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A large-scale test of the effects of time discounting, risk aversion, loss aversion, and present bias on household adoption of energy-efficient technologies

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Abstract

This paper empirically and jointly analyses the relations between standard time discounting, risk aversion, loss aversion, and present bias and household stated adoption of low to high stake energy efficiency technologies (EETs): light emitting diodes (LEDs), energy-efficient appliances, and retrofit measures. The analysis relies on a large representative sample drawn from eight European Union countries. Preferences over time, risk, and losses were elicited and jointly estimated from participant choices in incentivized, context-free multiple price list experiments. The findings from econometrically estimating EET adoption equations provide some support for the hypothesis that individuals who are more loss-averse, or more risk-averse, or who exhibit a lower time discount factor are less likely to have adopted EETs. Yet, some of the results (significance levels and effect sizes) appeared sensitive to the addition of covariates, which may be an indication of bad controls. Finally, omitting one or several of the parameters capturing preferences over time, risk, and losses when estimating the EET adoption equations, did not appear to cause omitted variable bias.

Key words: time discounting, risk aversion, loss aversion present bias, energy efficiency, adoption.

JEL codes: D23, D81, Q41, Q48

Highlights:

- Time discounting, risk aversion and loss aversion negatively affect energy efficiency technology adoption.
- Failure to include all time, risk, and loss parameters does not appear to cause an omitted variable bias.
- Results appear sensitive to degrees of freedom and to the addition of covariates.

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1 Introduction

Several empirical studies have recently explored the role of time and risk preferences on household adoption of energy-efficient technologies (EETs; e.g. Qiu et al. 2014; Allcott and Taubinsky 2015; Newell and Siikamäki 2015; Fischbacher et al. 2015). High discount rates, present bias, and/or risk aversion may help explain the so-called ‘energy efficiency paradox’, according to which households fail to invest in EETs even though these appear to pay off under prevailing market conditions (e.g. Allcott and Mullainathan 2010; Allcott 2011; Gerarden, et al. 2015, 2017; Ramos et al. 2015; Schleich et al. 2016)[1]. Exploring the distinct effects of standard time discounting, present bias, and risk preferences on EET adoption is particularly relevant to identify appropriate 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 aimed at mitigating the effects of present bias. In addition, the distinction between preferences (i.e. standard time preferences and risk preferences) and behavioral-based biases such as loss aversion or present bias is important because there are different welfare implications of the associated policies. Although preferences may keep individuals from adopting energy efficient technologies, they lead to rational decisions; consequently, policies designed to counteract these preferences would not make these individuals better off. In contrast, loss-averse or present-biased individuals may make technology choices that are at odds with their own long-term objectives. In this sense, loss aversion and present bias represents a behavioral failure, since they cause a difference between decision utility (maximized at the time of technology choice) and experienced utility (experienced after decision is made; Kahnemann et al. 1997; Gillingham and Palmer 2014)[2]. Thus, policies that address present bias or loss aversion may improve individual welfare.

There is a growing body of evidence on the effects of time and risk preferences on EET adoption; however, comprehensive evaluations that consider time and

1 Gerarden et al. (2015, 2017) and Gillingham and Palmer (2014) provide recent reviews of factors explaining the energy efficiency paradox such as bounded rationality, split incentives/agency issues, or capital market failures.

2 There does not seem to exist a clear consensus in the literature as to whether loss aversion is a behavioral failure or not. For this paper, we adopt the definition as in Gillingham and Palmer (2014) or Heutel (2017), among others.

risk preferences together are still needed. Moreover, the effects of other preferences, such as loss aversion, which can be expected to affect EET adoption, remain largely unstudied. This paper contributes to filling that gap.

Our analysis relies on a large representative sample from eight EU countries. It therefore adds to the emerging literature that relates the preference measures employed in laboratory experiments (multiple price lists) to actual stated behavior for representative samples (e.g. Dohmen et al. 2011). With over 15,000 observations, our analysis builds on the largest sample assessing the impact of risk and time preferences on EET adoption to date. Additionally, we investigated the effects of loss aversion on EET adoption, which no previous study has addressed (with the exception of the parallel effort in Heutel 2017). Further, we simultaneously considered the effects of risk aversion, standard time discounting, present bias, and loss aversion on EET adoption to avoid mistakenly conflating their effects and also jointly calculated the parameters for standard time discounting, risk aversion, loss aversion, and present bias at the individual level to ensure internally consistent parameter estimates. Following state-of-the-art approaches, preferences for time discounting, risk, loss aversion, and present bias were elicited via (partly incentivized) decontextualized multiple price list lotteries. To expand on previous literature, we surveyed decision-makers for low- (LED light bulbs), medium- (appliances) and high- (retrofit) stake EETs. Finally, the study accounted for relevant household control variables (such as intention to move, renting, socio-demographics, and individual traits), as well as dwelling characteristics such as dwelling size and age.

The remainder of the paper is organized as follows. Section 2 discusses the existing literature that links preferences over time, risk, and losses to EET adoption. Section 3 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 5 summarizes the main findings and discusses their implications.

2 Literature review

Standard time discounting

The adoption of EETs 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 EET adoption provide mixed evidence. For households in the USA, 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. (2017) 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 in renovation decisions among Swiss homeowners. Finally, Bruderer Enzler et al. (2014) do not find consistent effects of standard time discounting on the adoption of a variety of high- and low-cost EETs for Swiss households.

Present bias

The traditional economic model for 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 discounting function (Ainslie, 1974; Laibson, 1997).

The body of work that has explored the effects of present bias on the adoption of EETs is inconclusive. Bradford et al. (2017) find that present bias is statistically associated with self-reports of driving a fuel-efficient car, having a well-insulated home, and 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 artefactual field experiment in the USA. 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 UK.

Risk preferences

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-efficiency light bulbs and thermostats (but not appliances or vehicles) in the USA (Heutel 2017).

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 of the ten measures considered (i.e. high-efficiency light bulbs, replacement of air conditioners, alternative fuel vehicles)[3]. Heutel (2017) calls for future analyses to consider larger samples than his sample of about 2000 observations.

Reflections on the literature

As can be seen from the literature reviewed above, there is an emerging set of empirical evidence on the effects of time and risk preferences and loss aversion on EET adoption. 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).

