The impact of preferences over risk, time, and losses on household adoption of energy efficient technologies in Europe

Joachim Schleich[a,b], Xavier Gassmann[a], Thomas Meissner[c], Corinne Faure[a]

[a] Grenoble Ecole de Management, 12 rue Pierre Sémard, 38000 Grenoble, France;
Joachim.schleich@grenoble-em.com / joachim.schleich@isi.fraunhofer.de

[b] Fraunhofer Institute for Systems and Innovation Research, Breslauer Str. 48, 76139 Karlsruhe, Germany

[c] Maastricht University, Tongersestraat 53, 6211 LM Maastricht, The Netherlands

Abstract

This paper empirically and jointly analyses the effect of risk aversion, standard time preferences, present bias and loss aversion on household stated adoption of light emitting diodes (LEDs), energy efficient appliances, and retrofit measures. Our analysis relies on a large representative sample drawn from eight EU countries. Time, risk and loss aversion preferences were elicited and jointly estimated from participant choices in context-free multiple price list experiments. The findings suggest that present-biased individuals are less likely to adopt LEDs, energy efficient appliances and retrofit measures. Lower standard time discount rates are positively related with LED adoption but have no effect on the adoption of energy efficient appliances or retrofit measures. Risk aversion and loss aversion are not found to be related to the adoption of LEDs, appliances or retrofit measures. Our findings support the view that present bias contributes to explaining the energy efficiency paradox, thus providing a rationale for policy intervention.

JEL classification: D03; D12; Q40; Q58;

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

1 Introduction

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

For household technology choices, insights from the psychology and behavioral economics literatures suggest that both time and risk preferences may help explain the energy efficiency paradox (e.g. Allcott and Mullainathan 2010, Allcott 2011, Gerarden et al. 2015, Ramos et al. 2015, or Schleich et al. 2016). There is some growing body of evidence on the effects of time discounting and risk preferences on energy-efficient technology adoption; however, a comprehensive test of these effects is missing. Moreover, the effects of other domains of preference, such as loss aversion, that can be expected to affect energy-efficient technology adoption remain largely unstudied. This paper aims to fill that gap.

To our knowledge, we are the first to empirically analyze the effects of loss aversion on household adoption of energy efficient technologies. Thus, our study contributes to the emerging literature that relate preference measures employed in laboratory experiments to actual behaviour for representative samples (e.g. Dohmen et al. 2011). We are also the first to simultaneously consider the effects of, risk aversion, standard time discounting, present bias, and of loss aversion on energy efficient technology adoption to avoid mistakenly conflating their effects. Methodologically, to get internally consistent parameter estimates, the parameters reflecting standard time discounting, risk aversion, loss aversion, and of present bias are calculated jointly at the individual level. Preferences for time discounting, present bias, risk and loss aversion were elicited via (partly incentivized) decontextualized multiple price list (MPL) lotteries. To address concerns with previous literature, adoption decisions were surveyed from decision-makers for low- (LED light bulbs), medium- (appliances) and high- (retrofit) –stake energy-efficient technologies. Further, the study includes many household control variables (such as intention to move, renting, socio-demographics and individual traits), as well as dwelling characteristics such as size or dwelling age. Finally, empirically, our study is the first to utilize representative samples in a cross-country comparison and with roughly 15,000 respondents, our sample size is much larger than in previous studies, allowing for more generalizable results.

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

2 Literature on Preferences and Energy Efficient Technology Adoption

The adoption of energy-efficient technologies typically involves an up-front investment followed by dispersed gains in the future. Individual time preferences are therefore expected to affect technology choice. Yet, the few empirical studies linking individual time discounting to energy-efficient technology adoption provide mixed evidence. For US households, Newell and Siikamäki (2015) find that standard time discounting 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. In a recent NBER working paper in the USA, Bradford et al. (2014) find a positive correlation for low cost measures such as CFLs or thermostats, but not for higher cost measures such as thermal insulation. Fischbacher et al. (2015) conclude that standard time preferences play no role for the renovation decisions of 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 energy-efficient technologies for Swiss households.

