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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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Working Paper Sustainability and Innovation  
No. S 04/2018



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## **Abstract**

This paper empirically and jointly analyses the relations between risk aversion, standard time discounting, present bias, and loss aversion 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 suggest that present-biased individuals are less likely to adopt EETs. They also provide (weak) evidence that individuals which are more risk-averse, or more loss-averse, or which exhibit a lower discount factor are less likely to adopt EETs. Finally, omitting one or several of the time and risk or loss-aversion parameters when estimating the EET adoption equations did not appear to cause omitted variable bias.

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

**JEL codes:** D23, D81, Q41, Q48

## **Highlights:**

- Present-biased individuals are less likely to adopt energy-efficiency technologies.
- Loss- and risk-aversion are linked with lower energy-efficiency technology adoption.
- Failure to include all time, risk and loss parameters does not OVB.

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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; Ramos et al. 2015; Schleich et al. 2016). 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. In addition, the distinction between preferences (i.e. standard time preferences and risk preferences) and behavioral-based biases such as present bias is important because there are different welfare implications of the associated policies. Although preferences may keep individuals from adopting energy-efficiency technology adoption, they lead to rational decisions; consequently, policies designed to counteract these preferences would not make these individuals better off. In contrast, present-biased individuals exhibit inconsistent time preferences and may make technology choices that are at odds with their own long-term objectives. Thus, policies that address present bias may improve individual welfare.

There is a growing body of evidence on the effects of time and risk preferences on EET adoption; however, comprehensive evaluation that consider time and 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 contributes 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 investigate 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 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, present bias, risk, and loss aversion 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 or age.

The remainder of the paper is organized as follows. Section 2 discusses the existing literature that links preferences over risk, time, 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. (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 dis-

counting 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. (2014) 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<sub>2</sub>-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).

### *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.<sup>1</sup> Heutel (2017) calls for future analyses to consider larger samples than his sample of about 2000 observations.

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<sup>1</sup> 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.

### *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. 2014, 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 and 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.

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 Williams 1999, Holt and Laury 2002), which allow for parametric estimations of preferences.<sup>2</sup> 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., Bradford et al. 2014, Fischbacher et al. 2015,

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<sup>2</sup> 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.

Heutel 2017)<sup>3</sup>. 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. So far, incentivization has only been used in a few demographically representative studies, including Bradford et al. (2014) 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 should 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. (2014), Fischbacher et al. (2015) and Heutel (2017) 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) 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 omitted variables concerns. Finally, many adoption studies that have used rep-

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<sup>3</sup> 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.

representative samples of the population, 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 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, present bias, risk aversion, and loss aversion. Then, a subsection 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 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):

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

where  $x$  means wealth,  $\alpha$  ( $\geq 0$ ) is the parameter reflecting risk aversion and  $\lambda$  is the parameter capturing loss aversion<sup>4</sup>. The utility specification in equation (1) implies that relative risk aversion is constant (CRRA) and identical for losses and gains. We also assume a reference wealth of zero.

### *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)

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

where  $U_t(x_t, \dots, x_T)$  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  $t$ ,  $\delta$  is the standard time discount factor, and  $\beta$  is the parameter reflecting present bias. In our model  $t$  is expressed in years and  $\delta$  is the annual time discounting factor.<sup>5</sup>

### *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  $\alpha$  results in overestimating  $\alpha$  (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

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4  $\alpha=1$  /  $0<\alpha<1$  /  $\alpha>1$  means the participant is risk neutral / risk averse / risk loving;  $\lambda=1$  /  $0<\lambda<1$  /  $\lambda>1$  means the participant is loss neutral / loss seeking / loss averse.

5  $\delta=1$  /  $0<\delta<1$  means that the participant is not discounting future outcomes / discounting future outcomes.

$\beta=1$  /  $0<\beta<1$  /  $\beta>1$  means the participant is neither present nor future biased / present biased / future biased.

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 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. 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.

