certificates for buildings, labelling for appliances and bulbs), command-and-control type interventions referring to building codes (for insulation), individual metering (electricity or gas) requirements, or regulations on embedding costs for retrofit-measures into a lease. Most of these policies are already in place to varying degrees in the countries included in our sample.

Literature

Abdellaoui, M., Bleichrodt, H., Paraschiv, C., 2007. Loss aversion under prospect theory: A parameter-free measurement. Management Science, 53(10), 1659-1674.

Ainslie, G.W., 1974. Impulse control in pigeons. Journal of the experimental analysis of behavior 21, 485–9. doi:10.1901/jeab.1974.21-485

Allcott, H., 2011. Social norms and energy conservation. Journal of Public Economics 95, 1082–1095. doi:10.1016/j.jpubeco.2011.03.003

Allcott, H., Mullainathan, S., 2010. Behavioral science and energy policy. Science 327, 1204–1205. doi:10.1126/science.1180775.

Allcott, H. and Greenstone, M., 2012. Is There an Energy Efficiency Gap? Journal of Economic Perspectives 26 (1), 3-28.

Allcott, H. and Taubinsky, D., 2015, Evaluating Behaviorally Motivated Policy: Experimental Evidence from the Lightbulb Market. American Economic Review 105(8), 2501–2538, http://dx.doi.org/10.1257/aer.20131564.

Allcott, H., Wozny, N., 2014. Gasoline prices , fuel economy, and the energy paradox. Review of Economics and Statistics XCVI, 1–59. doi:10.1162/REST_a_00419.

Andersen, S., Harrison, G. W., Lau, M. I., Rutström, E. E., 2008, Eliciting risk and time preferences. Econometrica, 76(3), 583-618.

Becker, G., DeGroot, M., Marschak, J., 1964. Measuring utility by a single-response sequential method. Behavioral science 9, 226–232.

Bradford, D., Courtemanche, C., Heutel, G., McAlvanah, P., Ruhm, C., 2014. Time preferences and consumer behavior. Working Paper Series. doi:10.3386/w20320.

Bruderer Enzler, H., Diekmann, A., Meyer, R., 2014. Subjective discount rates in the general population and their predictive power for energy saving behavior. Energy Policy 65, 524–540. doi:10.1016/j.enpol.2013.10.049.

Busse, M.R., Knittel, C.R., Zettelmeyer, F., 2013. Are consumers myopic? Evidence from new and used car purchases. American Economic Review 103, 220–256. doi:10.1257/aer.103.1.220.

Castillo, Ferraro, P., M., Jordan, J., Petrie, R., 2011. The dotay and tomorrow of kids: time preferences and educational outcomes of children. Journal of Public Economics 95, 1377-1385.

Castillo, M., Jordan, J., Petrie, R., 2018. Chirldren's rationality, risk attitudes and field behavior. European Economic Review 102, 62-81.

Cohen, F., Glachant, M., Söderberg, M., 2017. Consumer myopia, imperfect competition and the energy efficiency gap: Evidence from the UK refrigerator market. European Economic Review 93, 1-23.

Coller, M., Williams, M.B., 1999. Eliciting individual discount rates. Experimental Economics 2, 107–127. doi:10.1007/BF01673482

Dohmen, T., Falk, A., Huffman, D., Sunde, U., 2010. Are risk aversion and impatience related to cognitive ability? American Economic Review 100 (3), 1238–1260. https://doi.org/10.1257/aer.100.3.1238.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: measurement, determinants, and behavioral consequences. Journal of the European Economic Association 9, 522–550. doi:10.1111/j.1542-4774.2011.01015.x

Falk, A., Dohmen, T., Becker, A., Huffman, D., Sunde, U., 2016. The preference survey module: A validated instrument for measuring risk, time, and social preferences. IZA Discussion Paper No. 9674.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., 2017. Global Evidence on Economic Preferences. NBER Working Paper No. 23943 (October 2017). doi:10.3386/w23943

Farsi, M., 2010. Risk aversion and willingness to pay for energy efficient systems in rental apartments. Energy Policy 38, 3078–3088. doi:10.1016/j.enpol.2010.01.048

Fischbacher, U., Schudy, S., Teyssier, S., 2015. Heterogeneous preferences and investemnts in energy savings measures. Munich Discussion Paper No. 2015-11. Department of Economics, University of Munich.

Frederick, S., Loewenstein, G., O'Donoghue, T., 2002. Time discounting and time preference: A critical review. Journal of Economic Literature 40, 351–401. doi:10.1257/002205102320161311.

Frederick, S., 2005. Cognitive Reflection and Decision Making. Journal of Economic Perspectives 19, 25–42. doi:10.1257/089533005775196732.

Gerarden, T., Newell, R.G., Stavins, R.N., 2015. Deconstructing the energy-efficiency gap: Conceptual frameworks and evidence. American Economic Review: Papers and Proceedings 105, 183–186. doi:10.1257/aer.p20151012.

Gillingham, K., Palmer, K., 2014. Bridging the energy efficiency gap: policy insights from economic theory and empirical analysis. Rev. Environ. Econ. Policy 81 (1), 18–38.

Greene, D. L., 2011. Uncertainty, loss aversion, and markets for energy efficiency. Energy Economics 33 (4), 608-616.

Greene, D., German, J., Delucchi, M., 2009. Fuel economy: The case for market failure. In Reducing Climate Impacts in the Transportation Sector, ed. D. Sperling, and J. Cannon. Philadelphia: Springer Science+Business Media.

Harrison, G., Johanson, E., McInnes, M., Rutström, E., 2005. Risk Aversion and Incentive Effects: Comment. The American Economic Review 95(3), 897-901.

