Exploring the diffusion of low energy houses: An empirical study in the European Union

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Highlights

- Risk aversion negatively relates to adoption of zero-net or energy-plus buildings.
- Mixed results for the effects of time discounting on low-energy house adoption.
- No evidence that environmental attitudes and social norms matter.

Abstract

Diffusion of low-energy houses is an important part of energy and climate policy in the European Union (EU) and in individual EU countries. Key barriers to the adoption of low-energy houses include additional construction costs and uncertainty surrounding actual energy and cost savings.

In this paper, we econometrically analyze determinants of low-energy house adoption, including time and risk preferences. We rely on original data from a large survey conducted among households in eight EU countries. To our knowledge, this is the first empirical study of low-energy building adoption to rely on a demographically representative sample. Our set of covariates includes parameters of time and risk preferences that were elicited via state-of-the-art incentivized multiple price list experiments and via self-assessment scales.

We find mixed results for the effects of time discounting on low-energy house adoption. Risk preferences do appear to matter: as risk proneness increases, so does the adoption of zero net or energy plus building (but not passive houses). Consistent with the low-cost hypothesis about environmental attitude and action, we find no results for environmental attitudes and social norms.

Key words: passive houses; low-energy houses; adoption; buildings; risk; patience

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1 Introduction

Buildings account for about 40 percent of final energy consumption and 36 percent of CO_2-emissions in the European Union (EU; European Commission 2016). Thus, lowering energy use in this sector is a key strategy for achieving ambitious medium- and long-term energy and climate targets in the EU and its individual countries. Policies to lower energy use in buildings typically involve building codes. For new buildings, the EU Energy Performance of Buildings Directive 2010/31/EU (EPBD) of 2010 mandates that all new residential buildings be *nearly zero-energy* (nZEB)[1] by 2021. Yet, the EPBD does not specify concrete thresholds or ranges of energy use. Instead, EU member states have defined their own criteria for nZEBs, which account for country-specific climate conditions, ambition levels, calculation approaches, and building traditions, thus making comparisons of nZEBs across member states unfeasible (Annunziata et al. 2014; ZEBRA 2016).[2] Still, various agreed-upon standards for low-energy buildings have been developed, including passive houses, zero net energy buildings, and energy-plus buildings. First, residential buildings meeting the so-called *Passive House* standard must not use more than 15 kWh per year (or 10 W peak demand) for space heating per square meter of usable living space. Passive houses still use electricity for hot water heating, appliances, electronics, or lighting, but often require no active heating system. Passive houses are

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1 According to Article 9, EPBD, a nearly Zero-Energy Building is a "building that has a very high energy performance…"

2 For example, the nZEB definition in France corresponds to the actual thermal regulation (primary energy use must be below 50kWh/m^2/year. Therefore, in France all new buildings which comply with the current regulation are also nZEBs.

characterized by a compact design (e.g. low surface-to-volume ratio, triple-glazed windows, or passive use of solar energy), comprehensive thermal insulation, orientation of the building to allow for passive solar heating, and automated air flow management. Passive houses have been built since the early 1990s, mostly in German-speaking countries, and have recently also started spreading to other European (especially Scandinavian) countries (Müller and Berker 2013). Beyond passive houses, more recent low-energy building concepts account for improved technical and economic potentials of on-site energy production of electricity and thermal energy from renewable sources. A *zero net energy building* (ZNEB) produces sufficient renewable energy to roughly meet its occupants' annual energy demand over the course of the year[3]; going even further, in an *energy-plus building (E+)*, annual on-site production of renewable energy exceeds annual energy demand (Cole and Fedoruk 2015).

Besides reducing energy expenditures by typically over 70 percent compared to existing building codes, low-energy houses are associated with several co-benefits (e.g. Ürge-Vorsatz et al. 2009; Berry and Davidson 2015). Controlled mechanical ventilation continuously exchanges humid indoor air with fresh outdoor air, leading to better air quality and health benefits. Comfort is improved by reduced temperature variations within and between rooms, thus avoiding drafts. Better insulation also means less exposure to outdoor noise. In a survey conducted in Austria, Klinglmair and Grussmann (2015) found

3 While conceptually similar to nZEBs, ZNEBs typically meet more ambitious standards; depending on the definition, the concept of ZNEBs may also include the embodied energy used during the construction of the building.

that owners of passive houses also value increased self-sufficiency of energy supply as well as lower emissions of local and global pollutants.

The diffusion of low-energy houses in the residential sector seems to be happening slowly, yet information on this diffusion is scarce and limited to passive houses (e.g. Kozma et al. 2013). Key barriers to the adoption of low-energy houses are their additional construction costs (e.g. Klinglmair and Grussmann 2015).[4] Compared to new houses of equivalent layout and size that meet existing building standards, passive houses are estimated to cost an additional 5 to 15 percent to build in Germany (Galvin 2014) and an additional 11 percent in Austria (Klinglmair and Grussmann 2015). Similarly, Badea et al. (2014) found that the additional capital costs of low-energy houses in Romania may be recovered in between 9 and 28 years, depending on the implemented technologies and the fuel types that are replaced. Carrilho da Graça et al. (2012) calculated payback times of 11 to 18 years for ZNEBs in Portugal. These payback times are long enough to suggest that individual time preferences may affect the diffusion of low-energy houses. More patient individuals, i.e. those discounting future utility less, are more likely to prefer investments with higher up-front costs but lower future operating costs, than less patient individuals.

Furthermore, financial viability of low-energy houses depends on uncertain factors like the development of future fuel prices, household-consumption levels, and the performance of the implemented technologies. Conversely, occupants of low-energy houses are less exposed to energy price fluctuations. Thus, individual risk preferences may affect

4 Other important barriers include lack of information, aesthetics, and loss of autonomy (for ventilation).

adoption of low-energy houses. When exposed to uncertainty, risk-averse individuals prefer investments with known but possibly lower returns rather than investments with unknown but higher returns.

The scarce literature that empirically analyzes the adoption of low-energy houses based on large samples has so far focused on costs and benefits as well as socio-economic factors (Klinglmair and Grussmann 2015). But the role of time and risk preferences, which have been found to affect adoption of other, lower-cost energy-efficient technologies, has yet to be explored.

In this paper, we econometrically analyze factors associated with the adoption of low-energy houses. We rely on original data from a large survey conducted among households in eight EU countries within the BRISKEE project (www.briskee-cheetah.eu).[5] To our knowledge, ours is the first empirical study of low-energy building adoption to rely on a demographically representative sample. Our set of covariates includes parameters of time and risk preferences that were elicited via state-of-the-art incentivized multiple price list experiments and via self-assessment scales.

