Adoption of retrofit measures among homeowners in EU countries:

The effects of access to capital and debt aversion

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Abstract

Energy efficiency policies often involve low-interest loans for retrofit measures in private buildings; the main target of these loans are meant to be households with otherwise poor access to capital. However, such programs can only be successful if the targeted households also take up these loans. This paper studies the relation between access to capital and debt aversion and the adoption of retrofit measures in European Union countries, employing a demographically representative household survey including about 6,600 homeowners in France, Germany, Italy, Poland, Romania, Spain, Sweden, and the United Kingdom. The findings suggest that debt aversion negatively affects the adoption of retrofit measures by homeowners. In particular, debt-averse homeowners with poor access to capital are less likely to have adopted retrofit measures than non-debt-averse homeowners with poor access to capital. The findings further provide evidence that low-interest loan programs should be targeted at younger homeowners with lower income and less formal education.

Key words: energy efficiency; debt aversion; soft loans; energy policy; econometrics;

Highlights:

- Debt aversion impedes the adoption of retrofit measures.
- Debt aversion impedes the effectiveness of soft loans for retrofit measures.
- Soft loans should target non-debt-averse homeowners with poor access to capital.
- Soft loans should target young homeowners with low income and low education.

1 Introduction

Lack of access to capital is often considered to be a major barrier to energy efficiency in private households (e.g., Marchand et al., 2015; Schleich et al., 2019), especially for the undertaking of costly investments such as heating system replacement or retrofit measures. To palliate this issue, national, regional, and local administrations in many countries implement financial support measures to speed up the adoption of energy-efficient technologies in households. These measures often involve low-interest loans (i.e., soft loans) for retrofit measures such as insulation of the building hull, or double and triple glazing of windows. Such loan programs are designed to provide homeowners with poor access to capital with the possibility to invest in costly energy efficiency measures.

The effectiveness of these soft loan programs depends on two main factors: free riding and take-up by the targeted households. Free riding occurs when subsidies such as rebates or low-interest loans are offered to customers who would have purchased the technology even without the subsidy. Several studies have found free riding to exist in utility demand side management and other subsidy programs for residential energy efficiency measures in Europe (Grösche, 2010; Alberini et al., 2014; Nauleau, 2014; Olsthoorn et al., 2017) and North America (Joskow and Marron, 1992; Malm, 1996; Loughran and Kulick, 2004; Boomhower and Davis, 2014). While the focus of these studies has been on rebate programs, soft loan programs may also be subject to free riding when the programs are not restricted to households with low access to capital. In such a case, funds from soft loan programs may be spent on the wrong targets. For example, in reviewing evaluations of key energy efficiency programs, Rosenow and Galvin (2014) report that the CO_2 Building Rehabilitation Program--the predecessor of the energy-efficient refurbishment program--suffered from free-rider problems.

The second problem stems from the fact that the targeted households (here homeowners with low access to capital) may not take up these programs as expected. This may occur for a variety of reasons: for instance, the program may not be well-known, the conditions offered not attractive, or the transaction costs too high.

In this paper, we empirically study a fairly novel explanation for the low take-up of soft loans for energy-efficient technology by homeowners with low access to capital: debt aversion. Homeowners targeted by these programs may refuse to take up a loan to finance investments in capital-intensive energy-efficient technologies because they intrinsically dislike being in debt.

Previous empirical analyses have related household adoption of energy-efficient technologies to individual characteristics such as pro-environmental preferences (e.g., di Maria et al., 2010; Ramos et al., 2015), social norms (e.g., Schleich et al., 2019), time discounting (e.g., Newell and Siikamäki 2015; Schleich et al., 2019), risk aversion (e.g., Farsi, 2010; Qiu et al., 2014), loss aversion (e.g., Heutel, 2019; Schleich et al., 2019 Blasch and Daminato, 2020), or present bias and myopia (e.g., Cohen et al., 2017; Schleich et al., 2019). In a recent conceptual framework of the factors explaining household adoption of energy-efficient technologies, Schleich et al. (2016) propose that debt aversion may -- as an internal barrier to energy efficiency -- impede investment in expensive energy-efficient technologies for households with poor access to capital--an external barrier to energy efficiency. To our knowledge, this proposition has not been tested empirically. Trotta (2018a) finds that households in the UK who have taken out a mortgage are more likely to have invested in retrofit measures than household who own their dwelling outright, thus providing indirect evidence for a negative correlation between debt aversion and adoption of energy-efficient technologies. Previous empirical studies have directly linked debt aversion to individuals' life-cycle consumption and saving decisions (Meissner, 2016) and to decisions to pursue or not a higher education degree (Eckel et al., 2007; Field, 2009); we are the first to empirically link debt aversion to energy-efficient technology adoption.