Harrison, G., Lau, M., Rutström, E., 2007. Estimating Risk Attitudes in Denmark: A Field Experiment. Scandinavian Journal of Economics, Vol. 109, No. 2, pp. 341-368. http://dx.doi.org/10.1111/j.1467-9442.2007.00496.x

Heutel, G., 2017. Prospect theory and energy efficiency. NBER Working Paper 23692. August. http://www.nber.org/papers/w23692.

Hey, J.D., Orme, C., 1994. Investigating generalizations of expected utility theory using experimental data. Econometrica 62, 1291–1326.

Holt, C., Laury, S., 2002. Risk aversion and incentive effects. American Economic Association 92, 1644–1655. doi:10.2139/ssrn.893797.

International Energy Agency (IEA) 2016. World Energy Outlook 2016. International Energy Agency, Paris.

Jaffe, A.B., Stavins, R.N., 1994. The energy paradox and the diffusion of conservation technology. Resources and Energy Economics 91–122.

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 66, 497–527.

Karlan, D.S. 2005. Using Experimental Economics to Measure Social Capital and Predict Financial Decisions. The American Economic Review 95, 1688–1699.

Krishnamurthy, C.K.B., Kriström, B., 2015. How large is the owner-renter divide in energy efficient technology? Evidence from an OECD cross-section. The Energy Journal 36(4), 85-104. doi:10.5547/01956574.36.4.ckri.

Laibson, D., 1997. Golden eggs and hyperbolic discounting. Quarterly Journal of Economics 112, 443–477. doi:10.1162/003355397555253.

Liu, E.M., 2013. Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in China. Review of Economics and Statistics 95, 1386–1403. doi:10.1162/REST_a_00295.

Loewenstein, G., Prelec, D., 1992. Anomalies in intertemporal choice: Evidence and an interpretation. The Quarterly Journal of Economics 107, 573–597. doi:10.2307/2118482.

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

Mills, B.F., Schleich, J., 2014. Household transitions to energy efficient lighting. Energy Economics 46, 151–160. https://doi.org/10.1016/j.eneco.2014.08.022.

Newell, R.G., Siikamaki, J. V, 2015. Individual time preferences and energy efficiency. American Economic Review 105, 196–200. doi:10.1257/aer.p20151010.
O'Donoghue, T., Rabin, M., 1999. Doing it now or later, American Economic Review, 89(1), 103-124.
Prelec, D., 1998. The Probability Weighting Function. Econometrica, 66(3), 497-527. doi:10.2307/2998573
Qiu, Y., Colson, G., Grebitus, C., 2014. Risk preferences and purchase of energy-efficient technologies in the residential sector. Ecological Economics 107, 216–229. doi:10.1016/j.ecolecon.2014.09.002
Ramos, A., Gago, A., Labandeira, X., Linares, P., 2015. The role of information for energy efficiency in the residential sector. Energy Economics 52, S17–S29. doi:10.1016/j.eneco.2015.08.022
Samuelson, P. A., 1937. A note on measurement of utility. The Review of Economic Studies, 4(2), 155-161.
Schleich, J., Gassmann, X., Faure, C. Meissner, T., 2016. Making the Implicit Explicit: A Look inside the Implicit Discount Rate. Energy Policy 97, 321-331. http://dx.doi.org/10.1016/j.enpol.2016.07.044
Sorrell, S., O'Malley, E., Schleich, J., Scott, S., 2004. The economics of energy efficiency. Edward Elgar.
Takeuchi, K., 2011. Non-parametric test of time consistency: Present bias and future bias. Games and Economic Behavior 71 (2), 456-478. http://dx.doi.org/10.1016/j.geb.2010.05.005
Tanaka, T., Camerer, C.F., Nguyen, Q., 2010. Risk and time treferences: linking experimental and household survey data from Vietnam. American Economic Review 100, 557–571. doi:10.1257/aer.100.1.557
Thaler, R.H., 1991. Some empirical evidence on dynamic inconsistency. Economics Letters 8(3), 201–207. doi:10.1016/0165-1765(81)90067-7.
Tversky A., Kahneman D., 1992. Advances in Prospect Theory: Cumulative Representation of Uncertainty. Journal of Risk and Uncertainty 5(4), 297-323.
Whitmarsh, L., O'Neill, S., 2010. Green identity, green living? The role of pro-environmental self-identity in determining consistency across diverse pro-environmental behaviours. Journal of Environmental Psychology 30, 305–314. doi:10.1016/j.jenvp.2010.01.00
Zuckerman, M. 1994. Behavioral Expression and Biosocial Bases of Sensation Seeking. New York : Cambridge University Press.

Annex

Table A1: Summary statistics, mean and standard deviation of the dependent variable and covariates.