Previous studies have widely differed in their approaches to study time and risk preferences. So far, few empirical studies have looked at the effects of time and risk preferences on EET adoption simultaneously (Bradford et al. 2017, Fischbacher et al. 2015), and only Heutel (2017) has considered loss aversion. 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. Similarly, not accounting for loss aversion may result in biased estimates of risk parameters (e.g. Abdellaoui et al. 2007). In addition, failure to simultaneously include preferences for time, risk, and losses may lead to an omitted variable bias of parameter estimates in econometric analyses of adoption behavior. Consequently, policy recommendations based on the findings of such analyses may be erroneous.

3 Note that loss aversion is often assessed for different levels of probability that the loss event may occur (probability distortion); Heutel (2017) allows for probability distortion, but does not find probability distortion to be related with any of the ten energy efficiency measures considered in his study.

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 multiple price lists (MPLs; Coller and Williams 1999, Holt and Laury 2002), which allow for parametric estimations of preferences[4]. Even among the studies using MPLs for the elicitation of preferences, some have used contextualized price lists (e.g. Qiu et al 2014) while others relied on the more widely accepted context-free MPLs (e.g. Bradford et al. 2017, Fischbacher et al. 2015, Heutel 2017)[5]. Although contextualized MPLs have been shown to be better at predicting targeted behaviors, these higher correlations are somewhat confounded because contextualized MPLs mix preferences with the behaviors under study (here energy technology adoption). Finally, the experimental economics literature stresses the importance of using incentivization (paying respondents as a function of their responses) to induce incentive-compatible choices (Johnston et al. 2017). So far, incentivization has only been used in a few demographically representative studies, including Bradford et al. (2017) through gift cards and 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.

Previous studies 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 could affect preferences, especially perceived risk; 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. (2017), Fischbacher et al. (2015), and Heutel (2017) rely on stated adoption behavior;

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4 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.

5 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.

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) and at times may include respondents who are not “in the market” (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 concerns about omitted variables. Finally, many adoption studies that have used representative samples of the population were single-country studies almost exclusively conducted in Switzerland or in the USA.

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 countries.

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 representative survey in eight EU countries; together, these countries account for 80 percent of the EU population, energy use, and greenhouse gas emissions.

3 Methods

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

3.1 Theory

Modelling risk preferences and loss aversion

To account for the widely-recognized fact that “losses loom larger than gains” (see Starmer (2000) for a review), we model individual preferences for risk and loss aversion using a simplified version of the utility function derived from Prospect Theory (Kahneman and Tversky, 1979):

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

where *x* denotes wealth, α is the parameter reflecting risk aversion, and λ is the parameter capturing loss aversion[6]. We also assume a reference wealth of zero and abstract from other aspects of prospect theory, such as probability weighting. This specification of preferences is commonly used in the literature and provides a parsimonious way to identify parameters for risk preferences and loss aversion[7].

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):

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

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

6 In our specification, the parameter α describes the curvature of utility in both the gain and loss domains. Given our functional form, a person who is risk averse in the gain domain would be risk loving in the loss domain (see e.g. Al-Nowaihi et al. 2008 for a theoretical argument in favor of using identical parameters in the risk and loss domains). In this sense, a value of $\alpha < 1$ describes both risk aversion in the gain domain and risk seeking in the loss domain at the same time. However, since with our elicitation method α is uniquely identified through choices in the gains domain (see Section 3.2 and Appendix AI), we will refer to α as the parameter that describes risk aversion in the remainder of this paper.

7 See for instance Tanaka et al. (2010), von Gaudecker et al. (2011), or Andersson et al. (2014).

wealth x at the date t, δ is the annual standard time discount factor, and β is the parameter reflecting present bias[8]. In our model, t is expressed in years.

Need to jointly estimate parameters reflecting preferences over time, risk, and losses

Equations (1) and (2) illustrate the need to jointly estimate the parameters reflecting preferences over time, risk, and losses to derive internally consistent parameters for given functional forms such as (1) and (2). 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.

3.2 Empirical methods

An online survey was implemented in July and August 2016 by Ipsos GmbH via computer-assisted web interviews (CAWI) using existing household panels. About 15,000 participants from France, Germany, Italy, Poland, Romania, Spain, Sweden, and the United Kingdom completed the survey and received a participation fee upon full completion of the survey[9]. 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.

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 atti-

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8 δ=1 / 0<δ<1 means that 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.

9 Since participants were recruited from the Ipsos GmbH household panel, response rates were not available.

tudes 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.

Since the same survey was conducted in eight different countries, some steps were taken to ensure measurement equivalence. First, as advised by Caramelli and van de Vijver (2013), particular attention was given to develop items that are relevant for all countries; for instance, we included a large range of income categories to cover both low-income and high-income countries. Second, since the majority of the questions in the survey were quite concrete (dwelling characteristics, EET adoption, choice between financial lotteries), concerns about a possible lack of cultural equivalence were limited (as stressed by Wagner et al. (2014), such concerns are particularly strong for culturally-bound psychological constructs such as values and beliefs). As a consequence, the main focus was on obtaining translation equivalence. Following standard procedure in cross-cultural research (Brislin 1970), the surveys were first professionally translated by bilingual speakers from the original language (English) to the target language of each country, and subsequently back translated to minimize differences that could be attributed to language; the few discrepancies raised through the back translation procedure were resolved with help of energy experts from each of the target countries.

Elicitation of time and risk preferences and of loss aversion via MPLs

The MPLs employed to elicit time and risk preferences and loss aversion were adapted from Coller and Williams (1999) for time preferences and present bias and from Holt and Laury (2002) for risk preferences (See Tables 1–3). In each MPL, participants faced a list of choices between two options, A and B, and were asked to indicate their preferred option for each choice[10]. 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

10 Since decisions may be influenced by the order in which the choices are presented (order bias), we randomized the order of the decisions presented to participants. Across all MPLs, participants had a 50% chance of seeing AB and a 50% chance of seeing 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.

participants were identical; for Sweden, the UK, Poland, and Romania, monetary amounts were multiplied by their respective factors. Similar to Bradford et al. (2017), but in contrast to Qiu et al. (2014), the MPLs in our study were not contextualized.

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 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)[11].

11 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 participants 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 participants 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 at 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.

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

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 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€

Elicitation of loss aversion

In MPL3, which was designed to elicit 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€

Different stakes

We also varied the monetary amounts shown to participants in each of the decisions. The MPL design otherwise remained the same. 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.