The traditional economic model presumes an exponential discounting function implying a constant rate of discounting (Samuelson, 1937). Yet, the experimental psychology and experimental economics literature (e.g. Laibson 1997, Loewenstein and Prelec 1992, or Thaler 1991) suggests that individuals tend to systematically overvalue the present compared to the future. This so-called present bias has been shown to play an important role in explaining the energy efficiency paradox. In particular, individuals subject to present bias may not account for future energy cost savings in the way that the traditional economic model of discounting presumes. Present bias is typically modelled with a (quasi) hyperbolic discounting function (Ainslie, 1974; Laibson, 1997). The few studies that have explored the effects of present bias on the adoption of energy efficient technologies are inconclusive. Bradford et al. (2014) find that present bias is statistically associated with self-reports of driving a fuel-efficient car, having a well-insulated home, and with the temperature setting on one's thermostat (but not with other energy efficiency measures). In comparison, Allcott and Taubinsky (2015) do not find present bias to be correlated with CFL adoption decisions in their choice experiment. Busse et al. (2013), Allcott and Wozny (2014) and Cohen et al. (2017) explore whether individuals behave myopic, 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 for myopia, while Busse et al. (2013) conclude that individuals do not act myopic. Cohen et al. (2017) find myopia to moderately impede the (observed) adoption of energy-efficient refrigerators in the United Kingdom.

Because the profitability of energy-efficient technology adoption depends on several uncertain factors such as future energy prices, technology performance, or regulation (e.g. energy tax rates, CO_2-prices), these investments can be considered as risky and 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 one with the lower risk. The scant empirical literature on risk aversion and energy-efficient technology 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 various retrofit measures and appliances (but not air conditioners) in the US (Qiu et al., 2014).

Another domain of preference that has received a lot of attention in the experimental psychology and economics literatures is loss aversion. Accordingly, individuals 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). Loss aversion may affect the adoption of energy-efficient technologies if decision-makers evaluate the initial investment costs as a loss. To our knowledge, the effects of loss aversion on energy-efficient technology adoption have not been empirically investigated so far.

As can be seen from the literature reviewed above, there is little empirical evidence on the effects of time and risk preferences on energy-efficient adoption. Few studies include both time and risk preferences, and the evidence is scant and often inconsistent. To allow for a comprehensive understanding of these effects, it is necessary to understand the differences between studies that may explain inconsistent results and can help design a better empirical survey. 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). We critically evaluate the different approaches used as a basis for designing a comprehensive empirical test that would be as free of biases as possible. So far, only few empirical studies have looked at the effects of time or risk preferences on energy efficient technology adoption simultaneously (Bradford et al. 2014). Andersen et al. (2008) stress the importance of a joint identification of risk and time preferences: they show that not accounting for the curvature of the utility function (typically described by the parameter of risk aversion) leads to biased estimates of individual discount rates ("curvature bias"). Similarly, not accounting for loss aversion (which has not been included in previous studies so far) may result in biased estimates of risk parameters (e.g. Abdellaoui et al. 2007). More generally, failure to simultaneously include loss aversion and time and risk preferences may lead to an omitted variable bias of parameter estimates in econometric analyses of adoption behavior. Consequently, policy recommendations based on the findings of such analyses may be erroneous. This literature therefore indicates that for a better understanding of different domains of preference, these should not only be estimated jointly, but also included simultaneously when estimating adoption behavior.

Furthermore, differences across studies can also be noted with regard to the methods used to elicit preferences. While some of the studies have used simple lotteries (Becker et al. 1964, Hey and Orme 1994) or Likert scales (Zuckerman 1994, Dohmen et al. 2011), most studies have relied on multiple price lists (MPLs) (Coller and Williams 1999, Holt and Laury 2002). Still, 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)[1]. Although contextualized MPLs have been shown to be better at predicting targeted behaviors, these higher correlations are somewhat confounded because contextualized MPLs confound preferences with the behaviors of focus (here energy technology adoption). Finally, the experimental economics literature stresses the importance of using incentivization (paying respondents as a function of their responses) to guarantee valid results. So far, incentivization has only been used in Bradford et al. (2014) through gift cards and in Fischbacher et al. (2015) through bank transfers. To summarize, 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, this literature stresses the importance of eliciting these preferences through decontextualized multiple price lists, and to incentivize respondents to ensure valid results.