The remainder of our paper is organized as follows. Section 2 reviews the empirical literature on factors related to the adoption of energy-efficient technologies, especially focusing on the role of time and risk preferences. Because there is hardly any literature on adoption of low-energy houses, we use literature on the adoption of other energy-

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5 BRISKEE (Behavioral Response to Investment Risks in Energy Efficiency) was carried out under the European Union Horizon 2020 Framework Programme) and explores factors related with the adoption of energy-efficient technologies in households, thereby focusing on preferences for time and risk (see also Schleich et al. 2016, 2019; Schleich 2019). Also relying on the BRISKEE survey of eight EU countries, the empirical studies by Schleich et al. (2019) and Schleich (2019) analyze the adoption of light-emitting diodes (LEDs), appliances, and retrofit measures.

efficient technologies to develop our hypotheses. The data, variables, and econometric models are described in Section 3. Section 4 presents and discusses the results of the econometric analyses. The concluding Section 5 summarizes the main findings and provides policy implications.

2 Literature: Characteristics of adopters of energy-efficient technologies

In this section, we review the empirical literature on factors related to household adoption of energy-efficient technologies. We focus on the scarce literature on low-energy house adoption, as well as literature on the adoption of other energy-efficient technologies (EETs). Because low-energy houses are a very high-stake investment, we put a higher weight on results obtained for other high-stake investment decisions (such as heating systems or insulation) in contrast to low-stake decisions such as light bulb adoption. We focus this literature review on the role of time and risk preferences in EET adoption, but also briefly address environmental attitudes, perceived relevance of investment costs, and social norms.

2.1 *Time preferences*

Like most energy-efficiency technologies (EETs), low-energy houses have higher up-front costs than conventional houses but lower costs of use. The cost savings, however, are dispersed over time and generally require years if not decades to offset the cost premium. Therefore, time preferences are expected to affect whether individuals buy a low-energy house. For other EETs, the empirical literature provides mixed evidence. For households in the USA, time discounting was shown to negatively affect the adoption of energy-efficient water heaters (Newell and Siikamäki 2015) and deter from choosing compact fluorescent lightbulbs (CFLs) over incandescent lightbulbs (Allcott and Taubinsky 2015; Bradford et al. 2014).[6] Schleich et al. (2019) analyzed households from eight EU countries and found evidence that more patient households are more likely to adopt LEDs and retrofit measures. Bradford et al. (2014) found a positive correlation for thermostats, but not for thermal insulation in the USA. For Swiss homeowners, Fischbacher et al. (2015) concluded that standard time preferences are not related to renovation decisions and Alberini et al. (2013) found that they apply low implicit discount rates (1.5% – 3%). Also, for Switzerland, Bruderer Enzler et al. (2014) failed to find consistent effects of time discounting on the adoption of several high- and low-cost EETs.

This body of empirical evidence on the role of time preferences in the context of adoption of EETs appears equivocal. If anything, time discounting seems to relate to higher-cost EETs less systematically than to lower-cost EETs. Also, laboratory experiments (typically with university students) and field experiments have found that the *level* of time discounting is lower for higher stakes compared to lower stakes (Frederick et al. 2002; Warner and Pleeter 2001). Therefore, time preferences may be less relevant for the cost premiums of low-energy buildings, which involve larger sums than most energy technologies usually studied in the extant empirical literature.

6 In this paper, we use the term time discounting to refer to pure time preferences. A time discount rate generally differs from the so-called implicit discount rate, which is typically calculated from observed or stated technology choices as the discount rate that renders the preferred technology choices rational. Thus, in addition to pure time preferences, the implicit discount rate also captures preferences for risks, losses, the environment, behavioral biases (e.g. present bias) or external barriers to energy efficiency (e.g. split incentives, lack of information, or lack of capital). See Schleich et al. (2016) for a conceptual treatment of the factors underlying the implicit discount rate.

2.2 *Risk preferences*

The profitability of low-energy houses hinges on some uncertain factors such as future energy prices and energy consumption levels, technology performance, regulations (e.g. energy taxes), and resale value. Therefore, individual risk preferences may also play a role in the decision to buy a low-energy house. When deciding between two investment projects with similar expected returns but different levels of risk a risk-averse investor will prefer the project with lower risk. However, since implementing energy-efficient technologies also reduces household energy expenditures and thus limits the financial risks of uncertainty about future energy prices, the relationship between risk aversion and energy-efficient technology adoption is ambiguous from a theoretical perspective. The rather scant body of 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 (except air conditioners) in the USA (Qiu et al. 2014). Schleich et al. (2019) found no relation between risk aversion and the adoption of LEDs, but evidence that risk-averse households are less prone to adopt energy-efficient appliances and retrofit measures. Finally, Dharshing and Hille (2017) observed that risk aversion, measured on a 3-item psychometric scale, is negatively related to attention to future energy savings associated with a hypothetical home renovation; they infer that this leads to lower EET adoption rates. The results from laboratory experiments suggest that (relative) risk aversion increases as the stakes increase (e.g. Holt and Laury 2002). Since the additional investment costs of low-energy houses are high compared to most other investment decisions and other energy-efficient technologies considered in the literature, risk aversion may be expected to hamper the adoption of low-energy houses.

2.3 *Attitudes and norms*

Low-energy houses have environmental benefits: they use less energy for heating purposes, thereby lowering resource use and local and global emissions. *Pro-environmental attitudes* may therefore positively relate to adoption of low-energy houses. The empirical evidence of the effects of pro-environmental attitudes on actual investment decisions for energy-efficient technologies is mixed. Pro-environmental attitudes appear to be positively correlated with the adoption of low-cost measures such as light bulbs (Di Maria et al. 2010, Mills and Schleich 2014), but less relevant for predicting high-cost investments such as those made for a thermal retrofit (e.g. Ramos et al. 2015; Whitmarsh and O'Neill 2010). Accordingly, the "low-cost hypothesis" maintains that the link between a pro-environmental attitude and action disappears as the cost of action rises (Diekmann and Preisendörfer 1998, 2003). Such a negative interaction with costs suggests a trade-off between financial cost and environmental benefit that is rational from an individual's payoff perspective: the environmental payoff of an individuals' adoption of an EET is practically zero (except for some "warm glow"), whereas the upfront costs are clearly non-zero. Finally, financial motives tend to dominate environmental motives in individuals' subjective rankings of purchasing criteria (e.g. Caird et al. 2008; Whitmarsh 2009). This literature therefore suggests that pro-environmental attitudes may not be related to the adoption of low-energy houses. However, in their multivariate analysis of residents in Austria, Klinglmair and Grussmann (2015) found a positive relation between environmental awareness and the adoption of passive houses.7)

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7 Their sample includes 285 observations but is probably not representative. For example, the share of passive house owners in their sample is about 18 percent.