Incentivization

To mitigate hypothetical bias, more than half the sample were incentivized (54%). Of those who were incentivized, we paid a random subset (1%) of the participants based on their actual choices. Incentivization was only implemented for baseline and low stakes. For each selected participant, one question was randomly chosen as the pay-out question. 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[12]. 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. Processing and shipping of these payments took one week's time, which is why the earliest payment date in all MPLs was one week from the date participants completed the survey. Perceived payment reliability is an issue that may confound the elicitation of preferences, especially when an earlier payment may be deemed more reliable, or may involve lower transaction costs[13]. 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

12 Note that unlike Heutel (2017), we did not account for probability distortion (which he did not find to have any effect on EET adoption). However, we did incentivize gains and losses; in contrast, Heutel (2017) incentivized gains only.

13 This may be an issue, for instance, in laboratory experiments, where earlier (now) payments are awarded instantaneously in cash, while later payments make use of other payment modalities (e.g. bank transfer, or mailed check).

specified in the survey, and provided an email address that participants could contact in case of questions regarding the payment modalities. The survey drew from an existing panel, consisting mostly of participants who had 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).

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 are consistent with 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: for instance, 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 chose 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. We refer to Appendix AI for more details on how the preference parameters were calculated and to Brown and Kim (2014) who employ a similar method. We also note that, unlike using the switch-points to calculate the four preferences parameters individually, the joint estimation has no implications for the sign of the correlation between those preference parameters, assuming the model holds true. 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 A1 in Appendix AII.

Table A1 suggests that the average standard annual time discount rate across the entire sample was about 17.5% [(1/0.851-1)*100], which is within the range found in previous studies employing MPLs to elicit standard time preferences (Frederick et al. 2002). On average, participants were risk-averse. Our mean value of α = 0.822 is similar to the mean value found by Heutel (2017, 0.809) or to that found among 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 did not exhibit present bias. Thus, our mean value of β= 1.007 is higher than the values for present bias typically found in the literature (Tanaka et al. 2010, 0.64 for villages in Vietnam; Bradford et al. 2017, 0.94). We also note that a large share of participants in our sample appeared to be future biased, like in Takeuchi (2011). 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. The average participant in each of the surveyed countries was loss averse. Our mean value of λ = 3.424 is 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).

In general, the country averages of our parameter estimates of standard time preferences, loss aversion, and present bias (and to a lesser extent also for risk aversion) varied little across countries. In comparison, the relatively large standard deviations suggest that there was substantial heterogeneity within countries[14]. Table A2 in Appendix AII displays the correlation of the estimated preference parameters. Thus, in our sample, each parameter is highly correlated with the other three parameters (p<0.01).

3.3 Econometric Model

We employed binary response models to estimate the adoption of the three types of energy efficiency technologies.

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

(4) $$y_{ik}^* = \gamma_{0k} + \gamma_{1k}\alpha_i + \gamma_{2k}\delta_i + \gamma_{3k}\beta_i + \gamma_{4k}\lambda_i + \sum_{j=5}\gamma_{jk}X_{ijk} + \varepsilon_{ik} \quad ,$$

where i denotes the individual household, k stands for the technology type, α_i,δ_i, β_i, and λ_i are the parameters reflecting risk preferences, standard time

14 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.

preferences, present bias, and loss aversion of individual *i*, respectively[15]; y_{ik}^{*} is the latent variable, X_{ijk} are control variables, and ε_{ik} is the error term. Our econometric estimations employ a probit model, ε_{ik} is assumed to be normally distributed.

Dependent variables

We used three types of dependent variables derived from participants' stated adoption decisions on light bulbs, appliances, and retrofit measures.

First, participants who had purchased a new light bulb within the previous 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 previous 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.

Third, if participants had implemented a retrofit measure within the previous 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[16]. 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 EET and non-

15 To facilitate the interpretation of the coefficients, these variables entered the adoption equations as z-scores.

16 Since these retrofit measures are typically implemented all at once, we did not ask which of the measures was implemented last (unlike for appliances).

EET for one specific decision; furthermore, respondents indicated the adoption decision date, which allowed us to mitigate recall bias [17].

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) to capture differences across countries and appliances. Descriptive statistics are summarized in Table A3 in Appendix AI.

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[18]. In this case, the effects of the preference parameters on the adoption of EET may occur mainly through these bad control variables, potentially leading to erroneous inferences.

To assess the impact of bad controls on our findings, we 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. (2017), for example. Finally, Model 3 (M3) includes the most comprehensive set of covariates and is expected to 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 5.

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17 However, considering only decisions which took place within the previous two years (for light bulbs), five years (for appliances) or ten years (for retrofit) way may introduce a sampling bias, thus leading to a trade-off with recall bias. As shown in Appendix Table A4, limiting the sample in this way leads to a loss in observations of about 11% for light bulbs, 17% for appliances, and 14% for retrofit measures.

18 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).

Table 5: 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	Variable = 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 as the average of 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?"

Label	Description
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 using robust standard errors. First, we present and discuss results for our preferred model specification. Then, we summarize the findings of a series of additional robustness checks.

4.1 Preferred model results

Estimation results for our preferred specification appear in Table 6. In this specification, we dropped the 2.5% largest and smallest observations for β.[19]. For M1, the findings for α suggest that less risk-averse respondents (i.e. a higher α) were more likely to have adopted an LED, purchased an energy-efficient appliance, and implemented retrofit measures. For example, an increase in α by one standard deviation is associated with a 1.2 percentage-point increase in the propensity to adopt an LED, which corresponds to an increase in LED adoption of about 3% for a sample adoption rate of 41% (see Table A3).

Individuals with high standard time discount factors (i.e. a higher δ) were also more likely to have selected an LED as their most recent light bulb purchase or implemented a retrofit measure. In comparison, the associated coefficient for appliances is just shy of being statistically significant at conventional levels[20]. The preference parameter reflecting present bias (β) is not significantly correlated with the adoption of any of the three EETs.

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19 We eliminated observations when β was higher than 1.171 or lower than 0.743, leading to a loss of 550 observations. In comparison, the distributions of α, δ, and λ did not include small shares of extreme outliers.

20 Note that the discount rates elicited in our survey are calculated for a time horizon of at most one year. Investments in EET often involve payments and savings that exceed this time horizon. In order to identify an effect of discount rates on EET adoption with our method, we would have to assume that the elicited discount rates over one year are sufficiently strongly correlated with discount rates over longer time horizons. We believe that this is a reasonable assumption, given that the discount rates elicited in MPL1.1 and MPL1.2 (abstracting from present bias) are highly and significantly correlated ($\rho = 0.812$, p-value < 0.0001).

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 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 lifetime energy cost savings". In this case though, the effect of risk (or time) preferences cannot be distinguished from context-specific factors (here: environmental benefits). The findings for standard time discounting and for present bias for energy-efficient light bulb adoption are generally consistent with Allcott and Taubinsky (2015) and Bradford et al. (2017). Compared to Bradford et al. (2017), though, we also find standard time discounting to be related with the adoption of high-cost measures. 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-efficiency lights, AC replacement, and alternative fuel vehicles.