Previous studies have also differed in their operationalization of energy-efficient technology adoption. A variety of technologies and behaviors have been studied, from technologies such as light bulbs or high mileage cars to behaviors such as switching off the lights, 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 for cars or retrofit measures, which should affect for instance perceived risk; the stake level should therefore be systematically accounted for. The method of elicitation of adoption also differs sharply across studies: while for instance in Newell and Siikamäki (2015) and Allcott and Taubinsky (2015), technology adoption is inferred from stated preference choice experiments, Bradford et al. (2014) and Fischbacher et al. (2015) rely on stated adoption behaviour; Bruderer Enzler et al. (2014) rely on 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

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

"in the market" (for instance, applying hypothetical stated choice experiments to all respondents, even those who are not normally involved in such decisions). Further, so far studies have included very few control variables on household or dwelling characteristics; to the extent that such variables affect adoption decisions, their impact has not been assessed, thereby also raising omitted variables concerns. Finally, while previous studies have usually used representative samples of the population, most were single-country studies conducted in the USA (e.g., Bradford et al. (2014)) or in single European countries (e.g., Bruderer Enzler et al. (2014) in Switzerland), therefore not allowing for comparisons across different levels of economic development or of stages of technology adoption. In summary, looking at the operationalization of adoption decisions in previous studies stresses the importance of considering adoption of technologies requiring different investment levels, of focusing on adoption and not just owning, on including many household and dwelling characteristics as controls, and on using representative samples of actual decision-makers.

Building upon this critical evaluation of the literature, in this paper we empirically analyze the effects of time preferences, risk aversion, loss aversion and present bias on household adoption of low-, medium- and high-cost energy efficient technologies. We field a representative survey in eight EU countries, accounting 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 reflecting standard time preferences, present bias, risk aversion and loss aversion. Then, the sub-section on empirical methods describes the survey, displays the multiple price lists (MPLs) which are employed to elicit these parameters, and presents the econometric model together with the dependent variables and control variables used.

2.1 Theory

2.1.1. Modelling risk preferences and loss aversion

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

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

where *x* reflects wealth, α (≥0) is the parameter reflecting risk aversion and λ is the parameter capturing loss aversion[2]. The utility specification in equation (1) implies that relative risk aversion is constant (CRRA) and identical for losses and gains. Compared to the original cumulative Prospect Theory (Tversky and Kahneman, 1992) or (Prelec, 1998) we abstract from probability distortion since in our MPL experiments, all lotteries are symmetric in terms of probability. We also assume a reference wealth of zero.

2.1.2. Modelling time preferences

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

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

where $\boldsymbol{U_t}(x_t, \dots, x_T)$ is the expected utility of a stream of wealth gains $x_0, \dots, x_T$ at different points in time from 0 (now) to T. $u(x_t)$ is the utility of the wealth x at the date t, δ is the standard

2 α=1 / 0<α<1 / α>1 means the participant is risk neutral / risk averse / risk loving; λ=1 / 0<λ<1 / λ>1 means the participant is loss neutral / loss seeking / loss averse.

time discounting parameter, and β is the parameter reflecting present bias. In our model t is expressed in years and δ is the annual time discounting factor.[3]

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

2.2. Empirical methods

An online survey was implemented by Ipsos GmbH via computer-assisted web interviews (CAWI) using existing household panels. About 15,000 participants from eight EU countries (France, Germany, Italy, Poland, Romania, Spain, Sweden, and the United Kingdom) completed the survey. In each country, participants were selected via quota sampling to be representative for a particular country in terms of gender, age (between 18 and 65 years), and region; 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 translated back to English to test for and eliminate any differences that could be attributed to language.

3 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.