	All countries	*France*	*Germany*	*Italy*	*Poland*	*Romania*	*Spain*	*Sweden*	*United Kingdom*
LED	0.409 (0.492)	0.375 (0.484)	0.489 (0.500)	0.422 (0.494)	0.489 (0.500)	0.248 (0.432)	0.515 (0.500)	0.367 (0.482)	0.314 (0.464)
Appliances	0.754 (0.431)	0.617 (0.486)	0.824 (0.381)	0.881 (0.324)	0.717 (0.451)	0.836 (0.370)	0.770 (0.421)	0.613 (0.487)	0.729 (0.445)
Retrofit	0.469 (0.499)	0.516 (0.500)	0.323 (0.468)	0.391 (0.488)	0.636 (0.481)	0.782 (0.413)	0.347 (0.476)	0.336 (0.472)	0.456 (0.498)
WillRisk†	0.000 (1.000)	-0.089 (0.942)	-0.237 (0.942)	-0.131 (0.984)	0.144 (0.998)	0.374 (1.012)	0.139 (0.941)	0.001 (1.010)	-0.113 (1.050)
WillGiveup†	0.000 (1.000)	-0.201 (0.995)	-0.053 (0.945)	0.083 (0.954)	0.044 (1.044)	0.263 (1.160)	0.013 (0.927)	-0.134 (0.988)	0.016 (0.947)
Impulsiveness†	0.000 (1.000)	0.238 (0.957)	-0.029 (0.922)	-0.124 (0.968)	0.028 (1.065)	-0.291 (0.936)	0.063 (1.001)	0.152 (1.067)	-0.069 (0.995)
Age	40.882 (12.870)	41.996 (13.574)	42.405 (13.219)	42.792 (12.650)	38.299 (11.868)	36.203 (10.215)	41.482 (12.317)	41.766 (13.893)	41.231 (13.318)
Gender	0.500 (0.500)	0.493 (0.500)	0.504 (0.500)	0.495 (0.500)	0.502 (0.500)	0.508 (0.500)	0.504 (0.500)	0.496 (0.500)	0.496 (0.500)
Income	30.087 (23.139)	29.694 (19.736)	36.499 (21.303)	29.022 (17.490)	14.469 (10.211)	10.384 (10.479)	27.448 (16.813)	42.117 (25.512)	47.951 (28.769)
Education	0.640 (0.480)	0.575 (0.495)	0.508 (0.500)	0.820 (0.385)	0.523 (0.500)	0.663 (0.473)	0.614 (0.487)	0.879 (0.326)	0.605 (0.489)
Hhsize	2.841 (1.503)	2.694 (1.267)	2.456 (1.441)	3.085 (1.273)	3.179 (1.433)	3.239 (2.429)	3.008 (1.179)	2.369 (1.319)	2.680 (1.318)
Likelymove	0.899 (0.891)	1.001 (0.891)	0.769 (0.883)	0.738 (0.864)	0.885 (0.898)	0.948 (0.889)	0.811 (0.882)	1.112 (0.875)	0.995 (0.879)
Renting	0.314 (0.464)	0.357 (0.479)	0.558 (0.497)	0.203 (0.402)	0.164 (0.371)	0.213 (0.409)	0.226 (0.419)	0.465 (0.499)	0.337 (0.473)
Inidvidual meter	0.864 (0.343)	0.941 (0.237)	0.880 (0.325)	0.908 (0.288)	0.835 (0.371)	0.952 (0.215)	0.828 (0.377)	0.791 (0.406)	0.777 (0.416)
HomeSize	1.050 (0.451)	1.081 (0.435)	1.080 (0.440)	1.144 (0.432)	0.916 (0.451)	0.902 (0.424)	1.078 (0.431)	1.041 (0.450)	1.119 (0.478)
BuildAge	42.160 (25.960)	42.779 (29.071)	46.292 (26.357)	38.966 (23.439)	38.741 (24.715)	37.056 (18.477)	30.294 (20.797)	49.166 (24.322)	54.501 (28.988)
Detached housing	0.334 (0.472)	0.498 (0.500)	0.332 (0.471)	0.308 (0.462)	0.318 (0.466)	0.366 (0.482)	0.271 (0.445)	0.344 (0.475)	0.243 (0.429)
Main bulb	0.724 (0.447)	0.713 (0.452)	0.674 (0.469)	0.796 (0.403)	0.791 (0.407)	0.882 (0.323)	0.772 (0.420)	0.419 (0.494)	0.670 (0.470)
Capitalaccess†	0.000 (1.000)	-0.136 (0.944)	0.048 (0.968)	-0.202 (0.982)	0.105 (0.957)	-0.196 (1.013)	-0.145 (0.968)	0.226 (1.136)	0.309 (0.928)
Env_ID†	0.000 (1.000)	0.092 (0.919)	-0.139 (0.978)	0.300 (0.870)	0.013 (0.980)	0.142 (0.964)	0.160 (0.934)	-0.450 (1.093)	-0.193 (1.081)
Socialnorm†	0.000 (1.000)	-0.485 (1.020)	0.307 (0.897)	-0.065 (1.023)	-0.009 (0.934)	-0.008 (1.096)	0.122 (0.959)	0.200 (0.965)	-0.016 (0.917)
Incentivized	0.552 (0.497)	0.600 (0.490)	0.449 (0.497)	0.450 (0.498)	0.600 (0.490)	0.719 (0.450)	0.600 (0.490)	0.601 (0.490)	0.449 (0.498)
Last appliance: refrigerator	0.319 (0.466)	0.318 (0.466)	0.279 (0.449)	0.316 (0.465)	0.298 (0.457)	0.397 (0.490)	0.321 (0.467)	0.257 (0.437)	0.358 (0.479)

Last appliance: freezer	0.082 (0.274)	0.091 (0.287)	0.099 (0.299)	0.065 (0.246)	0.047 (0.213)	0.074 (0.261)	0.080 (0.271)	0.108 (0.310)	0.103 (0.304)
Last appliance: dishwasher	0.179 (0.384)	0.236 (0.425)	0.210 (0.408)	0.167 (0.373)	0.191 (0.393)	0.051 (0.221)	0.184 (0.387)	0.297 (0.457)	0.121 (0.327)
Last appliance: washing machine	0.420 (0.494)	0.355 (0.479)	0.411 (0.492)	0.453 (0.498)	0.464 (0.499)	0.478 (0.500)	0.416 (0.493)	0.338 (0.473)	0.418 (0.493)
N	15055	2000	2002	2000	2008	1529	2001	1515	2000

†z-score of the variable was used

Table A2: Results (average marginal effects) of probit models for *LED* adoption decisions for experiment-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis).