#### *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 Collier and Williams (1999) for time preferences and present bias and Holt and Laury (2002) for risk preferences). In each MPL, participants faced a list of choices between two options, A and B, and were asked for each choice to indicate their preferred option.<sup>6</sup> 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 pur-

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<sup>6</sup> 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% percent 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.

chasing 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.

### *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).<sup>7</sup>

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<sup>7</sup> 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.

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 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€

### *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, 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<sup>8</sup>. For participants who were not incentivized, the instructions stated that these were hypothetical choices. In all countries, the selected participants re-

<sup>8</sup> 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.

ceived 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 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 a sooner payment may be deemed more reliable, or involves less transaction costs.<sup>9</sup> 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 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: 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 pa-

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<sup>9</sup> This may be an issue, for instance, in laboratory experiments, where sooner (now) payments are awarded instantaneously in cash, while later payments make use of other payment modalities (e.g. bank transfer, or mailed check).

rameters (see Appendix A1 for more details on how the preference parameters were calculated. See also e.g. Brown and Kim (2014) who use 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. 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 the Appendix.

Table A1 suggests that the average standard annual time discount rate across the entire sample was about 28% ( $(1/0.78-1)*100\%$ ), which is in 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 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 did not exhibit present bias. Thus, our mean value for  $\beta = 1.007$  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. (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. The average participant in each of the surveyed countries was loss averse. Our mean value for  $\lambda = 3.414$  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<sup>10</sup>. Table A2 in the Appendix displays the correlation of the estimated

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<sup>10</sup> 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.

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.

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

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

where  $i$  denotes the individual household,  $k$  stands for the technology type,  $\alpha$ ,  $\delta$ ,  $\beta$  and  $\lambda$  are the parameters reflecting risk preferences, standard time preferences, present bias, and loss aversion, respectively<sup>11</sup>;  $y_{ik}^*$  is the latent variable,  $X_{ijk}$  are control variables, and  $\varepsilon_{ik}$  is the error term. In a probit model,  $\varepsilon_{ik}$  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, 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

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<sup>11</sup> To facilitate the interpretation of the coefficients, these variables were entered in the regressions as z-scores.

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.<sup>12</sup> 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 allowed us to mitigate recall bias.

### *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 are summarized in Table A3 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*, *likelystay*, *renting*, or *capitalaccess* could be driven by these preference parameters.<sup>13</sup> In this case, the effects of the preference parameters on the adoption of

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<sup>12</sup> Since these retrofit measures are typically implemented all at once, we did not ask which of the measures was implemented last (unlike for appliances).

<sup>13</sup> 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).

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 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.

Table 5: Description of control variables

Label	Description
M2 and M3	
<i>Age</i>	Respondent age in years.
<i>Gender</i>	Dummy = 1, if respondent is male.
<i>Income</i>	Household annual income (after taxes) in 1000 euro per year (using midpoint of eleven income categories, and the lower level of the highest category).
<i>Education</i>	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.
<i>Household size</i>	Number of household members.
M3	
<i>Likelymove</i>	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.
<i>Renting</i>	Dummy = 1, if the household is renting the current dwelling.
<i>individual_meter</i>	Dummy = 1 if the household has its own electricity meter.
<i>Homesize</i>	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).
<i>Buildage</i>	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.

Label	Description
<i>Detached housing</i>	Dummy = 1 if house was detached.
<i>Main bulb</i>	Dummy = 1, if the new bulb was a main bulb (or part of the main fixture) in the living/dining room.
<i>Env_ID</i>	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."
<i>Socialnorm</i>	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?"
<i>Capitalaccess</i>	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?"
<i>Incentivized</i>	Dummy = 1, if respondent was incentivized.

## 4 Results

We estimated three probit models using robust standard errors. Estimation results appear in Table 6. We first present and discuss the findings for M1. The findings for  $\alpha$  suggest that less risk averse respondents (i.e. a higher  $\alpha$ ) 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 ( $\delta$ ) 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  $\beta$  is positively and significantly correlated with the adoption of all three EETs. Thus, individuals with a higher present bias (i.e. a lower  $\beta$ ) 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).