When deciding on energy-efficient technology adoption, individuals may also be influenced by *social norms* (Cialdini 2007; Goldstein et al. 2008), which have been shown to relate to pro-environmental behaviors (e.g. Bamberg and Möser 2007), including adoption of EETs (*e.g.,* Schleich et al 2019). The effect of social norms on behavior may act through various mechanisms. First, behavior of peers may act as a source of information, signaling what is acceptable or normal behavior (Sherif 1936; Allcott 2011). This effect is emphasized in programs that provide feedback to households about their energy use in comparison to that of their peers (Allcott 2011). Second, individuals may conform to peer behavior for fear of losing their social capital or due to feelings of guilt (Bamberg and Möser 2008). Midden and Ritsema (1983) find that social norms only weakly affect intentions to conserve energy, whereas Black et al. (1985) suggest that the relevance of norms depends on the extent to which energy-conserving behavior is constraining. Akin to the "low-cost hypothesis," low-cost energy-efficiency measures might be influenced by norms, but not high-cost measures (Steg and Vlek 2009). According to the first two mechanisms described here, we do not expect social norms to be related to the adoption of low-energy houses. Moreover, low-energy houses are rare, and it is thus unlikely that adopters of such houses follow peer behavior: they are probably the first within their reference group to move into a low-energy house.

This however brings to the fore a third mechanism by which social norms might be at play in the adoption of low-energy houses: individuals may choose behaviors to pursue status gains in their reference groups (Tornatzky and Klein 1982). One such behavior is early adoption of innovative technologies. Klinglmair and Grussmann (2015) found that people who are generally early adopters of new technologies are more likely to adopt a passive house. An interest in technology and technical innovations is a recurring characteristic of early adopters of innovative technologies in general (Gatignon et al. 2016), including new capital-intensive energy technologies such as solar-PV systems (Schelly 2014) and hybrid cars (Ozaki et al. 2011).

A final attitude factor that is likely to play a role in low-energy house adoption is the impact of the *perceived relevance of investment costs*. There is substantial evidence that households generally react to costs and benefits of EET, in particular to initial investment costs (see for instance Skelton et al. 2009) and operating costs over time. Roy et al. (2007) and Caird et al. (2008), looking at consumer reasons for adopting or not adopting energy-efficiency measures (including condensing boilers, thermostatic radiator valves (TRVs), compact fluorescent lamps (CFLs) and light emitting diodes (LEDs)) concluded that consumers typically adopt these EETs to save energy, money, and/or the environment. Overall, there is evidence that households that pay more attention to investment costs are also less likely to adopt EETs.

2.4 *Sociodemographic and house characteristics*

Richer households tend to be associated with stronger EET adoption (e.g. Michelsen and Madlener 2012; Mills and Schleich 2010a, 2014; Ramos et al. 2015; Schleich et al. 2019); they are less likely to suffer from capital constraints, and they experience relatively lower risk compared to their financial wealth for the same EET investment than low-income households. Similarly, a higher level of education is expected to reduce the costs of information acquisition and improve information processing (Schultz et al. 1975). Multiple studies confirm the expected positive relationship between education and household propensity to adopt energy-efficient technologies (e.g. Di Maria et al. 2010; Michelsen and Madlener 2012; Mills and Schleich 2014, 2012, 2010b, 2009; Ramos et al. 2015). In line with these prior results for energy-efficient technologies, Klinglmair and Grussmann (2015) found that household propensity to adopt passive houses increases with income and education level. Their study further suggests that owners of passive houses tend to be younger, have children, and live in rural areas. We will therefore include these factors in the study.

3 Methodology

The relationships between low-energy house adoption and time and risk preferences, pro-environmental attitudes, social norms, perceived relevance of energy costs, and various socio-demographic characteristics were tested through a large-scale empirical survey. The first section describes in detail the data collection. The second section presents the econometric models used.

3.1 Data and variables

This section first describes the survey and then presents the dependent and explanatory variables.

3.1.1 *Survey*

An online survey was distributed in July and August 2016 to participants of the Ipsos GmbH online access panel. In total, data were collected from 15,055 respondents from France, Germany, Italy, Poland, Romania, Spain, Sweden, and the United Kingdom. Quota sampling was used to ensure that the sample was representative for age (between 18 and 65[8]), gender, and regional population distribution in each country. To ensure

[8] Due to the structure of the online panel, we had to cut age at 65 years. We acknowledge that this may limit the generalizability of our results since our study excluded house purchases by older households.

measurement equivalence, the survey items were professionally translated and back translated between English and each of the target languages.

The survey included stated adoption of low-energy houses, measures of time and risk preferences, dwelling characteristics, socio-demographic information, as well as questions related to the relevance of various purchasing criteria, environmental identity, and social norms.

3.1.2 *Sample*

For this study, we used a subsample of the initial 15,055 responses. In the subsample we only included homes built in the year 2000 or later (*N* = 2773) and households who owned their primary residence (owner-occupiers) (*N* = 2134). This means that houses built before 2000 that were renovated are not part of the subsample, potentially limiting somewhat the external validity. Some missing values across variables further excluded several observations from the subsample for model estimations.

3.1.3 *Dependent variable*

Owner-occupier participants, whose primary residence was built after the year 2000, were asked whether their residence was constructed according to a particular energy-efficiency standard. The response categories were the following:

1. Standard according to building-code regulation
2. Passive house standard
3. Zero net-energy or energy-plus building
4. Others
5. No particular standard
6. Don’t know.

Responses were used to construct two dependent variables: (i) an ordinal variable *EElevel*, taking the value 3 if the house was a zero net-energy or an energy-plus building (ZNEB/+), 2 if the house was built according to the passive-house standard, and 1 for any of the other categories (1, 4, 5, 6), and (ii) a binary variable *NZEB*, taking the value of 1 if the house was a *near zero energy building* meeting at least passive house efficiency standards and 0 otherwise. The distribution of the sampled homes across the three levels of energy efficiency of *EElevel*, for all countries together and per country, is shown in Table 1.