Turning to M2, we observe that most of the findings for the four preference parameters are rather similar to M1; however, as expected, the p-values tend to be higher. The increase in the p-value (and decline in the marginal effect size) is particularly large for the coefficient of risk aversion. Arguably, higher p-values and smaller effect sizes may be due to bad controls. The findings for the additional covariates in M2 suggest that age is positively related with energy- efficient appliance adoption and with implementing retrofit measures. 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, energy-efficient appliances and retrofit measures, arguably because the related financial incentives, i.e. energy costs savings, are higher for larger households.

Looking at the results for M3, we note that the marginal effects associated with α, δ, and λ 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 covariates are generally able to predict adoption of EET, they may be bad controls. 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.

Table 6: Results (average marginal effects) of probit models for energy efficiency technology adoption decisions (p-values in parenthesis)

	LED			Appliances			Retrofit		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
$\alpha^{\dagger}$	0.012*	0.009	0.004	0.016**	0.013*	0.006	0.016**	0.010	0.003
	(0.087)	(0.232)	(0.539)	(0.024)	(0.064)	(0.330)	(0.029)	(0.177)	(0.679)
$\delta^{\dagger}$	0.017**	0.016**	0.013**	0.010	0.008	0.004	0.016**	0.012*	0.006
	(0.010)	(0.018)	(0.047)	(0.103)	(0.199)	(0.485)	(0.021)	(0.097)	(0.321)
$\beta^{\dagger}$	-0.000	0.001	-0.002	0.000	-0.000	-0.003	0.008	0.006	0.002
	(0.970)	(0.868)	(0.665)	(0.994)	(0.962)	(0.446)	(0.137)	(0.223)	(0.690)
$\lambda^{\dagger}$	-0.013**	-0.008	-0.006	-0.011**	-0.010**	-0.005	-0.005	-0.003	-0.000
	(0.019)	(0.131)	(0.257)	(0.028)	(0.049)	(0.267)	(0.340)	(0.538)	(0.947)
Age		-0.001	-0.002***		0.002***	0.001		0.004***	0.000
		(0.163)	(0.000)		(0.000)	(0.155)		(0.000)	(0.692)
Gender		0.077***	0.074***		-0.008	-0.002		-0.005	0.003
		(0.000)	(0.000)		(0.376)	(0.848)		(0.616)	(0.738)
Income		0.002***	0.001***		0.001***	0.001**		0.003***	0.001**
		(0.000)	(0.000)		(0.000)	(0.023)		(0.000)	(0.013)
Education		0.028**	0.023**		0.030***	0.019*		-0.007	-0.019*
		(0.013)	(0.039)		(0.003)	(0.051)		(0.545)	(0.080)
Hhsize		0.006*	0.001		0.009**	0.005		0.018***	0.002
		(0.082)	(0.699)		(0.011)	(0.159)		(0.000)	(0.499)
Likelymove			-0.025***			-0.015***			-0.013**
			(0.000)			(0.008)			(0.030)
Renting			-0.068***			-0.024**			-0.283***

	LED			Appliances			Retrofit		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
			(0.000)			(0.030)			(0.000)
Individ-ual_met er			0.029*			0.056***			0.059***
			(0.083)			(0.000)			(0.000)
Home-Size			0.014			0.045***			0.048***
			(0.258)			(0.000)			(0.000)
BuildAg e			-0.001***			-0.000**			0.001***
			(0.002)			(0.025)			(0.001)
De-tached housing									0.0725***
									(0.000)
Main bulb			0.069***						
			(0.000)						
Capital-access†			0.031***			0.024***			0.025***
			(0.000)			(0.000)			(0.000)
Env_ID†			0.033***			0.066***			0.063***
			(0.000)			(0.000)			(0.000)
Social-norm†			0.013**			0.028***			0.012**
			(0.015)			(0.000)			(0.026)
Incentiv-ized			-0.006			-0.005			0.000
			(0.547)			(0.547)			(0.978)
Country dum-mies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Product dum-mies				YES	YES	YES			
N	9166	9166	9166	8270	8270	8270	8035	8035	8035

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

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.

4.2 Robustness checks[21]

We conducted a number of additional analyses to assess the sensitivity of our findings for the effects of standard time discounting, risk aversion, loss aversion, and present bias on household adoption of the three EETs considered. These robustness checks are organized in four categories: (i) outliers and missing values, (ii) alternative variable and model specifications, (iii) distributional and sampling assumptions, and (iv) heterogeneity across countries. In addition, we analyze whether failure to include any of the four variables reflecting standard time discounting, risk aversion, loss aversion, and present bias when modelling EET adoption results in an omitted variable bias.

Outliers and missing values

Our preferred model employed a trimmed sample, which excludes the 2.5% smallest and largest values for β. The findings are very similar to those of the preferred model if we trim at 5 % or 1.25% (rather than at 2.5%). In comparison, Appendix Table A5 reports the findings for the untrimmed sample. In this case, and in contrast to the findings reported in Table 6, the coefficient associated with β is statistically significant in the equations for LED and retrofit (for M1, M2, and M3). Thus, less present-biased individuals are more likely to have adopted LEDs and retrofit measures. This contrast in findings to those using the untrimmed sample can be explained by the fact that β does not differ much between most respondents, i.e. the distribution is fairly concentrated, but with a small share of outliers concentrated at either end of the distribution[22]. Therefore, when included, these outliers are driving the observed correlation with adoption of EETs. For these reasons, our preferred model and all subsequent robustness checks employ the trimmed sample.

Missing values were an issue for income, with more than 15% of the respondents not reporting income (see Appendix Table A4). To save degrees of freedom, we replaced missing values by the country mean and included a control dummy *Missing_income*. As shown in Appendix Table A6, the findings are very

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21 Results from those robustness checks not shown to save space are available upon request.

22 For α, , δ, and λ the distribution was much more dispersed than for β.

similar to those of our preferred model, yet p-values tend to be lower, most likely because of the increase in degrees of freedom. Respondents who refused to report their income were typically less likely to have adopted any of the three EETs.

In conclusion, our results appear to be robust to missing values for income, but sensitive to outliers for β.