Finally, respondents with higher loss aversion (i.e. a higher  $\lambda$ ) 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 life-time 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 (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).<sup>14</sup> 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.

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

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<sup>14</sup> Since the lines in the MPL tasks to elicit standard time preferences and present bias were similar, and since all payments were delayed by one week (to accurately reflect payment processing delays), our measure of present bias may actually capture whether participants chose consistently, thus reflecting cognitive ability. In this case, participants choosing consistently may appear to be less present biased. To check for the robustness of our findings, we also included participants’ scores in a standard cognitive reflection test (CRT) (Frederick 2005). While the CRT score variable was found to be significant for LED (but not for appliances or retrofit), all other findings are virtually identical. Therefore cognitive ability did not eliminate the effects of present bias.

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.

Looking at 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  $\alpha$  and  $\lambda$  (and to a lesser extent also for  $\delta$ ), 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-variables are generally able to predict adoption of EET, they may be bad controls, in particular for preferences over 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.

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
$\alpha^\dagger$	0.00878 (0.196)	0.0065 (0.277)	0.0036 (0.542)	0.0143** (0.045)	0.0126* (0.072)	0.0083 (0.216)	0.0087 (0.169)	0.0052 (0.403)	-0.0008 (0.899)
$\delta^\dagger$	0.0123** (0.033)	0.0131** (0.022)	0.0119** (0.036)	-0.0002 (0.979)	-0.0012 (0.852)	-0.0032 (0.610)	0.0093 (0.125)	0.0068 (0.253)	0.0037 (0.510)
$\beta^\dagger$	0.0147*** (0.003)	0.0160*** (0.001)	0.0160*** (0.001)	0.0126*** (0.005)	0.0121*** (0.005)	0.0115*** (0.005)	0.0107** (0.028)	0.0105** (0.027)	0.0123*** (0.009)
$\lambda^\dagger$	-0.0121** (0.024)	-0.0080 (0.135)	-0.0063 (0.224)	-0.0102* (0.077)	-0.0089 (0.123)	-0.0047 (0.405)	-0.0048 (0.378)	-0.0027 (0.611)	0.0002 (0.969)
<i>Age</i>		-0.0006 (0.119)	-0.0021*** (0.000)		0.0018*** (0.000)	0.0003 (0.563)		0.0037** * (0.000)	0.0002 (0.677)
<i>Gender</i>		0.0749*** (0.000)	0.0711*** (0.000)		-0.0013 (0.902)	0.0022 (0.826)		-0.0020 (0.841)	0.0072 (0.445)
<i>Income</i>		0.0020*** (0.000)	0.0010*** (0.000)		0.0012*** (0.000)	0.0006** (0.041)		0.0027** * (0.000)	0.0007*** (0.007)
<i>Education</i>		0.0310*** (0.005)	0.0247** (0.024)		0.0288** (0.012)	0.0140 (0.206)		-0.0079 (0.478)	-0.0205** (0.049)
<i>Hhsize</i>		0.0057* (0.089)	0.0011 (0.757)		0.0041 (0.353)	-0.0006 (0.869)		0.0187** * (0.000)	0.0037 (0.261)
<i>Like-lymove</i>			-0.0247*** (0.000)			-0.0233*** (0.000)			-0.0121** (0.037)
<i>Renting</i>			-0.0701*** (0.000)			-0.0397*** (0.002)			- 0.2794*** (0.000)
<i>Individual_meter</i>			0.0298* (0.070)			0.0515*** (0.001)			0.0535*** (0.001)
<i>Home-Size</i>			0.0134 (0.269)			0.0280** (0.026)			0.0436*** (0.001)