Table 1. Distribution of efficiency levels (within variable *EElevel*) within countries.

EElevel category		All countries	FR	DE	IT	PL	RO	ES	SE	UK
Building code/	*N*	1907	314	122	267	324	154	496	93	137
No standard	*%*	(89.4)	(94.9)	(69.3)	(84.0)	(89.8)	(93.3)	(94.3)	(93.0)	(87.3)
Passive house	*N*	126	11	38	15	18	9	22	3	10
	%	(5.9)	(3.3)	(21.6)	(4.7)	(5.0)	(5.5)	(4.2)	(3.0)	(6.4)
ZNEB/+	*N*	101	6	16	36	19	2	8	4	10
	%	(4.7)	(1.8)	(9.1)	(11.3)	(5.3)	(1.2)	(1.5)	(4.0)	(6.4)
Total	*N*	2134	331	176	318	361	165	526	100	157

3.1.4 *Explanatory variables*

The set of explanatory variables includes variables that reflect individuals' time and risk preferences and covariates that have typically been included in empirical studies of household adoption of energy efficient or renewable technologies (e.g. Mills and Schleich 2012; Ameli and Brandt 2015). Table 2 provides more detailed information about each variable's definition and measurement. Descriptive statistics appear in Table 3.

Table 2. Description of dependent variables and covariates

Label	Description
Dependent variables	
EElevel	House's level of energy efficiency. 3 categories: 1 – building code/no standard/other/don't know, 2 – passive house, 3 – zero net-energy or energy plus (ZNEB/+).
NZEB	Dummy = 1 if respondent's house met passive house standard or better.
Time and risk preferences	

α	Parameter reflecting risk preferences; elicited via multiple price list experiments; a higher value means lower risk aversion.
WTRisk	Z-score of item: “In general, how willing are you to take risks?” (1 = “not at all willing” to 5 = “very willing”).
δ	Time-discount factor reflecting time preferences; elicited via multiple price list experiments; a higher value means less time discounting.
WTWait	Z-score of item: How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future? (1 = “not at all willing” to 5 = “very willing”).
Other covariates	
Environmental_ID	Z-score of equally weighted items: “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” (1 = strongly disagree to 5 = strongly agree).
SocialNorm	Z-score of item: “In general, what do you think your family’s, friends’ or colleagues’ views would be of you purchasing energy efficient products?” (1 = “Very unfavorable” to 5 = “Very favorable”).
RelevanceInvestmentCosts	Z-score based on respondent stated importance of investment costs in a (hypothetical) decision to invest in insulation measures or heating systems in general (1= played no role to 5= very important).
Age	Respondent‘s age in years.
Male	Dummy = 1 if the respondent is a man.
Size	Number of persons living in the household.
Income	Household annual income (after taxes) in 1000 euro per year (using midpoint of eleven income categories, and the lower level of the highest income category).
Education	Dummy = 1 if level equal to or higher than country median. Considered levels: no degree or certificate/trade or vocational certificate /high school or equivalent/higher education.
Detached	Dummy = 1 if respondent lives in a detached house (with just 1 or 2 residences, e.g. houses/apartments).
Urban	Dummy = 1 if respondent lives in the center of a major town or in a suburb (i.e. fringes of a major town).
≥2010	Dummy = 1 if the house was built in 2010 or later (youngest age bracket)

Time and risk preferences

To capture time and risk preferences, we employed both scale-based and experiment-based measures. First, preferences for time discounting and risk aversion were elicited and estimated jointly via non-contextualized multiple price list experiments (MPLEs) adapted from Holt and Laury (2002) and Coller and Williams (1999). More than half the participants were incentivized. The theoretical model underlying the calculation of the parameters reflecting time and risk preferences is provided in Appendix A. Appendix A further describes in detail the MPLEs and the procedure employed to jointly calculate the individual parameters for each participant. Equation (A1) illustrates the need to jointly estimate the time and risk preference parameters to derive internally consistent parameters for given functional forms (e.g. Abdellaoui et al. 2007; Andersen et al. 2008). For example, estimating the parameter reflecting time preferences without simultaneously accounting for risk preferences would have resulted in an underestimation of the time preference parameter for a risk-averse individual.

Second, the survey also elicited time and risk preferences using the self-assessment scales employed and validated by Dohmen et al. (2011) or Falk et al. (2017) to construct *WTWait and WTRisk* (see Table 2). Dohmen et al. (2011) argued that eliciting individuals' general assessment of their willingness to take risks yields a good predictor of behavior in several, including non-financial domains. In comparison, the experiment-based risk measures are good predictors of behavior in the financial domain but may be less informative for risk taking in non-financial decisions (Dohmen et al. 2011, p. 543). Further, a general willingness to take risks may be associated with an interest in trying innovative technologies. The latter, as we discussed above, has been a consistent predictor of new energy technology adoption in empirical studies.

Following Falk et al. (2017), we construct an aggregate of experiment- and scale-based measures for time and risk preferences, respectively. Our aggregate measure of time preferences, *Patience*, is the sum of z-scores[9] for the scale-based measure *WTWait* and the experimental measure δ. Analogously, *RiskProneness* is the sum of z-scores for the scale-based measure *WTRisk* and the experimental measure α.

Other covariates

The first set of covariates reflect individual attitudes. *Environmental_ID* reflects households' environmental identities, measured using three items adapted from Whitmarsh and O'Neill (2010). *SocialNorm* accounts for the effect of the attitude of a respondent's social network toward the adoption of EETs. *RelevanceInvestmentCosts* assesses the extent to which investment costs are a relevant decision criterion when a homeowner decides to invest in energy-saving home improvements. Thus, *RelevanceInvestmentCosts* serves as a proxy for the relevance of total costs of acquiring a house.

The second set of covariates controls for individual or household demographic and economic characteristics. *Age* and *Male* control for individual characteristics related to the respondent's age and gender. *Size* controls for the effect of a household's size measured by the number of household members. *Income* and *Education* control for the effect of household income and level of education on the likelihood of adopting an energy efficient home.