The survey contained non-contextualized MPL questions to elicit time preferences, risk preferences and loss aversion, questions on the adoption of energy-efficient technologies, on dwelling characteristics, as well as questions designed to assess 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.

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

All MPLs employed to elicit time and risk preferences and loss aversion had a similar design, mimicking the prevalent MPL design introduced by Coller and Williams (1999) to elicit standard time preferences and by Holt and Laury (2002) to elicit risk preferences. Participants were facing a list of choices between two options, A and B, and were asked for each choice to indicate their preferred option.[4] Since the survey was conducted in countries with different currencies, the monetary amounts displayed to participants were adjusted to keep the relative value similar between countries in terms of purchasing power. To this end, the following rates were applied: Poland: 1€ = 3 PLN; Romania: 1€ = 3 RON; Sweden: 1€ = 10 SEK; UK: 1€ = 1£. In all Euro-zone countries, the monetary amounts shown to participants were identical; for Sweden, UK, Poland and Romania, monetary amounts were multiplied with the respective factors. Similar to Bradford et al. (2014), but in contrast to Qiu et al. (2014), the MPLs in our study were not contextualized.

2.2.1.1 Elicitation of time preferences

The first price list (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

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

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).

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 (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

2.2.1.2 Elicitation of risk preference

MPL 2 elicited people's risk preferences and was adapted from Holt and Laury (2012). 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 expended value in Lines One to Seven; after Line Seven, 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€

2.2.1.3 Elicitation of loss aversion

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

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

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

2.2.1.4 Different stakes

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

2.2.1.5 Incentivization

To mitigate hypothetical bias, more than half the sample was incentivized (54%). Of those, we paid a random subset of 1% of the participants based on their actual choices to the MPL questions. Incentivization was only implemented for medium and low stakes. For each selected participant, one question was randomly chosen as the payout question. For participants who were not incentivized, the instructions stated that these were hypothetical choices. In all countries, the selected participants received a prepaid credit card (MasterCard) by postal mail. A separate letter stated the amount, provided the PIN code and included the terms and conditions for credit card use. The stated amount could be spent in any online or offline shop accepting MasterCard (due to processing time, a one-week delay was added to the MPLs). Payments to the 75 winning participants averaged 54.43 euros and ranged from 0 to 250 euros.

2.2.2. 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 that can explain the observed switching behavior. Rather than calculating 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 One of MPL1.2 and Option B in the remaining lines was assumed to be indifferent between 96€ in six months and one week and 100€ in twelve months. Participants who never (immediately) switched, i.e. always choose A (B) in one MPL, were assumed to be indifferent at the last (first) line of this MPL. The switch-points thus provided four equations (one for each MPL) that could be solved for the four unknown preference parameters. Participants with multiple switch-points were dropped, resulting in a loss of 10.75% of the sample. Compared to most other studies, this share is relatively low and comparable to Harrison et al. (2005). Results of these calculations are presented in Table 5.[5]

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

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

Table 5 suggests that the average standard annual time discount rate across the entire sample was about 28% ((1/0.78+1)*100%*0.5), with little differences across countries. In general, comparing our estimates of standard time preferences (or present bias, risk aversion and loss aversion) across studies is difficult because of differences in participants, stakes, framing, elic-

5 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.

itation method, incentivization or methodologies. The later include assumptions about the underlying preferences (i.e. utility function), or estimation procedures. In any case, our estimates of the annual discount factors are in the range of those found in previous studies employing MPLs to elicit standard time preferences (Frederick et al. 2002).

For each country, the average participant did not exhibit a present bias. Thus, our parameter estimate for β was higher than the values for present bias found in the literature, such as in Tanaka et al. (2010) (0.64) for villages in Vietnam or in Bradford et al. (2014) (0.94). We also note that a fairly large share of participants in our sample appeared to be future biased, similar to Takeuchi (2011). Note that this lack of evidence for present bias may be explained in part by the fact that the nearest point in time at which subjects could receive their incentivization was one week away. Nevertheless, as documented in later parts of this paper, we did find that our measure of present bias played a role in efficient adoption behavior.