Alternative variable and model specification

We first tested the robustness of the results for different specifications using an alternative variable operationalization for efficient appliance adoption. In Table 6, we used the answer to the question "was your last purchased appliance an energy-efficient appliance?" as the dependent variable for energy-efficient appliance adoption. In the survey, 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 model 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 from the two years preceding the survey. Findings for this alternative specification are consistent with those reported in Table 6 but p-values were generally higher, most likely because of a lower sample size (5364 compared to 8270).

In an alternative specification, we also tested the effects of accounting for stake levels. Including dummies reflecting the different stakes in the MPLs only marginally affects the findings presented in Table 6.

Thus, our findings appear to be robust to alternative operationalizations for efficient appliance adoption, and to controlling for the stake levels used to elicit preferences over time, risk, and losses in the MPLs.

Distributional and sampling assumptions

Next, we allowed for alternative distributional assumptions to the probit model. Running logit models and complementary log-log models produced similar results as our preferred model; yet, based on AIC/BIC fit measures, the probit model fared slightly better on average.

Since the adoption of EETs may be correlated, we also employed a multivariate probit and three bivariate probit models, where the error terms capture possible correlations between the dependent variables. For the multivariate probit model, none of the coefficients associated with the four preference parameters α, β, δ, and λ were statistically significant at $p<0.1$, arguably because of a substantial loss in the sample size (5455 compared to 9166, 8270, and 8035 in single LED, appliance, and retrofit probit models, respectively). Based on a Likelihood-Ratio test, we also failed to accept the assumption of zero covariances at $p<0.01$, but the coefficients of all variables (for M1, M2, and M3) were almost identical to those obtained from running univariate probit models for these 5455 observations. Thus, running individual probit models rather than a multivariate probit model does not appear to affect the findings.

We further tested for sensitivity to sampling assumptions. While quota sampling yields a representative sample with respect to the quota criteria, such samples are typically not representative for other household criteria. We therefore estimated equation (4) employing sampling weights provided by the survey institute. For all models M1, M2, and M3, and all EETs, the findings were virtually identical to those reported in Table 6 for our preferred model.

In sum, our findings appear to be robust to alternative distributional and sampling assumptions, but sensitive to degrees of freedom.

Heterogeneity across countries

To test for differences across countries, we interacted country dummies with α, β, δ, and λ and included these interaction terms in equation (4). Appendix Table A7 provides the marginal effects of α, β, δ, and λ for a discrete change in the respective country dummy, exemplarily for M2. A statistically significant effect for a particular country indicates that the marginal effect differs compared to the average of the other countries. Based on results of Likelihood-Ratio tests between these interaction models and the (nested) non-interaction models (see Appendix Table A8 for M1, M2, and M3), we fail to reject the hypotheses for LED and retrofit (but not for appliances) that all interaction terms are zero[23]. Thus, for appliances, the effects of time discounting, risk aversion, loss aversion or present bias on household adoption of EETs appear to vary by country.

Omitted variable bias

In addition, we explored whether failure to include any of the four preference variables when modelling EET adoption results in an omitted variable bias. We estimated probit models with only one of these preference variables included as a covariate in the adoption regression equations. The findings presented in Appendix Tables A9, A10, and A11 for M1, M2, and M3 provide no empirical evi-

23 Lagrange Multiplier and Wald tests provided similar results as the Likelihood-Ratio tests.

dence 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.

5 Conclusion

This paper empirically studies the relation between household adoption of low-cost, medium-cost and high-cost EETs (LEDs, energy-efficient appliances, retrofit measures) and risk aversion, standard time preferences, present bias, and loss aversion. The analysis relies on a large representative sample drawn from eight EU countries, making it substantially larger than previous studies. Preferences over time, risk, and losses were elicited and jointly estimated from participant choices in context-free MPLs, more than half of which were incentivized.

Our findings provide some support for the hypothesis that more risk-averse individuals, more loss-averse individuals and individuals exhibiting a lower time discount factor are less likely to have adopted EETs. Present bias was only found to be related with EET adoption when the sample was not trimmed to exclude observations at the extreme ends of the distribution of the parameter reflecting present bias. In this case, individuals are less likely to have adopted LEDs, energy-efficient appliances, and retrofit measures.

Some of the findings (significance levels and effect sizes) for standard time preferences, risk aversion, and loss aversion were sensitive to including covariates reflecting socio-demographic information, dwelling characteristics or environmental attitudes in the regression. The covariates reflecting income, education, planned moving behavior, rental status or access to capital were found to be highly correlated with the adoption of EET, but they are likely to be also driven by preferences for time, risk, and losses. Thus, for preferences over time, risk, and losses, some of these variables appear to be bad controls.

These findings are generally robust to a wide range of robustness checks involving missing data on income or different distributional and sampling assumptions. However, we find some evidence (for appliances) that the effects of time discounting, risk aversion, loss aversion or present bias on household adoption of EETs differ across countries. Therefore, including country dummies to capture heterogeneity across countries in econometrically analyzing EET adoption decisions may not be sufficient. Further exploring such differences via country-specific models would require larger samples and must be left for future research.

In addition, our empirical findings provide no empirical evidence that omitting one or several of the time and risk- or loss-aversion parameters leads to an omitted variable bias when estimating any of the three EET adoption equations. This finding should be reassuring when assessing previous research (which typically only includes one or two of these parameters). It also indicates that future studies may focus on the impact of some of the preference parameters individually, without having to include all four parameters.

The findings on the relation between socio-demographic characteristics, individual attitudes (notably environmental identity and social norms) and dwelling characteristics with EET adoption are consistent with the extant empirical literature. Of particular interest are the results for the variables reflecting split incentives, especially because our study included not only ownership status (i.e. renters versus owners), but also the likelihood of the household moving in the near future, as well as whether household electricity use was measured individually. All three types of split-incentives variables were found to have significant effects on EET adoption.

Finally, our results also offer insights for policy making. Specifically, the findings on loss aversion may have implications for individual welfare and warrant policy measures, conditional upon the outcomes of cost-benefit analyses. Following Gillingham and Palmer (2014), if information explaining the implications of loss aversion on technology choices was available for consumers at low cost, this could be a first-best approach, assuming that consumers respond to this information. Nudging could be proposed as a second-best solution. In this case, framing energy technology decisions such that failure to adopt an EET is portrayed as a loss, may effectively accelerate the diffusion of EETs by loss-averse consumers. Identifying and targeting loss-averse individuals may however prove challenging in practice.