Third, we include two characteristics of the house itself. *Detached* controls for potential differences in the likelihood of energy-efficient houses being detached or non-

9 As mentioned by Uluman et al (2016) and DiStefano et al (2009), adding items after having standardized them is a standard procedure when items are on different scales and have varying standard deviations. Compared to aggregation procedures that rely on endogenously derived weights, this unit-weighted factor score approach presents the advantage to offer results that are stable across samples and do not depend on the sample used in the focal study (Grice and Harris 1998).

detached houses. Highly energy-efficient houses exist as innovative showcases, which are easier to realize in detached dwellings on private property because of lower decision-making hurdles. *Urban* was included to control for potential differences in the adoption of zero- and low-energy houses between urban and non-urban areas (Klinglmair and Grussmann 2015). *≥2010* was used to capture the expected trend that adoption of low-energy houses has increased over time due to, for instance, decreasing cost differences with conventional houses.

Table 3. Summary statistics.

Variable	N	Mean	Std. Dev.	Min	Max
Dependent variables					
EElevel:	2134			1	3
1. Buiding code/no standard	2134	0.894	0.308	0	1
2. Passive house	2134	0.059	0.236	0	1
3. ZNEB/+	2134	0.047	0.212	0	1
NZEB	2134	0.106	0.308	0	1
Time and risk preferences					
δ	1901	-0.022	0.996	-3.850	0.767
a	1901	0.024	1.012	-0.761	3.122
WTWait	2134	0.057	0.991	-2.890	1.663
WTRisk	2134	0.086	0.998	-2.148	1.998
Patience	1901	0.036	1.371	-5.602	2.430
RiskProneness	1901	0.085	1.477	-2.910	5.120
Covariates					
Environmental_ID	2134	0.091	0.954	-3.182	1.672
SocialNorm	2134	-0.003	1.015	-2.760	1.565
RelevanceInvestmentCosts	2134	-0.011	0.938	-5.408	2.954
Size	2134	3.066	1.410	1	29
Income	1804	33.6	22.9	2.4	114.6
Education	2124	0.716	0.451	0	1
Age	2134	40.0	10.8	18	65
Male	2134	0.530	0.499	0	1
Detached	2134	0.441	0.497	0	1
Urban	2134	0.542	0.498	0	1
≥2010	2134	0.322	0.467	0	1
Country dummies					
FR	2134	0.155	0.362	0	1
DE	2134	0.082	0.275	0	1
IT	2134	0.149	0.356	0	1
PL	2134	0.169	0.375	0	1
RO	2134	0.077	0.267	0	1
ES	2134	0.246	0.431	0	1
SE	2134	0.047	0.211	0	1
UK	2134	0.074	0.261	0	1

3.2 Econometric models

We employ a generalized ordered response model to reflect household decisions to invest in a new house, which is characterized by different energy-efficiency levels *EElevel*. The generalized ordered logit model (gologit, Williams 2006) can be written as

$$P(Y_i > j) = g_j(.) = \frac{\exp(\alpha_j + X_i\beta_j + C_i\gamma_j)}{1 - \exp(\alpha_j + X_i\beta_j + C_i\gamma_j)}, \qquad j = 1,2$$

In our case, the outcome variable Y_i for owner-occupier *i* may take on the values 1, 2 and 3. Time and risk-preferences are captured in *X*, and *C* includes the covariates. The probability that *Y* takes on a particular value is equal to

$$P(Y_i = 1) = 1 - g_1(.)$$

$$P(Y_i = 2) = g_1(.) - g_2(.)$$

$$P(Y_i = 3) = g_2(.)$$

The constants $\boldsymbol{\alpha}$ and the coefficients $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are estimated via maximum likelihood methods. Essentially, this involves estimating two logit models with categories of the dependent variable combined. For example, in a first model, *EElevel* category 1 is contrasted with categories 2 and 3. In a second model *EElevel* category 1 and 2 are contrasted with category 3. The gologit model collapses to the familiar ordered logit model, when the β's and γ's (but not the α's) are the same for all values of *j*. In this case, the parallel-lines assumption is said to hold. When estimating the model, we allow relaxing the parallel-lines constraint for those variables where it is violated.

We estimate three model specifications, varying the composition of $\boldsymbol{x}$. In the first model, $\boldsymbol{x}$ contains the experiment-based parameters of time and risk preferences δ and α. In the second model, we employ the scale-based measures *WTWait* and *WTRisk*. In the third model, we use the aggregate time and risk preference measures *Patience* and

RiskProneness. The covariates vector ***c*** is the same for all specifications and contains the covariates listed in Table 2.

Individual country models could not be estimated due to low degrees of freedom. Instead, observations from all countries were pooled and country-specific effects were captured by country dummies. These are assumed to capture unobserved differences across countries such as in regulations (e.g. zoning laws) or cultural values.

4 Results and Discussion

4.1 Results on the role of time and risk preferences

Table 4 reports the estimation results for the three model specifications (using robust standard errors). Since the parallel-lines assumption was rejected in all models for several explanatory variables (often country dummies), we ran generalized ordered logit models as presented in 3.2 and report the estimates of the marginal effects for each of the three response levels[10]. The number of observations varies across the panels because of missing values in δ and α.

The results in Panel 1 show a statistically significant effect of individual risk preferences, measured using MPLEs, on the adoption of ZNEB/+ homes compared to houses

10 To address potential concerns about collinearity of risk and time preferences, we calculated variance inflation factors (VIFs) for all thee model specifications of Table 4. The VIFs for the time and risk preferences variables are 1.73 and 1.75, respectively, for the experiment-based measures, 1.27 and 1.31 for the scale-based measures, and 1.09 and 1.10 for the aggregate measures. The highest VIFs are for the country dummies but do not exceed 3.4. Mean VIFs for the three model specifications are 1.70, 1.67, and 1.64, respectively. Therefore, the VIFs do not raise concerns about collinearity.

built with passive house or less stringent efficiency standards. The likelihood of an owner-occupied home being ZNEB/+ increases by 1.4 %-points for a 1-standard deviation increase in the risk parameter α. The marginal effects of the time discounting parameter exhibit the expected signs and are shy of statistical significance at conventional levels.

In Panel 2, we find a statistically significant effect of risk preferences but not of time preferences on low-energy house adoption when simple psychometric scales are used. Owners of low-energy houses appear to have a higher general willingness to take risks, on average, but we find no higher willingness to wait for future benefits. The average marginal effect of a one-standard deviation increase in *WTRisk* is a 2.5 %-points increase in the likelihood of owning a ZNEB/+ house.