On average participants in most countries were risk averse ($\alpha < 1$) across most countries, except for participants from Romania and Sweden who were, on average, risk neutral. Our estimates of risk aversion are similar to the ones found for university students by Kahneman and Tversky (1979) (0.88), but higher than in the country representative study for Denmark by Harrison et al. (2007) (0.67) or in Tanaka et al. (2010) (0.60) or Liu (2013) (0.52).

The average participant in each of the survey countries was loss averse. Our estimates for loss aversion are higher than those previously elicited in Tanaka et al. (2010) (2.63), or in Kahneman and Tversky (1979) (2.25) but similar to the values found in Liu (2013) (3.47) for farmers. To our knowledge though, there are no estimates of loss aversion available from country representative analyses.

We further found that 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. Table 6 displays the correlation of the estimated preference parameters.

Table 6: Correlation of preference parameters

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

***<0.01

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

2.2.3 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 measures, respectively.

First, participants who had bought a new light bulb in the two preceding years were asked to identify the type of bulb they had acquired last, showing pictures of a light emitting diode (LED), a compact fluorescent light bulb, a halogen bulb, and an incandescent light bulb. Purchase of an LED was considered an energy-efficient decision.

Second, participants who had bought a new appliance (refrigerator or fridge/freezer combination, freezer, dishwasher, washing machine) in the preceding five years were asked whether the appliance they had purchased last (to minimize recall bias) was, to the best of their knowledge, a top-rated energy-efficient appliance. 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.

Purchase of a top-rated energy efficient appliance or – in an alternative specification – an appliance with a label of A++ or better was considered an energy-efficient decision.[6]

Third, if participants had implemented a retrofit measure in the preceding 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.[7] 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). In particular, participants who indicated that their landlord or property management would decide on retrofit measures were excluded.

Compared to previous literature, the method chosen to elicit technology adoption therefore had the advantage to only focus on adoption and to compare adoption of energy-efficient and non-energy-efficient technology for one specific decision; furthermore, respondents indicated the adoption decision date, which allows controlling for recall bias.

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

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

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

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

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6 To further limit the effects of recall bias we only used appliance adoption decisions from 2012 forward. In an alternative specification, we only used appliance adoption decisions from 2015 and 2016.

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

2.2.4 Control variables

We included information on demographic characteristics, dwelling characteristics and participant attitudes to control for potential confounders of the relationships between time and risk preferences on the one side and energy efficient adoption decisions on the other side. The demographic variables included *age* (in years), a *gender* dummy (male = 1, female = 0), *income* (using midpoint of eleven income categories, and the lower level of the highest income category) an *education* dummy (above country median = 1), and *household size* (number of members). The questionnaire further included items to capture split incentives, i.e. an ordered categorical variable *likelymove* (= 0 if the 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), a dummy *renting* (= 1 if the dwelling was rented), and a dummy *individual_meter* (= 1 if the household had its own electricity meter, to capture split incentives). Dwelling characteristics included the size of the dwelling *homesize* (in m^2), the age of the building (*buildage*) calculated by generally subtracting the midpoint year for the seven categories provided for the year the dwelling was built from the year of the survey (i.e. 2016)[8] and a dummy *detached housing* (= 1 if house was detached) that was used for the retrofit measures. The set of covariates further included a z-score on environmental identity scales (Whitmarsh and O'Neill 2010), and a z-score on a social norms scale [9]. To capture the effect of capital availability on adoption, we included the z-score of participants' subjective assessment of their access to capital (including loans and credits)[10]. We also included a

8 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.

9 *z_ENV_ID* was 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."

z_socialnorm was 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?"

10 *z_CapitalAccess* was 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?"

dummy to control for the aggregate effect of incentivizing part of the sample. For LEDs we asked whether the new bulb was a *main bulb* (or part of the main fixture) in the dining room / living room. Finally, the set of control variables contained country dummies and product category dummies (for appliances).