	France			Germany			Italy			Poland		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
$\alpha^{\dagger}$	-0.0223	-0.0225	-0.0275*	0.0115	0.0093	0.0008	0.0155	0.0133	0.0093	0.0163	0.0163	0.0160
	(0.174)	(0.177)	(0.096)	(0.511)	(0.589)	(0.965)	(0.402)	(0.468)	(0.614)	(0.344)	(0.342)	(0.335)
$\delta^{\dagger}$	-0.0089	-0.0107	-0.0087	0.0109	0.0129	0.0090	0.0288*	0.0275	0.0251	0.0162	0.0160	0.0135
	(0.576)	(0.498)	(0.573)	(0.514)	(0.437)	(0.583)	(0.090)	(0.103)	(0.136)	(0.314)	(0.318)	(0.387)
$\beta^{\dagger}$	-0.0231	-0.0217	-0.0248*	0.0636*	0.0675**	0.0660**	0.0229*	0.0249*	0.0221	0.0142	0.0137	0.0130
	(0.221)	(0.161)	(0.065)	(0.053)	(0.027)	(0.017)	(0.099)	(0.081)	(0.109)	(0.276)	(0.288)	(0.334)
$\lambda^{\dagger}$	0.0057	0.0098	0.0171	0.0002	0.0043	0.0079	0.0027	0.0033	0.0027	-0.0264*	-0.0200	-0.0156
	(0.689)	(0.490)	(0.220)	(0.990)	(0.777)	(0.593)	(0.861)	(0.834)	(0.855)	(0.100)	(0.211)	(0.323)
Age		-0.0009	-0.0030***		-0.0008	-0.0027**		-0.0019*	-0.0026**		-0.0009	-0.0028**
		(0.401)	(0.007)		(0.451)	(0.024)		(0.093)	(0.023)		(0.473)	(0.031)
Gender		0.0087	0.0141		0.1116***	0.1109***		0.0224	0.0081		0.0623**	0.0610**
		(0.750)	(0.595)		(0.000)	(0.000)		(0.424)	(0.773)		(0.025)	(0.027)
Income		0.0021***	0.0011		0.0025***	0.0014*		0.0024***	0.0018**		0.0022	0.0001
		(0.004)	(0.141)		(0.000)	(0.078)		(0.003)	(0.046)		(0.120)	(0.947)
Education		0.0548*	0.0543*		0.0096	0.0068		-0.0006	-0.0024		0.0430	0.0295
		(0.055)	(0.053)		(0.743)	(0.816)		(0.986)	(0.949)		(0.133)	(0.300)
Hhsize		0.0218*	-0.0018		0.0117	0.0011		-0.0114	-0.0120		0.0060	0.0042
		(0.056)	(0.878)		(0.240)	(0.910)		(0.311)	(0.285)		(0.592)	(0.711)
Likelymove			-0.0474***			-0.0442**			-0.0229			-0.0172
			(0.005)			(0.014)			(0.183)			(0.300)
Renting			-0.0428			0.0133			-0.0599			-0.0841**
			(0.215)			(0.698)			(0.129)			(0.038)
Individual_meter			0.1462*			0.0100			-0.0109			-0.0060
			(0.073)			(0.836)			(0.841)			(0.884)
HomeSize			0.0670*			0.0586			-0.0292			-0.0036
			(0.057)			(0.153)			(0.390)			(0.915)
BuildAge			-0.0008*			-0.0000			-0.0004			-0.0014**
			(0.073)			(0.976)			(0.523)			(0.017)

Main bulb			0.1184***			0.0648**			0.1253***			0.0520
			(0.000)			(0.030)			(0.000)			(0.130)
Capitalaccess†			0.0480***			0.0270*			0.0345**			0.0411***
			(0.000)			(0.080)			(0.023)			(0.004)
Env_ID†			0.0553***			0.0581***			0.0116			0.0506***
			(0.000)			(0.000)			(0.424)			(0.001)
Socialnorm†			-0.0057			0.0086			-0.0044			0.0189
			(0.680)			(0.561)			(0.761)			(0.185)
Incentivized			0.0039			-0.0255			0.0042			0.0271
			(0.885)			(0.363)			(0.881)			(0.334)
N	1272	1272	1272	1235	1235	1235	1231	1231	1231		1303	1303

*** p<0.01, ** p<0.05, * p<0.1; †z-score of the variable was used

Table A2: Results (average marginal effects) of probit models for *LED* adoption decisions for experiment-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis) – continued.

	Romania			Spain			Sweden			United Kingdom		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
$\alpha^{\dagger}$	-0.0013	-0.0041	-0.0041	-0.0197	-0.0218	-0.0148	0.0433***	0.0460***	0.0387**	0.0301*	0.0247	0.0232
	(0.939)	(0.808)	(0.808)	(0.232)	(0.181)	(0.354)	(0.010)	(0.005)	(0.019)	(0.065)	(0.133)	(0.147)
$\delta^{\dagger}$	0.0020	0.0028	0.0026	-0.0072	-0.0062	-0.0029	0.0392**	0.0499***	0.0458***	0.0268*	0.0226	0.0191
	(0.904)	(0.861)	(0.872)	(0.649)	(0.690)	(0.852)	(0.018)	(0.002)	(0.004)	(0.088)	(0.153)	(0.225)
$\beta^{\dagger}$	0.0269**	0.0270**	0.0297**	-0.0127	-0.0101	-0.0093	0.0127	0.0142	0.0085	0.0256*	0.0260**	0.0254**
	(0.043)	(0.029)	(0.011)	(0.459)	(0.549)	(0.575)	(0.411)	(0.343)	(0.557)	(0.054)	(0.035)	(0.025)
$\lambda^{\dagger}$	-0.0364**	-0.0324**	-0.0317*	0.0043	0.0106	0.0091	-0.0233	-0.0166	-0.0161	-0.0370**	-0.0260*	-0.0262*
	(0.023)	(0.048)	(0.053)	(0.773)	(0.473)	(0.531)	(0.176)	(0.331)	(0.354)	(0.012)	(0.078)	(0.076)
Age		0.0011	-0.0002		0.0002	-0.0018		-0.0018	-0.0037***		0.0007	-0.0009
		(0.374)	(0.884)		(0.875)	(0.138)		(0.119)	(0.005)		(0.480)	(0.460)
Gender		0.1076***	0.1024***		0.0781***	0.0732***		0.1263***	0.1242***		0.0963***	0.0942***
		(0.000)	(0.000)		(0.005)	(0.008)		(0.000)	(0.000)		(0.000)	(0.000)
Income		0.0028**	0.0019*		0.0008	0.0001		0.0017***	0.0007		0.0018***	0.0013**
		(0.012)	(0.092)		(0.348)	(0.904)		(0.007)	(0.354)		(0.000)	(0.013)
Education		0.0264	0.0145		0.1244***	0.1153***		-0.0808*	-0.0798*		-0.0149	-0.0127