In principle, market failures arising from split incentives could be addressed through a first-best solution. Assuming perfect information and zero transaction costs, landlords and tenants could negotiate an appropriate contract which, for example, adequately rewards the landlord who invests in retrofit measures. In a second-best world, policy interventions may be justified such as measures addressing information asymmetries (e.g. certificates for buildings, labelling for appliances and bulbs), command-and-control type interventions referring to building codes (for thermal insulation), individual metering requirements (for electricity or natural gas use), or regulations on embedding costs for retrofit measures into a lease. Despite rather scarce empirical evidence on their cost-benefit performance (e.g. Gillingham and Palmer 2014; Gerarden et al. 2015, 2017), most of these policies are already in place to varying degrees in the countries included in our sample. Future studies may explore for individual countries whether increasing the stringency of existing policies or introducing additional policies is likely to improve welfare.

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Appendix

A I Calculation of preference parameters

To calculate preference parameters, we solved the following four equations in the four unknown preference parameters (α,β,$\tilde{\delta}$,λ) for each subject that had a single switch point:[24]

$$u^*(x_{A1.1}) = \tilde{\delta} u^*(x_{B1.1}), (A1)$$

$$u^*\big(x_{A1.2}\big) = \beta \tilde{\delta} u^*\big(x_{B1.2}\big), (A2)$$

$$\frac{1}{2}u^*(x_{A2}(h)) + \frac{1}{2}u^*(x_{A2}(t)) = \frac{1}{2}u^*(x_{B2}(h)) + \frac{1}{2}u^*(x_{B2}(t)), (A3)$$

$$\frac{1}{2}u^*(x_{A3}(h)) + \frac{1}{2}u^*(x_{A3}(t)) = \frac{1}{2}u^*(x_{B3}(h)) + \frac{1}{2}u^*(x_{B3}(t)), (A4)$$

Where $x_{A1.1}$and $x_{B1.1}$ in equation (A1) are the monetary amounts that make a subject indifferent between Option A and B in MPL1.1, as determined by their switch-point. Analogously, $x_{A1.2}$and $x_{B1.2}$ in equation (A2) are the monetary amounts that make a subject indifferent between Option A and B in MPL1.2. The remaining two price lists involve coin flips, indicated with (h) for heads, and (t) for tails. In the third equation (A3), $x_{A2}(h)$ and $x_{A2}(t)$ are the monetary payments a subject would require in the case of heads (h) and tails (t) respectively, in Option A of MPL2, to be indifferent with Option B, yielding $x_{B2}(h)$ and $x_{B2}(t)$ in the case of heads and tails respectively. The notation is similar for the last equation, which states indifference in MPL3, which now may also involves losses.

MPL2 allowed very risk averse choices that would render the parameter associated with risk aversion (α) negative. Since utility as specified in Equation 1 would approach minus infinity as x->0 for gains and plus infinity for losses with < 0, we adjusted the utility function as:

$$u^*(x) = \begin{cases} ((x+\varepsilon)^\alpha - \varepsilon^\alpha)/\alpha & if\ x \geq 0 \\ -\lambda((-x+\varepsilon)^\alpha - \varepsilon^\alpha)/\alpha & if\ x < 0 \end{cases}$$

This transformation ensures that utility is well behaved for values $\alpha < 0$, while closely approximating CRRA utility as specified in Equation 1 for small values of

24 For the sake of parsimonious exposition, $\tilde{\delta}$ refers to the discount factor over 23 weeks. In the main text we exclusively use the yearly discount factor $\delta = \tilde{\delta}^{52/23}$

ε. In particular, this transformation ensures that $u^*(0)$=0 ∀ α, and thus that the derivatives of the utility function around the reference point do not diverge. See also Wakker (2008) for an illustration, and Vendrik and Woltjer (2007) for an example of the above transformation. For the calculation of preference parameters in this paper, we chose $\varepsilon = 0.001$.

A II Descriptive statistics

Table A1: Means of calculated 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	0.822 (1.102)	0.787 (1.010)	0.843 (1.119)	0.851 (1.074)	0.724 (1.092)	0.965 (1.389)	0.861 (1.132)	0.906 (1.093)	0.704 (0.936)
Standard time discounting: δ (annual rate)	0.851 (0.189)	0.875 (0.161)	0.856 (0.192)	0.844 (0.182)	0.837 (0.201)	0.807 (0.242)	0.843 (0.192)	0.862 (0.171)	0.870 (0.168)
Present bias: β	1.007 (0.449)	0.990 (0.181)	1.021 (0.545)	0.979 (0.287)	1.005 (0.397)	1.054 (0.747)	1.003 (0.435)	1.016 (0.451)	1.007 (0.445)
Loss aversion: λ	3.424 (3.886)	3.483 (3.727)	3.439 (4.107)	3.428 (3.963)	3.386 (4.030)	3.51 (3.942)	3.241 (3.620)	3.576 (3.998)	3.386 (3.728)
Number of observations	13,436	1,895	1,807	1,728	1,761	1,274	1,756	1,368	1,847

Table A2: Correlation of preference parameters

	α	δ	β	λ
Risk aversion: α	1.000			
Standard time discounting: δ (annual rate)	-0.664*** (0.000)	1.000		
Present bias: β	0.112*** (0.000)	-0.207*** (0.000)	1.000	
Loss aversion: λ	0.418*** (0.000)	-0.248*** (0.000)	0.122*** (0.000)	1.000

***<0.01

Table A3: 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)
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)
Indvidual 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: fridge	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 A4: Reasons for dropping observations and shares (based on N=15055)

	Percentage
Failure to report income category	15.84
Failure to report education level	0.38
Preferences parameters could not be calculated	9.01
No purchase of lightbulb in the last 2 years	10.80
No purchase of an appliance in the last 5 years	17.02
Not involved in retrofit decision	4.85
No implementation of a retrofit measure in the last 10 years	13.92

AIII Robustness checks

Table A5: Results (average marginal effects) of probit models for energy efficiency technology adoption decisions (p-values in parenthesis), untrimmed sample.