	LED			Appliances			Retrofit		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
<i>BuildAge</i>			-0.0006*** (0.003)			-0.0004** (0.033)			0.0007*** (0.001)
<i>Detached housing</i>									0.0706*** (0.000)
<i>Main bulb</i>			0.0686*** (0.000)						
<i>Capita-laccess<sup>†</sup></i>			0.0316*** (0.000)			0.0213*** (0.000)			0.0264*** (0.000)
<i>Env_ID<sup>†</sup></i>			0.0331*** (0.000)			0.0656*** (0.000)			0.0645*** (0.000)
<i>Social-norm<sup>†</sup></i>			0.0134** (0.011)			0.0215*** (0.000)			0.0121** (0.018)
<i>Incentiv-ized</i>			-0.0098 (0.324)			-0.0069 (0.509)			0.0008 (0.935)
<i>Country dummies</i>	YES	YES	YES	YES	YES	YES	YES	YES	YES
<i>Product dummies</i>				YES	YES	YES			
N	9630	9630	9630	5645	5645	5645	8430	8430	8430

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

### Robustness checks

We conducted a number of additional analyses to assess the robustness of our findings. We first tested the robustness of the results for different specifications using alternative variable operationalization for efficient appliance adoption, accounting for stake effects, and including interaction terms with the country dummies<sup>15</sup>. The second and largest robustness test consisted in an extended exploration of omitted variables biases.

In Table 6, we used the answer to the question “was your last purchased appliance an energy efficient appliance?” as 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

<sup>15</sup> Results from these analyses are available upon request.

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 (1550 compared to 5465).

In an alternative specification, we 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.

As an additional robustness check, we interacted country dummies with the four parameters reflecting preferences over 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.

Last but not least, 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 Table 7 for M1 provide no 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 Appendix Table A5 and Table A6).

Table 7: 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				
$\alpha^\dagger$	0.0078 (0.196)	-0.0011 (0.822)			
$\delta^\dagger$	0.0123** (0.033)		0.0082* (0.098)		
$\beta^\dagger$	0.0147*** (0.003)			0.0117** (0.019)	
$\lambda^\dagger$	-0.0121** (0.024)				- 0.0091* (0.067)
N	9630	9630	9630	9630	9630
	Appliances				
$\alpha^\dagger$	0.0143** (0.044)	0.0115** (0.039)			
$\delta^\dagger$	-0.0002 (0.975)		-0.0070 (0.193)		
$\beta^\dagger$	0.0123*** (0.006)			0.0119*** (0.004)	
$\lambda^\dagger$	-0.0102* (0.078)				-0.0038 (0.469)
N	5465	5465	5465	5465	5465
	Retrofit				
$\alpha^\dagger$	0.0087 (0.169)	0.0032 (0.538)			
$\delta^\dagger$	0.0093 (0.125)		0.0041 (0.417)		
$\beta^\dagger$	0.0107** (0.028)			0.0095** (0.046)	
$\lambda^\dagger$	-0.0048 (0.378)				-0.0020 (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 paper empirically studies the relation between household adoption of 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.

The results 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 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.

While the findings for present bias appear very robust to alternative model specifications, some of the findings for risk-aversion, standard time preferences and loss aversion were no longer significant at conventional levels, when the regression analysis also included covariates reflecting socio-demographic information, dwelling characteristics or environmental attitudes. In particular, 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. In particular for preferences over risk and losses, some of these variables appear to be bad controls.

In general, 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 present bias have welfare implications and 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 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 requirements (for electricity or natural gas use), 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. Future studies may explore for individual countries whether increasing the stringency of existing policies or introducing additional policies is likely to improve individual 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  $(\alpha, \beta, \tilde{\delta}, \lambda)$  for each subject that had a single switch point:<sup>16</sup>

$$x_{A1.1}^{\alpha} = \tilde{\delta} x_{B1.1}^{\alpha},$$

$$x_{A1.2}^{\alpha} = \beta \tilde{\delta} x_{B1.2}^{\alpha},$$

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

$$\frac{1}{2} * x_{A3}^{\alpha}(h) - \frac{1}{2} \lambda (-x_{A3}(t))^{\alpha} = \frac{1}{2} * x_{B3}^{\alpha}(h) - \frac{1}{2} \lambda (-x_{B3}(t))^{\alpha},$$

Where  $x_{A1.1}$  and  $x_{B1.1}$  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  $x_{B1.2}$  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  $x_{A2}(h)$  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 also involves losses.