		(0.343)	(0.605)		(0.000)	(0.000)		(0.087)	(0.088)		(0.600)	(0.653)
Hhsize		0.0033	0.0051		-0.0017	-0.0078		0.0155	0.0061		0.0036	0.0009
		(0.511)	(0.329)		(0.888)	(0.526)		(0.208)	(0.638)		(0.747)	(0.937)
Likelymove			-0.0029			-0.0431**			-0.0087			-0.0098
			(0.852)			(0.011)			(0.641)			(0.541)
Renting			-0.0378			-0.0368			-0.1168***			-0.1305***
			(0.284)			(0.320)			(0.001)			(0.000)
Individual_meter			0.1550**			0.0635			0.0266			0.0372
			(0.049)			(0.128)			(0.551)			(0.299)
HomeSize			0.0632**			-0.0070			0.0257			-0.0119
			(0.039)			(0.840)			(0.540)			(0.681)
BuildAge			-0.0005			-0.0010			0.0003			-0.0007
			(0.464)			(0.139)			(0.575)			(0.123)
Main bulb			0.0292			0.1220***			0.0430			0.0030
			(0.479)			(0.000)			(0.154)			(0.913)
Capitalaccess†			0.0182			0.0316**			0.0148			0.0152
			(0.181)			(0.036)			(0.398)			(0.292)
Env_ID†			0.0252*			0.0143			0.0322**			0.0113
			(0.060)			(0.318)			(0.044)			(0.439)
Socialnorm†			0.0219*			0.0414***			0.0269*			0.0025
			(0.096)			(0.004)			(0.093)			(0.859)
Incentivized			-0.0503*			-0.0398			-0.0055			0.0128
			(0.068)			(0.161)			(0.856)			(0.625)
N	1103	1103	1103	1245	1245	1245	998	998	998	1243	1243	1243

*** p<0.01, ** p<0.05, * p<0.1; †z-score of the variable was used

Table A3: Results (average marginal effects) of probit models for *appliance* adoption decisions for experiment-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis).

	France			Germany			Italy			Poland		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
$\alpha^{\dagger}$	0.0292	0.0299	0.0263	0.0239	0.0207	0.0219	0.0141	0.0081	-0.0024	0.0101	0.0087	0.0039
	(0.146)	(0.126)	(0.153)	(0.222)	(0.263)	(0.229)	(0.377)	(0.580)	(0.845)	(0.632)	(0.670)	(0.843)
$\delta^{\dagger}$	-0.0069	-0.0042	-0.0066	0.0007	0.0000	-0.0011	-0.0045	-0.0069	-0.0062	-0.0307	-0.0320	-0.0322*
	(0.715)	(0.823)	(0.708)	(0.965)	(0.998)	(0.948)	(0.737)	(0.580)	(0.576)	(0.120)	(0.103)	(0.087)
$\beta^{\dagger}$	0.0040	0.0032	-0.0062	0.0111	0.0079	0.0048	-0.0071	-0.0091	-0.0063	0.0539	0.0590	0.0804
	(0.760)	(0.801)	(0.610)	(0.258)	(0.325)	(0.541)	(0.506)	(0.345)	(0.440)	(0.345)	(0.334)	(0.298)
$\lambda^{\dagger}$	-0.0148	-0.0108	0.0004	-0.0162	-0.0167	-0.0174	-0.0166*	-0.0112	-0.0073	-0.0412**	-0.0346**	-0.0290*
	(0.379)	(0.512)	(0.982)	(0.216)	(0.211)	(0.191)	(0.074)	(0.203)	(0.426)	(0.015)	(0.034)	(0.067)
Age		0.0010	-0.0012		0.0023**	0.0017*		0.0015*	0.0005		-0.0001	-0.0023
		(0.402)	(0.342)		(0.010)	(0.067)		(0.060)	(0.474)		(0.933)	(0.116)
Gender		0.0343	0.0503		-0.0157	-0.0183		-0.0335*	-0.0426**		0.0095	0.0167
		(0.288)	(0.104)		(0.509)	(0.434)		(0.079)	(0.025)		(0.754)	(0.567)
Income		0.0011	0.0004		0.0016**	0.0012*		0.0017***	0.0011*		0.0070***	0.0060***
		(0.199)	(0.659)		(0.015)	(0.063)		(0.007)	(0.051)		(0.001)	(0.001)
Education		0.0266	0.0050		0.0188	0.0122		0.0270	0.0214		0.0295	0.0122
		(0.426)	(0.876)		(0.446)	(0.608)		(0.260)	(0.371)		(0.356)	(0.697)
Hhsize		0.0300**	0.0063		0.0069	0.0075		0.0147*	0.0080		-0.0170	-0.0234**
		(0.032)	(0.658)		(0.477)	(0.457)		(0.053)	(0.247)		(0.156)	(0.049)
Likelymove			-0.0514***			-0.0233			-0.0285**			-0.0240
			(0.008)			(0.100)			(0.012)			(0.170)
Renting			-0.0513			0.0231			-0.0378*			-0.1348***
			(0.194)			(0.376)			(0.086)			(0.002)
Individual_meter			0.0351			0.0112			0.0782***			0.0050
			(0.655)			(0.767)			(0.003)			(0.910)
HomeSize			0.0674			-0.0268			0.0189			-0.0018
			(0.103)			(0.422)			(0.418)			(0.959)
BuildAge			-0.0007			-0.0007*			0.0000			-0.0007
			(0.198)			(0.099)			(0.965)			(0.217)