	LED			Appliances			Retrofit		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
$\alpha^{\dagger}$	0.016**	0.012*	0.008	0.021***	0.018***	0.012*	0.015**	0.010	0.003
	(0.028)	(0.088)	(0.242)	(0.003)	(0.010)	(0.065)	(0.042)	(0.192)	(0.717)
$\delta^{\dagger}$	0.021***	0.019***	0.016**	0.013**	0.011*	0.008	0.016**	0.012*	0.007
	(0.002)	(0.005)	(0.014)	(0.041)	(0.082)	(0.194)	(0.022)	(0.082)	(0.265)
$\beta^{\dagger}$	0.015***	0.017***	0.016***	0.006	0.006	0.006	0.011**	0.011**	0.012***
	(0.003)	(0.001)	(0.001)	(0.269)	(0.258)	(0.198)	(0.022)	(0.025)	(0.009)
$\lambda^{\dagger}$	-0.012**	-0.008	-0.006	-0.011**	-0.010**	-0.005	-0.006	-0.004	-0.000
	(0.024)	(0.153)	(0.280)	(0.019)	(0.038)	(0.257)	(0.269)	(0.517)	(0.960)
Age		-0.001	-0.002***		0.002***	0.000		0.004***	0.000
		(0.115)	(0.000)		(0.000)	(0.276)		(0.000)	(0.679)
Gender		0.074***	0.071***		-0.010	-0.004		-0.002	0.007
		(0.000)	(0.000)		(0.256)	(0.664)		(0.823)	(0.451)
Income		0.002***	0.001***		0.001***	0.001**		0.003***	0.001***
		(0.000)	(0.000)		(0.000)	(0.033)		(0.000)	(0.008)
Education		0.030***	0.024**		0.029***	0.017*		-0.008	-0.021**
		(0.006)	(0.027)		(0.003)	(0.066)		(0.460)	(0.048)
Hhsize		0.006*	0.001		0.010***	0.005		0.019***	0.004
		(0.089)	(0.747)		(0.006)	(0.122)		(0.000)	(0.257)
Like-lymove			-0.025***			-0.013**			-0.012**
			(0.000)			(0.015)			(0.038)
Renting			-0.070***			-0.029***			-

	LED			Appliances			Retrofit		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
									0.279***
			(0.000)			(0.009)			(0.000)
Individual_meter			0.030*			0.054***			0.053***
			(0.069)			(0.000)			(0.001)
HomeSize			0.013			0.045***			0.044***
			(0.276)			(0.000)			(0.001)
BuildAge			-0.001***			-0.000**			0.001***
			(0.003)			(0.017)			(0.001)
Detached housing									0.071***
									(0.000)
Main bulb			0.069***						
			(0.000)						
Capitalaccess[†]			0.031***			0.024***			0.026***
			(0.000)			(0.000)			(0.000)
Env_ID[†]			0.033***			0.065***			0.064***
			(0.000)			(0.000)			(0.000)
Socialnorm[†]			0.013**			0.027***			0.012**
			(0.010)			(0.000)			(0.018)
Incentivized			-0.009			-0.007			0.001
			(0.367)			(0.407)			(0.923)
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Product dummies				YES	YES	YES			
N	9630	9630	9630	8693	8693	8693	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 (p-values in parenthesis) with dummy for missing income.

	LED			Appliances			Retrofit		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
α†	0.014**	0.011	0.007	0.014**	0.012*	0.006	0.017**	0.012*	0.005
	(0.031)	(0.103)	(0.266)	(0.030)	(0.070)	(0.308)	(0.013)	(0.084)	(0.443)
δ†	0.017***	0.016**	0.013**	0.012**	0.010*	0.006	0.012*	0.009	0.002
	(0.006)	(0.010)	(0.033)	(0.049)	(0.097)	(0.280)	(0.066)	(0.178)	(0.674)
β†	0.001	0.002	-0.001	0.002	0.001	-0.002	0.007	0.006	0.002
	(0.862)	(0.708)	(0.868)	(0.656)	(0.766)	(0.563)	(0.128)	(0.231)	(0.608)
λ†	-0.014***	-0.010*	-0.008	-0.011**	-0.010**	-0.006	-0.008	-0.006	-0.003
	(0.006)	(0.057)	(0.123)	(0.017)	(0.036)	(0.168)	(0.119)	(0.211)	(0.546)
Age		-0.000	-0.002***		0.002***	0.001*		0.004***	0.000
		(0.190)	(0.000)		(0.000)	(0.051)		(0.000)	(0.696)
Gender		0.077***	0.074***		-0.006	0.000		-0.005	0.004
		(0.000)	(0.000)		(0.496)	(0.958)		(0.605)	(0.686)
Income		0.002***	0.001***		0.001***	0.001***		0.003***	0.001**
		(0.000)	(0.000)		(0.000)	(0.009)		(0.000)	(0.014)
Missing Income		-0.020	-0.005		-0.052***	-0.034***		-0.029**	-0.002
		(0.126)	(0.708)		(0.000)	(0.003)		(0.029)	(0.903)
Education		0.029***	0.022**		0.034***	0.020**		-0.003	-0.017*
		(0.005)	(0.031)		(0.000)	(0.028)		(0.804)	(0.075)
Hhsize		0.006*	0.001		0.007**	0.003		0.019***	0.002
		(0.070)	(0.813)		(0.029)	(0.363)		(0.000)	(0.584)
Likelymove			-0.027***			-0.017***			-0.012**
			(0.000)			(0.001)			(0.026)
Renting			-0.070***			-0.025**			-0.268***
			(0.000)			(0.019)			(0.000)
Individual_meter			0.038**			0.072***			0.079***
			(0.011)			(0.000)			(0.000)
HomeSize			0.014			0.036***			0.063***
			(0.213)			(0.000)			(0.000)
BuildAge			-0.001***			-0.000**			0.001***
			(0.000)			(0.027)			(0.000)
Detached housing									0.066***
									(0.000)

	LED			Appliances			Retrofit		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
Main bulb			0.065***						
			(0.000)						
Capitalaccess†			0.029***			0.024***			0.024***
			(0.000)			(0.000)			(0.000)
Env_ID†			0.032***			0.066***			0.063***
			(0.000)			(0.000)			(0.000)
Socialnorm†			0.015***			0.028***			0.016***
			(0.002)			(0.000)			(0.001)
Incentivized			-0.007			-0.003			-0.006
			(0.447)			(0.759)			(0.494)
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Product dummies				YES	YES	YES			
N	10713	10713	10713	9710	9710	9710	9560	9560	9560

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

Table A7: Results (average marginal effects of α, β, δ, and λ for a discrete change in the country dummy) of probit models for energy efficiency technology adoption decisions (p-values in parenthesis) – M2 with country interaction terms.