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<sup>16</sup> 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  $\delta = \delta^{-52/23}$

## A II Additional tables

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: $\alpha$	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: $\delta$ (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: $\beta$	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: $\lambda$	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 A2: Correlation of preference parameters

	$\alpha$	$\delta$	$\beta$	$\lambda$
Risk aversion: $\alpha$	1.000			
Standard time discounting: $\delta$ (annual rate)	-0.522*** (0.000)	1.000		
Present bias: $\beta$	0.100*** (0.000)	-0.155*** (0.000)	1.000	
Loss aversion: $\lambda$	0.357*** (0.000)	-0.174*** (0.000)	0.123*** (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)
Individual 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 <sup>†</sup>	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 <sup>†</sup>	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 <sup>†</sup>	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)

	All coun-tries	France	Germany	Italy	Poland	Romania	Spain	Sweden	United Kingdom
Last appli- ance: 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




Table A4: 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			
$\alpha$ (risk aversion) <sup>†</sup>	0.0065 (0.277)	-0.0012 (0.808)			
$\delta$ (standard time discounting) <sup>†</sup>	0.0131** (0.022)		0.0087* (0.078)		
$\beta$ (present bias) <sup>†</sup>	0.0160*** (0.001)			0.0135*** (0.006)	
$\lambda$ (loss aversion) <sup>†</sup>	-0.0080 (0.135)				-0.0054 (0.274)
N	9630	9630	9630	9630	9630
		Appliances			
$\alpha$ (risk aversion) <sup>†</sup>	0.0126* (0.071)	0.0108** (0.050)			
$\delta$ (standard time discounting) <sup>†</sup>	-0.0012 (0.851)		-0.0074 (0.168)		
$\beta$ (present bias) <sup>†</sup>	0.0119*** (0.006)			0.0118*** (0.004)	
$\lambda$ (loss aversion) <sup>†</sup>	-0.0088 (0.126)				-0.0029 (0.583)
N	5465	5465	5465	5465	5465
		Retrofit			
$\alpha$ (risk aversion) <sup>†</sup>	0.0052 (0.403)	0.0017 (0.740)			
$\delta$ (standard time discounting) <sup>†</sup>	0.0068 (0.253)		0.0031 (0.536)		
$\beta$ (present bias) <sup>†</sup>	0.0105** (0.027)			0.0096** (0.039)	
$\lambda$ (loss aversion) <sup>†</sup>	-0.0027 (0.611)				-0.0007 (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 A5: 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					
$\alpha$ (risk aversion) <sup>†</sup>	0.0036 (0.542)	-0.0030 (0.540)			
$\delta$ (standard time discounting) <sup>†</sup>	0.0119** (0.036)		0.0087* (0.075)		
$\beta$ (present bias) <sup>†</sup>	0.0160*** (0.001)			0.0135*** (0.004)	
$\lambda$ (loss aversion) <sup>†</sup>	-0.0063 (0.224)				-0.0046 (0.345)
N	9630	9630	9630	9630	9630
Appliances					
$\alpha$ (risk aversion) <sup>†</sup>	0.0083 (0.216)	0.0090* (0.090)			
$\delta$ (standard time discounting) <sup>†</sup>	-0.0032 (0.610)		-0.0079 (0.131)		
$\beta$ (present bias) <sup>†</sup>	0.0115*** (0.005)			0.0119*** (0.002)	
$\lambda$ (loss aversion) <sup>†</sup>	-0.0047 (0.405)				0.0001 (0.979)
N	5465	5465	5465	5465	5465
Retrofit					
$\alpha$ (risk aversion) <sup>†</sup>	-0.0008 (0.899)	-0.0014 (0.771)			
$\delta$ (standard time discounting) <sup>†</sup>	0.0037 (0.510)		0.0022 (0.645)		
$\beta$ (present bias) <sup>†</sup>	0.0123*** (0.009)			0.0117** (0.012)	
$\lambda$ (loss aversion) <sup>†</sup>	0.0002 (0.969)				0.0010 (0.834)
N	8430	8430	8430	8430	8430



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