4 Results

We estimated all three Probit models using robust standard errors. Estimation results (average marginal effects) appear in Table 7.[11] We first note that β was positively and statistically significantly correlated with all three adoption measures. Thus, individuals with a higher present bias were less likely to adopt LEDs, appliances and retrofit measures. Individuals with high standard time discount factors (δ) were also more likely to have purchased an LED as their last light bulb. For appliances and retrofit, the correlation of δ was also positive, but not statistically significant at conventional significance levels. In contrast, the correlation of risk aversion and loss aversion was not found to be statistically significant for any of the three types of measures.

Our 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). Arguably, our findings that present bias 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).[12]

Our findings on risk aversion differ from Qiu et al. (2014), who found risk aversion to be correlated with the adoption of energy efficient appliances and retrofit measures. Among others, this difference may be explained by the fact that the MPLs to elicit risk preferences in Qiu et al. (2014) were context-specific, i.e. payments are expressed as "receiving life-time energy cost savings". While Karlan (2005) shows that parameters elicited context-free have a good predic-

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11 For appliances we report results where an efficient choice was defined by participant response to whether their last appliance purchase was a top-rated energy-efficient appliance. Findings for the alternative specification where an efficient choice was defined by the energy rating (>A++) are consistent, but P-values were generally higher, arguably because of a lower sample size (1550 compared to 5465).

12 Since the lines in the MPL tasks to elicit standard time preferences and present bias were similar, and since all payment were delayed by one week (for technical reasons), 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.

tive power, parameters elicited via context-specific MPLs are often found to be better predictors of behavior. In this case though, the effect of risk (or time) preferences cannot be distinguished from context-specific factors (here: environmental benefits). In addition, since the study by Qiu et al. (2014) considered risk preferences only, their parameter estimate may also reflect the correlation with time preferences.

Turning to the effects of the covariates, Table 7 suggests that age was negatively related with LED adoption and positively related with energy efficient appliance adoption, but the effects were rather small.

For every 10000 euro increase in annual disposable household income, the propensity to have purchased and LED as their last bulb, adopted an energy efficient appliance within the last four years, and implemented an retrofit measure increases by roughly one percentage points compared to sample adoption rates of 41% for LEDs, 63% for appliances and 42% for retrofit measures. Education appeared positively related to LED adoption and, similar to Bruderer Enzler et al. (2014), negatively with the adoption of retrofit measures. Possibly, higher income households live in better insulated dwellings, ceteris paribus. Household size was not significantly correlated with the adoption of any of the three measures. In comparison, and similar to the cross-country study in OECD countries by Krishnamurthy and Kriström (2015) for renters, the coefficients associated with variables reflecting split incentives (likelymove, renting, individual metering) exhibited the expected signs and were statistically significant for the adoption of all three measures. Home size was positively correlated with the adoption of all three measures, and statistically significant for appliances and retrofit, arguably because the related financial incentives--i.e. energy costs savings--are higher for larger dwellings. Similarly, retrofit measures were more likely to have been implemented in detached housing. As expected, the propensity to have purchase and LED is larger if the new bulb was a high-usage bulb (main bulb in the dining room / living room), reflecting greater financial savings incentives. Households living in younger buildings were more likely to have adopted LEDs as their last bulb and also an energy efficient appliance as last appliance purchase, but only the coefficient for the LED equation was statistically significant. In contrast, younger buildings were correlated with a lower retrofit rate, arguably because they tend to already be equipped with good insulation and windows.

Table 7: Results of Probit models for energy efficiency technology adoption decisions (P-values in parenthesis)