In Panel 3, we see that marginal effects of the aggregate measures for *Patience* and *RiskProneness* are statistically significant at the 5%-level. According to these estimations, more patient and less risk-averse homeowners are more likely to inhabit low-energy houses, on average. For *RiskProneness*, like for its component measures of risk preferences, we find a significant marginal effect on the adoption of ZNEB/+ houses but not passive houses. The results for *Patience* are surprising, because we did not find statistically significant effects when using the experiment-based nor the scale-based measures of time preferences. Upon further exploration of the data, we find that the correlation between the time and risk aggregate measures (*Patience* and *RiskProneness, r* = -0.12) is much lower than the correlations between the time and risk single measures (*WTWait* and *WTRisk*, r = 0.39; δ and α, r = -0.64). The higher collinearity between the single risk and time discounting measures may therefore explain the lack of significance for time discounting in these analyses. It also underscores that the experimental and scale-based measures capture different dimensions of patience.

All three model specifications include covariates, showing consistent results across the specifications. Environmental identity and social norms do not appear to be associated with the adoption of low-energy houses.

For *RelevanceInvestmentCosts*, we find a marginally statistically-significant relationship with adoption of low-energy houses in Panel 2 only. The direction is as expected, but the result depends on the way time and risk preferences were measured.

Somewhat unexpectedly, we do not find any relationship between household size, income, or education and low-energy house adoption.

We do however find statistically- significant coefficients for the dummies *Detached*, *Urban,* and *≥2010*. These indicate that owner-occupied low-energy homes are more likely to be found in urban or suburban settings, to be built as independent structures, and have increased their share among newbuilds over time. Furthermore, according to the country dummy results (not shown to save space), low-energy houses appear more prevalent in Italy and especially Germany compared to the other countries in the sample.

Table 4. Results of generalized ordered logit models. Marginal effects.

	Experiment-based measures			Scale-based measures			Aggregate measures[a]		
Variables	Building code	Passive house	ZNEB/+	Building code	Passive house	ZNEB/+	Building code	Passive house	ZNEB/+
δ^b	-0.013	0.006	0.007						
	(0.171)	(0.174)	(0.175)						
α^b	-0.007	-0.008	0.014**						
	(0.418)	(0.232)	(0.039)						
WTWait[b]				0.004	-0.002	-0.002			
				(0.571)	(0.571)	(0.572)			
WTRisk[b]				-0.029***	0.004	0.025***			
				(0.000)	(0.485)	(0.000)			
Patience							-0.012**	0.005**	0.006**
							(0.025)	(0.028)	(0.028)
RiskProneness							-0.010**	-0.006	0.016**
							(0.029)	(0.258)	(0.012)
Environmental_ID[b]	-0.005	0.002	0.002	0.003	-0.001	-0.001	-0.003	0.015**	-0.012
	(0.573)	(0.577)	(0.571)	(0.713)	(0.713)	(0.714)	(0.745)	(0.049)	(0.168)
SocialNorm[b]	-0.003	0.002	0.002	0.000	-0.000	-0.000	-0.001	0.001	0.001
	(0.628)	(0.629)	(0.627)	(1.000)	(1.000)	(1.000)	(0.866)	(0.866)	(0.866)
RelevanceInvestmentCosts[b]	-0.002	0.001	0.001	0.012	-0.006	-0.006	-0.005	0.002	0.002
	(0.777)	(0.777)	(0.776)	(0.129)	(0.125)	(0.137)	(0.583)	(0.586)	(0.581)
Age	-0.000	0.000	0.000	0.001	-0.002***	0.001	-0.000	-0.001*	0.001
	(0.869)	(0.869)	(0.869)	(0.414)	(0.008)	(0.121)	(0.916)	(0.079)	(0.100)
Male[c]	-0.012	0.006	0.006	-0.009	0.022**	-0.013	-0.007	0.003	0.004
	(0.398)	(0.402)	(0.397)	(0.547)	(0.043)	(0.194)	(0.609)	(0.611)	(0.608)
Size	0.001	-0.001	-0.001	-0.000	0.000	0.000	0.002	-0.001	-0.001
	(0.773)	(0.773)	(0.774)	(0.993)	(0.993)	(0.993)	(0.651)	(0.650)	(0.653)
Income	-0.000	0.000	0.000	-0.000	0.000	0.000	-0.000	0.000	0.000
	(0.335)	(0.332)	(0.342)	(0.701)	(0.700)	(0.701)	(0.399)	(0.396)	(0.403)
Education[c]	-0.010	0.005	0.005	0.006	-0.003	-0.003	-0.007	0.003	0.004
	(0.533)	(0.534)	(0.533)	(0.706)	(0.706)	(0.706)	(0.670)	(0.671)	(0.670)
Detached[c]	-0.042**	0.020**	0.023**	-0.054***	0.027***	0.027***	-0.043**	0.019**	0.024**
	(0.015)	(0.017)	(0.018)	(0.001)	(0.002)	(0.001)	(0.012)	(0.013)	(0.016)
Urban[c]	-0.036**	0.002	0.034***	-0.041***	0.021***	0.020***	-0.034**	0.000	0.034***
	(0.019)	(0.836)	(0.001)	(0.006)	(0.007)	(0.007)	(0.025)	(0.997)	(0.001)
≥2010[c]	-0.037**	0.017**	0.019**	-0.037**	0.000	0.037***	-0.037**	0.017**	0.020**
	(0.032)	(0.034)	(0.037)	(0.026)	(0.994)	(0.002)	(0.030)	(0.032)	(0.035)
Country dummies		Yes			Yes			Yes	
Observations	1606	1606	1606	1799	1799	1799	1606	1606	1606

p-values in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
[a] Violation of parallel-lines assumption is in the country dummies only.
[b] Variable values are z-scores of the observed values.
[c] The marginal effect for factor levels is the discrete change from the base level.

4.2 Robustness checks

Our analyses include a rich set of covariates. This should on the one hand help mitigate potential omitted variable bias concerns. On the other hand, this set of covariates may include so-called "bad controls" (Angrist and Pischke 2009, pp. 64), that is, control variables that may themselves be outcome variables. For example, income or education may be driven by time and risk preferences[11]. If this is the case, any effects of the preference parameters on the adoption of low-energy houses may be mainly through these bad control variables and potentially lead to erroneous inferences. To check for robustness, we therefore ran additional generalized ordered logit models where only the time and risk preferences were included together with the country dummies (using the same observations as for the full models in order to allow comparisons). Results of these analyses are presented in Table B1 in Appendix B. Since significance levels and parameter values are very similar to those reported for the models with the covariates, we find no evidence that our findings may suffer from bad controls.