	LED							
	France	*Germany*	*Italy*	*Poland*	*Romania*	*Spain*	*Sweden*	*United Kingdom*
α	-0.027	0.001	0.013	0.011	-0.014	-0.019	0.020	0.059***
$\delta^{\dagger}$	-0.025	0.001	0.033	-0.007	-0.010	-0.011	0.022	0.028
$\beta^{\dagger}$	-0.732	-0.386	0.090	-0.499	-0.770	-0.695***	-0.038	0.071**
$\lambda^{\dagger}$	0.021	0.020	0.013	-0.013	-0.024	0.026	-0.014	-0.027*
Others covariates	YES	YES	YES	YES	YES	YES	YES	YES
N	9166	9166	9166	9166	9166	9166	9166	9166
	Appliances							
	France	*Germany*	*Italy*	*Poland*	*Romania*	*Spain*	*Sweden*	*United Kingdom*
α	-0.005	0.001	0.002	0.007	-0.021	-0.010	0.074**	0.027
$\delta^{\dagger}$	-0.026	0.017	-0.004	-0.004	0.001	0.024	0.045	0.030
$\beta^{\dagger}$	-0.132	0.443	-0.125	-0.105	-0.086	0.525	0.869	0.515***
$\lambda^{\dagger}$	-0.005	0.016	-0.011	-0.030**	-0.008	0.021	-0.005	0.032**
Others covariates	YES	YES	YES	YES	YES	YES	YES	YES
N	8270	8270	8270	8270	8270	8270	8270	8270
	Retrofit							
	France	*Germany*	*Italy*	*Poland*	*Romania*	*Spain*	*Sweden*	*United Kingdom*
α	0.016	0.011	0.042*	0.053**	-0.002	-0.019	-0.003	-0.003
$\delta^{\dagger}$	0.033	0.019	0.041*	0.020	-0.003	0.005	0.008	0.019
$\beta^{\dagger}$	0.313	0.532	0.400	0.606	-0.442	-0.023	0.128	0.331
$\lambda^{\dagger}$	-0.018	-0.003	-0.007	-0.014	0.006	0.039**	0.009	-0.001
Others covariates	YES	YES	YES	YES	YES	YES	YES	YES
N	8035	8035	8035	8035	8035	8035	8035	8035

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

Table A8: Results of Likelihood-Ratio tests (H0: all country interaction terms associated with α, β, δ, and λ are equal to zero).

	LED			Appliances			Retrofit		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
Prob > □^{2}	0.261	0.276	0.383	0.063*	0.052*	0.198	0.951	0.946	0.745

* p<0.1

Table A9: Results (average marginal effects) of probit models (p-values in parenthesis). Results for risk preferences, standard time discounting, present bias and loss aversion – Specification M1.

	LED				
$\alpha^{\dagger}$	0.0122*	-0.0040			
	(0.087)	(0.432)			
$\delta^{\dagger}$	0.0174**		0.0123**		
	(0.010)		(0.017)		
$\beta^{\dagger}$	-0.0002			-0.0018	
	(0.970)			(0.725)	
$\lambda^{\dagger}$	-0.0131**				-0.0122**
	(0.019)				(0.017)
N	9166	9166	9166	9166	9166
	Appliances				
$\alpha^{\dagger}$	0.0156**	0.0042			
	(0.024)	(0.378)			
$\delta^{\dagger}$	0.0104		0.0028		
	(0.103)		(0.547)		
$\beta^{\dagger}$	0.0000			-0.0016	
	(0.994)			(0.736)	
$\lambda^{\dagger}$	-0.0108**				-0.0072
	(0.028)				(0.102)
N	8270	8270	8270	8270	8270
	Retrofit				
$\alpha^{\dagger}$	0.0163**	0.0032			
	(0.029)	(0.547)			
$\delta^{\dagger}$	0.0162**		0.0066		
	(0.021)		(0.209)		
$\beta^{\dagger}$	0.0078			0.0064	
	(0.137)			(0.218)	
$\lambda^{\dagger}$	-0.0054				-0.0025
	(0.340)				(0.631)
N	8035	8035	8035	8035	8035

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

Table A10: Results (average marginal effects) of probit models (p-values in parenthesis). Results for risk preferences, standard time discounting, present bias and loss aversion – Specification M2.

	LED				
$\alpha^{\dagger}$	0.0085	-0.0049			
	(0.232)	(0.337)			
$\delta^{\dagger}$	0.0158**		0.0121**		
	(0.018)		(0.018)		
$\beta^{\dagger}$	0.0008			-0.0003	
	(0.868)			(0.953)	
$\lambda^{\dagger}$	-0.0084				-0.0084*
	(0.131)				(0.096)
N	9166	9166	9166	9166	9166
	Appliances				
$\alpha^{\dagger}$	0.0127*	0.0033			
	(0.064)	(0.484)			
$\delta^{\dagger}$	0.0081		0.0022		
	(0.199)		(0.643)		
$\beta^{\dagger}$	-0.0002			-0.0015	
	(0.962)			(0.740)	
$\lambda^{\dagger}$	-0.0096**				-0.0066
	(0.049)				(0.131)
N	8270	8270	8270	8270	8270
	Retrofit				
$\alpha^{\dagger}$	0.0100	0.0008			
	(0.177)	(0.884)			
$\delta^{\dagger}$	0.0116*		0.0056		
	(0.097)		(0.274)		
$\beta^{\dagger}$	0.0064			0.0055	
	(0.223)			(0.291)	
$\lambda^{\dagger}$	-0.0034				-0.0020
	(0.538)				(0.700)
N	8035	8035	8035	8035	8035

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

Table A11: Results (average marginal effects) of probit models (p-values in parenthesis). Results for risk preferences, standard time discounting, present bias and loss aversion – Specification M3.

			LED		
$\alpha^{\dagger}$	0.0043	-0.0063			
	(0.539)	(0.205)			
$\delta^{\dagger}$	0.0132**		0.0117**		
	(0.047)		(0.020)		
$\beta^{\dagger}$	-0.0022			-0.0029	
	(0.665)			(0.555)	
$\lambda^{\dagger}$	-0.0061				-0.0074
	(0.257)				(0.132)
N	9166	9166	9166	9166	9166
			Appliances		
$\alpha^{\dagger}$	0.0064	0.0015			
	(0.330)	(0.735)			
$\delta^{\dagger}$	0.0043		0.0015		
	(0.485)		(0.745)		
$\beta^{\dagger}$	-0.0035			-0.0042	
	(0.446)			(0.353)	
$\lambda^{\dagger}$	-0.0053				-0.0040
	(0.267)				(0.350)
N	8270	8270	8270	8270	8270
			Retrofit		
$\alpha^{\dagger}$	0.0029	-0.0015			
	(0.679)	(0.755)			
$\delta^{\dagger}$	0.0064		0.0045		
	(0.321)		(0.337)		
$\beta^{\dagger}$	0.0020			0.0017	
	(0.690)			(0.729)	
$\lambda^{\dagger}$	-0.0003				-0.0006
	(0.947)				(0.898)
N	8035	8035	8035	8035	8035

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

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