	LED	**Appliances**	**Retrofit**
α (risk aversion)	0.00301	0.00777	-0.000629
	(0.542)	(0.245)	(0.899)
δ (standard time discounting)	0.0469**	0.0225	0.0144
	(0.036)	(0.447)	(0.510)
β (present bias)	0.0355***	0.0224*	0.0274***
	(0.001)	(0.080)	(0.009)
λ (loss aversion)	-0.00167	-0.00142	0.0000514
	(0.224)	(0.427)	(0.969)
Age	-0.00214***	0.00176***	0.000166
	(0.000)	(0.001)	(0.677)
Gender	0.0711***	0.00334	0.00719
	(0.000)	(0.792)	(0.445)
Income	0.00102***	0.00101***	0.000687***
	(0.000)	(0.003)	(0.007)
Education	0.0247**	0.0172	-0.0205**
	(0.024)	(0.213)	(0.049)
Hhsize	0.00111	-0.00520	0.00367
	(0.757)	(0.279)	(0.261)
Likelymove	-0.0247***	-0.0157**	-0.0121**
	(0.000)	(0.042)	(0.037)
Renting	-0.0701***	-0.0304*	-0.279***
	(0.000)	(0.061)	(0.000)
Individual_meter	0.0298*	0.0626***	0.0535***
	(0.070)	(0.003)	(0.001)
HomeSize	0.0134	0.0582***	0.0436***
	(0.269)	(0.000)	(0.001)
BuildAge	-0.000581***	-0.000499**	0.000701***
	(0.003)	(0.042)	(0.001)
Detached housing			0.0706***
			(0.000)
Main bulb	0.0686***		
	(0.000)		
Access capital	0.0316***	0.0143**	0.0264***
	(0.000)	(0.039)	(0.000)
z_ENV_ID	0.0328***	0.0634***	0.0639***
	(0.000)	(0.000)	(0.000)
z_socialnorm	0.0134**	0.0271***	0.0121**
	(0.011)	(0.000)	(0.018)
Incentivized	-0.00980	-0.00820	0.000784
	(0.324)	(0.525)	(0.935)
Country dummies	YES	YES	YES
Product category dummies		YES	
N	9630	5465	8430

*** p<0.01, ** p<0.05, * p<0.1

As intuitively expected households with good capital availability, with a higher environmental identity or with higher social norms were more likely to have adopted all three types of energy efficiency measures. Finally, whether MPLs to elicit time, risk, and loss aversion preferences or present bias were incentivized or not did not appear to affect the findings on the relation between these factors with the adoption of any of the three energy efficiency technologies.

To explore whether the estimates of preferences over risk, time, and losses may suffer from an omitted variable bias if not all variables reflecting these preferences are included in the regression, we estimated the probit models with subsets of these variables. Overall we find no evidence that omitted variable bias may be a problem.

5 Conclusion

This paper empirically analyses the effect of risk aversion, standard time preferences, present bias and loss aversion loss aversion on household stated adoption of LEDs, energy efficient appliances and retrofit measures. Our analysis relies on a large representative sample drawn from eight EU countries. Time, risk and loss aversion preferences were elicited and jointly estimated from participant choices in context-free MPLs, more than half of which were incentivized. Joint estimation of these preference parameters is expected to mitigate the “curvature” bias. Including all of these preference parameters when estimating technology adoption behavior is also expected to mitigate omitted variable bias. In addition to these preference parameters, our econometric analysis includes covariates for socio-demographic characteristics, individual attitudes and dwelling characteristics, thus controlling for a broad set of potentially confounding factors.

Our results suggest that present-biased individuals were less likely to adopt LEDs, energy efficient appliances and retrofit measures. Thus, we find present bias, which exemplifies a behavioural bias, to help explain the energy efficiency paradox. Lower standard time discount rates were positively related with LED adoption but appeared to have no effect on the adoption of energy efficient appliances or retrofit measures. Risk aversion and loss aversion did not appear to have an effect on the adoption of LEDs, appliances or retrofit measures. Thus, with the exception of standard time preferences for the adoption of LEDs, our findings do not support the view that standard time preferences and preferences for risk and losses help explain the energy efficiency paradox.

The distinction between preferences and behavioral biases is important because of the different welfare implications of policies. Although preferences may lead households to refrain from energy-efficiency technology adoption, they lead to rational decisions; as a consequence, policies trying to counteract these preferences would not be welfare improving (abstracting from environmental benefits). Behavioral biases in contrast lead households to make decisions that they may later regret; therefore, policies designed to counteract behavioral biases may be welfare improving, and therefore more efficient, to the extent that households recognize that their situation is improved. In this sense, our findings on present bias provide a rationale for policy interventions which alter the time path of the financial streams associated with technology adoption. Such policies include rebates or low-interest loans for energy efficiency measures rather than tax breaks, which generate financial benefits in the future only.