Capitalaccess†			0.0071			0.0196			0.0177*			0.0018
			(0.663)			(0.108)			(0.071)			(0.908)
Env_ID†			0.1168***			0.0456***			0.0369***			0.0584***
			(0.000)			(0.000)			(0.000)			(0.000)
Socialnorm†			0.0164			0.0177			-0.0073			0.0419***
			(0.302)			(0.162)			(0.420)			(0.006)
Incentivized			0.0224			-0.0422*			-0.0131			-0.0125
			(0.467)			(0.063)			(0.474)			(0.683)
N	887	887	887	784	784	784	730	730	730	696	696	696

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; †z-score of the variable was used

Table A3: Results (average marginal effects) of probit models for *appliance* adoption decisions for experiment-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis) – continued.

	Romania			Spain			Sweden			United Kingdom		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
$\alpha^{\dagger}$	-0.0068	-0.0081	-0.0053	-0.0095	-0.0041	-0.0044	0.0303	0.0340	0.0416	0.0204	0.0286	0.0317
	(0.702)	(0.651)	(0.773)	(0.550)	(0.814)	(0.805)	(0.242)	(0.224)	(0.152)	(0.260)	(0.143)	(0.118)
$\delta^{\dagger}$	0.0006	-0.0009	-0.0016	0.0159	0.0176	0.0184	-0.0169	-0.0094	-0.0009	0.0153	0.0187	0.0274
	(0.973)	(0.959)	(0.927)	(0.295)	(0.284)	(0.268)	(0.538)	(0.740)	(0.976)	(0.368)	(0.297)	(0.135)
$\beta^{\dagger}$	0.0137	0.0152	0.0147	-0.0017	-0.0023	-0.0040	0.0066	0.0039	0.0091	0.0296	0.0871	0.1127
	(0.305)	(0.192)	(0.152)	(0.853)	(0.836)	(0.727)	(0.683)	(0.813)	(0.567)	(0.277)	(0.250)	(0.154)
$\lambda^{\dagger}$	0.0063	0.0007	-0.0022	0.0261	0.0118	0.0077	-0.0048	-0.0009	-0.0010	0.0121	0.0057	0.0097
	(0.613)	(0.960)	(0.875)	(0.164)	(0.527)	(0.670)	(0.844)	(0.972)	(0.970)	(0.448)	(0.749)	(0.586)
Age	0.0007	0.0020		-0.0003	0.0013		0.0033	0.0054***		0.0012	0.0037***	
	(0.635)	(0.172)		(0.789)	(0.322)		(0.110)	(0.002)		(0.336)	(0.001)	
Gender	0.0491*	0.0378		0.0347	0.0433		-0.0397	-0.0467		-0.0476*	-0.0606**	
	(0.100)	(0.201)		(0.223)	(0.143)		(0.379)	(0.312)		(0.080)	(0.032)	
Income	0.0012	0.0016		0.0011	0.0019*		-0.0007	0.0001		0.0003	0.0008	
	(0.369)	(0.282)		(0.256)	(0.068)		(0.467)	(0.883)		(0.533)	(0.156)	
Education	-0.0120	-0.0044		0.0505	0.0614*		0.0059	0.0395		-0.0129	0.0206	
	(0.697)	(0.889)		(0.109)	(0.058)		(0.931)	(0.583)		(0.661)	(0.490)	
Hhsize	0.0011	-0.0012		-0.0134	-0.0076		0.0153	0.0150		-0.0045	-0.0035	

	(0.886)	(0.882)		(0.251)	(0.544)		(0.446)	(0.417)		(0.689)	(0.767)	
Likelymove	-0.0020			-0.0016			0.0026			-0.0320*		
	(0.902)			(0.922)			(0.929)			(0.064)		
Renting	-0.0527			-0.0487			-0.0447			0.0019		
	(0.141)			(0.178)			(0.432)			(0.953)		
Individual_meter	-0.0473			0.0731*			0.0857			0.0585*		
	(0.497)			(0.060)			(0.214)			(0.077)		
HomeSize	0.0484			0.0334			0.0271			0.0432		
	(0.162)			(0.354)			(0.653)			(0.157)		
BuildAge	-0.0001			-0.0012**			0.0005			0.0003		
	(0.860)			(0.041)			(0.627)			(0.508)		
Capitalaccess†	0.0215			0.0213			0.0303			0.0397***		
	(0.125)			(0.170)			(0.228)			(0.007)		
Env_ID†	0.0542***			0.0584***			0.0501**			0.0810***		
	(0.000)			(0.000)			(0.029)			(0.000)		
Socialnorm†	-0.0009			0.0277*			0.0387*			0.0268*		
	(0.950)			(0.067)			(0.099)			(0.074)		
Incentivized	0.0151			0.0187			-0.0377			0.0028		
	(0.632)			(0.510)			(0.414)			(0.917)		
N	602	602	602	674	674	674	410	410	410	862	862	862

*** p<0.01, ** p<0.05, * p<0.1; †z-score of the variable was used

Table A4: Results (average marginal effects) of probit models for *retrofit* measure adoption decisions for experiment-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis).