Further, because the differences between the passive house standard and the ZNEB/+ categories are small relative to the differences between the building code level to the passive house standard, we also estimated probit models with the binary dependent variable *NZEB* (collapsing the passive house level and the net-zero energy/energy-plus level together). The results (Table B2 in Appendix B) suggest that our initial results are not sensitive to the alternative specification of the dependent variable.

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

5 Conclusions and Policy Implications

5.1 *Main findings*

We tested for the role of individual time and risk preferences in households' adoption of low-energy houses. We used data from large demographically representative samples of households in eight EU countries and elicited time and risk preferences through incentivized multiple price lists as well as qualitative self-assessment scales. Our analysis focused on owner-occupiers of houses built in the 21st century.

We find mixed results for the effects of time discounting on low-energy house adoption. Time discounting appears significant only when using the aggregate measure combining experimental-based measures and a qualitative scale recommended by Falk et al. (2017). It is however also just shy of marginal significance for the experimental-based measures (p-values of 0.17), and clearly non-significant for the more general qualitative scale. Interestingly, we therefore find some evidence for an effect of time discounting on low-energy house adoption, while the literature review (section 2.1) suggested that such high-stake decisions are less affected by time discounting than lower-stake decisions.

We find that risk preferences matter for adoption of low-energy homes. Significant results obtained for all types of risk measurements show that as risk proneness increases, so does the adoption of ZNEB/+ houses but not passive houses. This finding is consistent with the prior literature, which has found an increasingly negative effect of risk aversion on adoption of energy-efficiency measures with rising investment costs. Results may hint at a convex relation between risk preferences and the level of risk associated with the perceived experimental nature of the technology or its deviation from the norm, as passive houses have a longer history than the more ambitious ZNEB/+ concepts.

The findings obtained for the attitude measures are consistent with the low-cost hypothesis (Diekmann and Preisendörfer 1998, 2003), according to which the link between pro-environmental attitudes and action disappears for higher-cost investments. In line with this hypothesis, we find no relationship between adoption of low-energy houses and pro-environmental attitudes and social norms; on the other hand, we do find some evidence for a significant relationship with the perceived relevance of investment costs. These results therefore provide some empirical support for the dominance of cost concerns in high-stake decisions.[12]

Interestingly, we find no statistically significant relationship between any of the socio-demographic characteristics (age, income, education, gender, household size) and adoption of low-energy houses. This is somewhat surprising since extant literature has suggested that income and education would be positively related to this decision, and previous research has found a relationship between socio-demographics and the adoption of passive houses (Klinglmair and Grussmann 2015). In addition, unlike in the study by Schleich et al. (2019), where implementing retrofit measures is positively and statistically significantly related to income, our findings show the expected positive sign, but the coefficients are not statistically significant at conventional levels of significance. Possibly, this difference in findings may be explained by differences in the degrees of freedom (>8400 observations in Schleich et al. 2019 versus ca. 1600 to 1800 in this paper). In addition, income is higher in the sample of house purchasers in this paper compared to the sample adopting retrofit measures in Schleich at al. (2019) (mean annual net income

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12 The findings from the BRISKEE survey for retrofit measures investment criteria suggest that the upfront costs are among the most relevant criteria – together with performance (e.g. quality, reliability, durability), energy costs, and indoor comfort (see Gassmann et al. 2018).

in our sample of around 33.600 Euros compared to around 30.000 Euros in Schleich et al. 2019). As a consequence, there is less variation in income to be exploited by the econometric analysis in our sample than in Schleich et al. (2019). On the other hand, the results indicate that low-energy houses are more likely to be found among detached houses, and in urban areas, which is consistent with the findings of Klinglmair and Grussmann (2015). The finding that houses built in 2010 or later are more likely to be low-energy than those built in the first decade of the century supports the notion that they can be built at decreasing additional costs compared to conventional houses.

5.2 *Implications for policy and future research*

The adoption of low-energy houses is recognized as an essential element to achieve ambitious energy and climate targets in the EU. Based on our large-scale survey of owner-occupiers of houses built since 2000 in eight EU countries, we show that the diffusion of these houses is still quite low (10.6% of owner-occupied homes built since 2000). Our findings have several implications for policy aimed at accelerating the diffusion of low-energy houses.

First, our findings on time preferences suggest that time discounting, and especially financially-focused time discounting, is hurting the adoption of low-energy houses. Therefore, because impatient investors prefer payments today rather than tomorrow, financial policies that reduce the effects of time discounting, such as upfront subsidies, are expected to be more effective than policies that reinforce time-discounting effects, such as tax rebates.

The findings on risk aversion also have policy implications. We find that both measures of risk aversion, financially-focused and more general, are related to the adoption of low-energy houses. Policies that help reduce perceived financial risk and more general risk appear therefore particularly relevant. To reduce perceived technological risk, information campaigns, model houses, and services warranties may be instrumental. Building certification programs should also help mitigate technological risk concerns. These may also reduce financial risk as they make the energy cost savings of a low-energy house transparent, which enables the capitalization of such savings into the (re-sale/collateral) value of the house (Brounen and Kok 2012; Walls et al. 2017). In addition, low-interest loan programs could help reduce financial risk.

Interestingly, our results on pro-environmental attitudes and social norms suggest that communication campaigns focusing on such attitudes may not be effective and should therefore not be given high priority.

Finally, our findings on socio-economic and house characteristics suggest that socio-economic factors play a small role in the adoption of low-energy houses, but that these houses appear more often adopted for detached buildings and in urban areas. Policies designed to compensate by targeting populations for which these houses are less diffused should therefore focus on multi-family buildings and rural areas but it does not appear necessary to target specific socio-demographic groups.

Our analysis is limited to new buildings in the EU and warrants caution when generalizing to other regions or vintages from before 2000. Analyzing diffusion of new buildings is relevant in the EU (especially because residential floor area per capita continues to rise in Europe; Serrano et al. 2017), but more so in regions with stronger growth in new housing. Nonetheless, for future studies, the more urgent question is how to achieve low-emission standards for the existing building stock through deep renovations. Studies from the US (Hammon-Hogan et al. 2016; Proctor and Wilcox 2016) and from the Netherlands (Smith 2016) show that this is technically feasible but involves high upfront costs. Hence, risk preferences may be even more relevant. Last but not least, we would like to point out that our findings provide no guidance as to whether promoting the take-up of low-energy houses (e.g. via subsidies) is economically efficient. For example, from a cost-benefit perspective, it may be more efficient to subsidize retrofitting the existing housing stock rather than zero-energy houses (compared to new building minimum standards).