Finally, for the data at hand our findings suggest that the effects of preferences over time, risk, and losses on energy efficiency technology adoption can be estimated without bias when only a subset of the variables reflecting these preferences is included in the econometric analysis.

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Annex

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

	All countries	*France*	*Germany*	*Italy*	*Poland*	*Romania*	*Spain*	*Sweden*	*United Kingdom*
Age	40.914 (12.873)	42.105 (13.554)	42.603 (13.081)	42.961 (12.617)	38.434 (11.856)	36.073 (10.292)	41.480 (12.318)	42.402 (13.755)	41.384 (13.333)
Gender	0.496 (0.500)	0.490 (0.500)	0.503 (0.500)	0.489 (0.500)	0.496 (0.500)	0.500 (0.500)	0.507 (0.500)	0.492 (0.500)	0.495 (0.500)
Income	0.625 (0.483)	0.591 (0.491)	0.674 (0.468)	0.576 (0.494)	0.714 (0.451)	0.712 (0.452)	0.520 (0.499)	0.536 (0.498)	0.675 (0.468)
Education	0.642 (0.479)	0.575 (0.494)	0.510 (0.500)	0.826 (0.378)	0.532 (0.499)	0.661 (0.473)	0.619 (0.485)	0.886 (0.317)	0.604 (0.489)
Hhsize	2.806 (1.480)	2.687 (1.265)	2.451 (1.409)	3.054 (1.254)	3.151 (1.397)	3.169 (2.466)	2.981 (1.154)	2.323 (1.320)	2.656 (1.287)
Likelymove	0.894 (0.891)	0.996 (0.890)	0.761 (0.882)	0.714 (0.859)	0.882 (0.897)	0.950 (0.890)	0.806 (0.885)	1.101 (0.878)	0.995 (0.880)
Renting	0.314 (0.464)	0.353 (0.478)	0.562 (0.496)	0.198 (0.399)	0.164 (0.371)	0.209 (0.406)	0.225 (0.417)	0.466 (0.499)	0.330 (0.470)
Inidvidual meter	0.869 (0.336)	0.943 (0.231)	0.889 (0.313)	0.908 (0.288)	0.837 (0.369)	0.952 (0.212)	0.841 (0.365)	0.806 (0.395)	0.783 (0.411)
HomeSize	2.343 (0.764)	2.390 (0.718)	2.401 (0.726)	2.535 (0.661)	2.041 (0.858)	2.079 (0.767)	2.438 (0.650)	2.308 (0.768)	2.464 (0.809)
BuildAge	5.132 (2.271)	5.152 (2.527)	4.761 (2.246)	5.363 (2.082)	5.450 (2.197)	5.523 (1.731)	6.239 (1.912)	4.472 (2.073)	4.121 (2.397)
Detached housing	0.329 (0.470)	0.496 (0.500)	0.328 (0.469)	0.301 (0.459)	0.316 (0.465)	0.364 (0.481)	0.251 (0.434)	0.344 (0.475)	0.238 (0.426)
Access capital	0.000 (1.000)	-0.147 (0.940)	0.047 (0.969)	-0.212 (0.987)	0.106 (0.952)	-0.202 (1.004)	-0.158 (0.971)	0.246 (1.129)	0.310 (0.931)
z_ENV_ID	0.000 (1.000)	0.105 (0.912)	-0.133 (0.978)	0.299 (0.868)	0.025 (0.968)	0.120 (0.968)	0.171 (0.934)	-0.445 (1.104)	-0.200 (1.082)
z-socialnorm	0.000 (1.000)	-0.500 (1.016)	0.322 (0.888)	-0.059 (1.030)	-0.007 (0.928)	-0.007 (1.086)	0.131 (0.960)	0.221 (0.954)	-0.020 (0.921)
N	13,436	1,895	1,807	1,728	1,761	1,274	1,756	1,368	1,847