	France			Germany			Italy			Poland		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
$\alpha^{\dagger}$	-0.0147	-0.0151	-0.0251*	0.0048	0.0021	-0.0113	0.0420**	0.0391**	0.0294*	0.0348	0.0311	0.0280
	(0.405)	(0.378)	(0.091)	(0.749)	(0.886)	(0.408)	(0.026)	(0.035)	(0.094)	(0.110)	(0.151)	(0.188)
$\delta^{\dagger}$	0.0010	-0.0056	-0.0083	-0.0025	-0.0007	-0.0038	0.0451**	0.0427**	0.0415**	0.0076	0.0034	0.0005
	(0.954)	(0.738)	(0.571)	(0.861)	(0.961)	(0.765)	(0.011)	(0.015)	(0.012)	(0.702)	(0.862)	(0.978)
$\beta^{\dagger}$	0.0239*	0.0207	0.0143	-0.0096	-0.0104	-0.0093	0.0179	0.0168	0.0113	0.0105	0.0120	0.0129
	(0.092)	(0.166)	(0.288)	(0.294)	(0.271)	(0.400)	(0.114)	(0.143)	(0.298)	(0.546)	(0.496)	(0.500)

$\lambda^{\dagger}$	-0.0179	-0.0109	0.0003	-0.0121	-0.0104	-0.0090	-0.0150	-0.0116	-0.0046	-0.0173	-0.0182	-0.0091
	(0.280)	(0.498)	(0.983)	(0.378)	(0.432)	(0.445)	(0.356)	(0.472)	(0.780)	(0.344)	(0.317)	(0.631)
Age		0.0058***	-0.0000		0.0016	-0.0023**		0.0019*	0.0005		0.0054***	0.0029**
		(0.000)	(0.981)		(0.108)	(0.019)		(0.094)	(0.637)		(0.000)	(0.035)
Gender		-0.0546*	-0.0411		0.0024	0.0102		0.0017	0.0136		-0.0387	-0.0190
		(0.061)	(0.108)		(0.923)	(0.650)		(0.953)	(0.625)		(0.232)	(0.540)
Income		0.0034***	0.0008		0.0026***	-0.0000		0.0025***	0.0009		0.0037**	0.0021
		(0.000)	(0.294)		(0.000)	(0.988)		(0.003)	(0.274)		(0.045)	(0.240)
Education		-0.0258	-0.0492*		-0.0282	-0.0318		0.0486	0.0342		0.0003	-0.0288
		(0.392)	(0.065)		(0.275)	(0.179)		(0.205)	(0.364)		(0.993)	(0.362)
Hhsize		0.0540***	-0.0005		0.0444***	0.0049		0.0098	-0.0014		0.0304**	0.0161
		(0.000)	(0.963)		(0.000)	(0.625)		(0.390)	(0.897)		(0.020)	(0.227)
Likelymove			-0.0213			-0.0263*			-0.0164			0.0218
			(0.187)			(0.084)			(0.338)			(0.238)
Renting			-0.3141***			-0.2428***			-0.2661***			-0.2919***
			(0.000)			(0.000)			(0.000)			(0.000)
Individual_meter			0.1130			0.0451			0.0264			0.0757*
			(0.119)			(0.299)			(0.608)			(0.089)
HomeSize			0.0943***			0.0752**			0.0598*			0.0190
			(0.008)			(0.032)			(0.087)			(0.691)
BuildAge			0.0019***			0.0020***			0.0009			-0.0003
			(0.000)			(0.000)			(0.143)			(0.688)
Detached housing			0.1044***			0.0334			0.0285			0.0325
			(0.000)			(0.216)			(0.368)			(0.458)
Capitalaccess†			0.0311**			0.0249*			0.0167			0.0143
			(0.023)			(0.053)			(0.260)			(0.393)
Env_ID†			0.0538***			0.0414***			0.0842***			0.0546***
			(0.000)			(0.000)			(0.000)			(0.001)
Socialnorm†			-0.0269**			-0.0053			0.0252*			0.0463***
			(0.040)			(0.651)			(0.084)			(0.004)
Incentivized			0.0472*			-0.0165			-0.0240			-0.0222
			(0.069)			(0.462)			(0.388)			(0.482)

N	1124	1124	1124	1202	1202	1202	1103	1103	1103	916	916	916

*** p<0.01, ** p<0.05, * p<0.1; †z-score of the variable was used

Table A4: Results (average marginal effects) of probit models for *retrofit* measure adoption decisions for experiment-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis) – continued.