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Appendix A: Eliciting time and risk preferences via multiple price list experiments

Modelling time and risk preferences

To model individual preferences for risk, we rely on a standard version of the expected utility framework, using the following utility function: $u(x) = x^{\alpha}$, where x reflects wealth, α (≥0) is the parameter reflecting risk preferences. To capture individual preferences for wealth at different points in time, we use the standard model of discounting

(A1) $$\boldsymbol{U_t}(x_t, \ldots, x_T) = E[\textstyle\sum_{k=0}^{T-t} \delta^k u(x_{t+k})]\ ,$$

where $\boldsymbol{U_t}(x_t, \ldots, x_T)$ is the expected utility of a stream of wealth gains $x_0, \ldots, x_T$ at different points in time from 0 (now) to T. $u(x_t)$ is the utility of the wealth x at the date t, and δ is the annual time discounting factor.[13]

Joint elicitation and calculation of preferences for time and risk

Time and risk preferences were elicited through multiple price list experiments presented in table format. In each table, study participants were shown a list of successive choices between two options, A and B, and had to provide their preferred option for each choice. [14] To account for exchange rates and purchase power parity, we applied rates in the three non-Euro-zone countries (Poland: 1€ = 3 PLN; Romania: 1€ = 3 RON; Sweden: 1€ = 10 SEK; UK: 1€ = 1£).

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13 δ=1 / 0<δ<1 means that the participant is not discounting future gains / discounting future gains.

14 To avoid order bias, we randomized the order of the decisions presented to participants, so that half saw Option A first, half Option B first.

Elicitation of time preferences

To elicit time preferences, participants chose for each line in Table A1 between Option A showing a monetary amount to be paid in six months and one week and Option B for an amount to be paid in 12 months. The amounts for Option A were successively adjusted down; the more often it was chosen over Option B, the more the respondent discounted future gains.

Table A1. Multiple price list for eliciting time preferences

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

To elicit risk preferences, participants selected among a series of 14 choices between two options A and B. In both options in Table A2, respondents faced a lottery that paid either a high or a low monetary gain with equal probability of 0.5 (presented as a coin flip). Note that Option A systematically had a lower variance compared to Option B, with a higher expected value in Lines 1 to 7 and a lower expected value after Line 7. The more often Option A was chosen, the more risk averse the person.

Table A2: Multiple price list for eliciting risk preferences

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€

Stake levels

To account for stake effects, all values shown in the tables were multiplied by 10 (divided by 10) for about 10% (7%) of the respondents.

Incentivization

To mitigate hypothetical bias, more than half the sample were incentivized (54%). Among those, a randomly selected subset (1%) were paid based on their actual choices. Incentivization was only implemented for medium and low stakes. The selected winners received a prepaid credit card (MasterCard) by postal mail. The stated amount could be spent in any online or offline shop accepting MasterCard. Payments to the winning participants ranged from 0 to 250 euros.

Calculation of preference parameters

Following the method used by Brown and Kim (2013), we calculated preference parameters individually by use of each respondent's switch-points, that is, the points at which a given person started choosing Option B over Option A in each of the tables (respondents with monotonous preferences should have had at most one switch-point in each of the tables). We assumed that respondents were indifferent at the mean values of the lines between which they switched: for instance, a participant choosing Option A in Line 1 of the time preference table 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, that is, always chose A (B) in one of the tables, were assumed to be indifferent at the last (first) line of this table. The switch-points thus provided two equations (one for each table) that could be solved for the two unknown preference parameters. Note that, unlike using individual switch points separately to calculate the two preference parameters, 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. This share is lower than in most other studies and comparable to Harrison et al. (2005).

Appendix B: Robustness check

Table B1. Generalized ordered logit models estimates without covariates. Marginal effects.

	Experiment-based measures			Scale-based measures			Aggregate measures		
Variables	Building code	Passive house	ZNEB/+	Building code	Passive house	ZNEB/+	Building code	Passive house	ZNEB/+
δ[a]	-0.008	0.004	0.004						
	(0.325)	(0.327)	(0.326)						
α[a]	-0.007	0.004	0.003						
	(0.375)	(0.375)	(0.377)						
WTWait[a]				-0.005	0.003	0.002			
				(0.477)	(0.479)	(0.476)			
WTRisk[a]				-0.017**	0.009**	0.008**			
				(0.016)	(0.015)	(0.021)			
Patience							-0.013**	0.007**	0.006**
							(0.010)	(0.012)	(0.011)
RiskProneness							-0.008*	0.004*	0.003*
							(0.060)	(0.057)	(0.069)
Observations	1901	1901	1901	2134	2134	2134	1901	1901	1901

p-values in parentheses

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

[a] Variable values are z-scores of the observed values.

Table B2. Probit estimates with dependent variable *NZEB*. Average marginal effects.

Variables	Experiment-based measures		Scale-based measures		Aggregate measures	
δ^a	0.013	(0.180)				
α^a	0.009	(0.329)				
WTWait[a]			-0.004	(0.573)		
WTRisk[a]			0.029***	(0.000)		
Patience					0.012**	(0.027)
RiskProneness					0.012**	(0.020)
Environmental_ID[a]	0.006	(0.512)	-0.003	(0.732)	0.002	(0.843)
SocialNorm[a]	0.004	(0.596)	0.001	(0.866)	0.002	(0.838)
RelevanceInvestmentCosts[a]	0.003	(0.744)	-0.011	(0.156)	0.005	(0.533)
Age	0.000	(0.906)	-0.000	(0.540)	0.000	(0.773)
Male[b]	0.011	(0.442)	0.007	(0.633)	0.006	(0.683)
Size	0.000	(0.984)	0.000	(0.936)	-0.001	(0.848)
Income	0.000	(0.433)	0.000	(0.625)	0.000	(0.510)
Education[b]	0.014	(0.400)	-0.006	(0.738)	0.010	(0.547)
Detached[b]	0.045**	(0.012)	0.062***	(0.000)	0.046***	(0.009)
Urban[b]	0.038**	(0.018)	0.041***	(0.006)	0.036**	(0.023)
≥2010[b]	0.037**	(0.033)	0.039**	(0.018)	0.038**	(0.027)
Country dummies	Yes		Yes		Yes	
Observations	1529		1799		1529	

p-values in parentheses

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

[a] Variable values are *z*-scores of the observed values.

[b] The marginal effect for factor levels is the discrete change from the base level.