	Romania			Spain			Sweden			United Kingdom		
	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
$\alpha^{\dagger}$	0.0058	0.0059	0.0061	0.0056	0.0034	-0.0033	0.0096	0.0111	0.0028	-0.0017	-0.0097	-0.0166
	(0.751)	(0.737)	(0.730)	(0.768)	(0.857)	(0.850)	(0.549)	(0.469)	(0.844)	(0.921)	(0.567)	(0.291)
$\delta^{\dagger}$	-0.0008	0.0005	-0.0026	0.0090	0.0079	0.0140	0.0163	0.0235	0.0124	0.0078	-0.0019	-0.0065
	(0.962)	(0.977)	(0.871)	(0.620)	(0.663)	(0.394)	(0.317)	(0.131)	(0.380)	(0.637)	(0.905)	(0.666)
$\beta^{\dagger}$	0.0375	0.0379	0.0560	0.0052	0.0096	0.0164	-0.0123	-0.0093	-0.0124	0.1040*	0.0901*	0.0483*
	(0.169)	(0.223)	(0.221)	(0.744)	(0.543)	(0.211)	(0.297)	(0.495)	(0.505)	(0.068)	(0.091)	(0.094)
$\lambda^{\dagger}$	0.0016	0.0028	0.0068	0.0152	0.0202	0.0243*	0.0025	0.0070	0.0034	-0.0026	-0.0003	-0.0050
	(0.910)	(0.839)	(0.621)	(0.351)	(0.200)	(0.086)	(0.869)	(0.597)	(0.770)	(0.863)	(0.983)	(0.703)
Age		0.0062***	0.0031**		0.0021*	-0.0008		0.0026**	-0.0019*		0.0062***	0.0012
		(0.000)	(0.017)		(0.090)	(0.525)		(0.017)	(0.088)		(0.000)	(0.273)
Gender		0.0398	0.0295		-0.0438	-0.0403		0.0498*	0.0465*		-0.0008	0.0223
		(0.142)	(0.257)		(0.155)	(0.166)		(0.077)	(0.066)		(0.977)	(0.368)
Income		0.0041**	0.0026		0.0029***	0.0015		0.0027***	0.0008		0.0019***	0.0003
		(0.027)	(0.111)		(0.002)	(0.102)		(0.000)	(0.178)		(0.000)	(0.528)
Education		-0.0141	-0.0349		0.0408	0.0422		0.0263	0.0224		-0.0552*	-0.0690***
		(0.621)	(0.218)		(0.222)	(0.179)		(0.566)	(0.576)		(0.050)	(0.009)
Hhsize		-0.0055	-0.0007		-0.0038	-0.0167		0.0356***	0.0029		0.0268**	0.0125
		(0.248)	(0.880)		(0.769)	(0.188)		(0.001)	(0.788)		(0.014)	(0.232)
Likelymove			-0.0056			-0.0020			-0.0142			-0.0205
			(0.713)			(0.910)			(0.367)			(0.176)
Renting			-0.1594***			-0.2272***			-0.2571***			-0.3082***
			(0.000)			(0.000)			(0.000)			(0.000)
Individual_meter			0.1427**			0.0858*			0.0091			0.0400
			(0.015)			(0.077)			(0.824)			(0.200)
HomeSize			0.0104			0.0523			0.0466			0.0152

			(0.776)			(0.182)			(0.212)		(0.583)
BuildAge			-0.0014*			0.0006			0.0011*		-0.0005
			(0.075)			(0.415)			(0.052)		(0.318)
Detached housing			0.0140			0.1022***			0.1013***		0.0984***
			(0.648)			(0.003)			(0.002)		(0.001)
Capitalaccess†			0.0274**			0.0305*			0.0081		0.0231*
			(0.042)			(0.061)			(0.575)		(0.096)
Env_ID†			0.0538***			0.0794***			0.0581***		0.0773***
			(0.000)			(0.000)			(0.000)		(0.000)
Socialnorm†			0.0117			0.0224			0.0208		0.0238*
			(0.384)			(0.154)			(0.120)		(0.072)
Incentivized			-0.0052			0.0733**			-0.0074		-0.0033
			(0.858)			(0.013)			(0.774)		(0.895)
N	938	938	938	900	900	900	910	910	910	1337	1337

*** p<0.01, ** p<0.05, * p<0.1; †z-score of the variable was used

Table A5: Results (average marginal effects) of probit models for energy efficiency technology adoption decisions for the all-countries model and experiment-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis). Specification M2.

			LED		
α (risk aversion)†	0.0065	-0.0012			
	(0.277)	(0.808)			
δ (standard time discounting)†	0.0131**		0.0087*		
	(0.022)		(0.078)		
β (present bias)†	0.0160***			0.0135***	
	(0.001)			(0.006)	
λ (loss aversion)	-0.0080				-0.0054
	(0.135)				(0.274)
N	9630	9630	9630	9630	9630
			Appliances		
α (risk aversion)†	0.0126*	0.0108**			
	(0.071)	(0.050)			
δ (standard time discounting)†	-0.0012		-0.0074		
	(0.851)		(0.168)		
β (present bias)†	0.0119***			0.0118***	
	(0.006)			(0.004)	
λ (loss aversion)	-0.0088				-0.0029
	(0.126)				(0.583)
N	5465	5465	5465	5465	5465
			Retrofit		
α (risk aversion)†	0.0052	0.0017			
	(0.403)	(0.740)			
δ (standard time discounting)†	0.0068		0.0031		
	(0.253)		(0.536)		
β (present bias)†	0.0105**			0.0096**	
	(0.027)			(0.039)	
λ (loss aversion)	-0.0027				-0.0007
	(0.611)				(0.887)
N	8430	8430	8430	8430	8430

*** p<0.01, ** p<0.05, * p<0.1; †z-score of the variable was used

Table A6: Results (average marginal effects) of probit models for energy efficiency technology adoption decisions for the all-countries model and experiment-based elicitation of preferences for time, risk and losses (robust P-values in parenthesis). Specification M3.

			LED		
α (risk aversion)†	0.0036	-0.0030			
	(0.542)	(0.540)			
δ (standard time discounting)†	0.0119**		0.0087*		
	(0.036)		(0.075)		
β (present bias)†	0.0160***			0.0135***	
	(0.001)			(0.004)	
λ (loss aversion)	-0.0063				-0.0046
	(0.224)				(0.345)

N	9630	9630	9630	9630	9630
			Appliances		
α (risk aversion)†	0.0083	0.0090*			
	(0.216)	(0.090)			
δ (standard time discounting)†	-0.0032		-0.0079		
	(0.610)		(0.131)		
β (present bias)†	0.0115***			0.0119***	
	(0.005)			(0.002)	
λ (loss aversion)	-0.0047				0.0001
	(0.405)				(0.979)
N	5465	5465	5465	5465	5465
			Retrofit		
α (risk aversion)†	-0.0008	-0.0014			
	(0.899)	(0.771)			
δ (standard time discounting)†	0.0037		0.0022		
	(0.510)		(0.645)		
β (present bias)†	0.0123***			0.0117**	
	(0.009)			(0.012)	
λ (loss aversion)	0.0002				0.0010
	(0.969)				(0.834)
N	8430	8430	8430	8430	8430

*** p<0.01, ** p<0.05, * p<0.1; †z-score of the variable was used