In this paper we first analyze the effect of debt aversion on adoption of retrofit measures. In particular, as soft loan programs are targeted towards homeowners with poor access to capital, we explore whether debt-averse individuals with poor access to capital are less likely to adopt retrofit measures than non-debt-averse individuals with poor access to capital. Second, we identify the socio-economic characteristics of the homeowners that belong to the target group of such soft loan programs (non-debt-averse homeowners with poor access to capital). Thus, our findings provide guidance for the design of effective policies accounting for the fact that homeowners may be debt averse.

The remainder of this paper is organized as follows. Next, section 2 provides a brief overview of the main policies addressing thermal energy use in residential buildings for the eight countries in our study. Section 3 describes the data, the econometric models and the variables employed in our empirical analyses. Then, section 4 presents and discusses the findings. Finally, section 5 concludes and provides policy implications.

2 Overview of polices addressing thermal energy performance of residential buildings

In the eight countries covered in our study, government policies addressing thermal energy efficiency in the residential building sector primarily pursue implementation of EU legislation. In particular, the Energy Performance of Buildings Directive (EPBD) (Directive 2010/31/EU, amended by Directive 2018/844/EU) sets standards for thermal energy use per area of floor space for new and modernized buildings. An earlier version of the EPBD (Directive 2002/91/EC) had already required an energy performance certificate for buildings constructed, sold, or rented out, thus allowing buyers (and renters) to make more informed decisions. More recently, the Energy Efficiency Directive (EED) (Directive 2012/27/EU) established a framework of measures to help lower energy consumption by at least 20% by 2020 compared to baseline consumption. Directive 2012/27/EU was amended by Directive 2018/2002, which foresees an energy reduction target of at least 32.5 percent by 2030. Most importantly, Article 7 of the EED requires EU countries to establish energy efficiency obligation schemes (EEOS) for energy distributors and/or retail energy sales companies lowering annual energy sales to final customers by at least 1.5% for the period 2014 to 2020. So far, 18 Member States have implemented EEOS, including France, Italy, Poland, Spain, and the UK. EEOS typically involve rebates for insulation measures and upgrades of heating systems in the residential sector (for comprehensive overviews and comparisons of EEOS across countries see for example ENSPOL, 2015; Rosenow and Beyer, 2017; Rosenow et al., 2019; Trotta et al., 2018).

Alternatively or complementarily to EEOS, national governments may introduce other measures as long as these deliver the same amount of energy savings. We briefly review these measures for each of the eight countries in our survey, thereby focusing on direct support measures available to private homeowners, that is, on the types of measures of relevance to our paper. We therefore do not cover indirect measures such as energy or CO_2-taxation or informational policies, nor support programs for housing cooperatives or homeowner associations. This review of existing measures is based on Economidou et al. (2018), Trotta et al. (2018), the Odyssee-Mure database (Odyssee-Mure, 2020), the national energy efficiency action plans (NEEAPs) and associated progress reports (European Commission, 2020).

In France, the sustainable development tax-credit energy transition scheme (CIDD-CITE) was implemented in 2014 and offers a tax credit of 30% (with amounts capped depending on family composition) for thermal insulation measures and boiler upgrades in existing buildings, among others. In addition, the interest-free eco-loan (Eco-PTZ) exists since 2009 and finances up to €30,000 Euro for deeper comprehensive energy efficiency refurbishments. Both schemes are still ongoing.

In Germany, the energy-efficient refurbishment program administered by the KfW (Bank for Reconstruction) exists since 1996 and currently offers homeowners loans of up to €120,000 with favorable interest rates (0.75%) for financing measures aimed at saving energy and reducing CO_2 emissions in the existing residential building stock.

In Italy, since 2013, the thermal account (Conto Termico) supports projects involving energy efficiency improvements in existing buildings or small-scale renewable thermal energy through annual installments on up to 65% of the capital costs for a period of 2 to 5 years depending on the measures implemented. In addition, since 2014, a fund (Plafond Casa) finances mortgage-backed loans for purchasing energy-efficient new homes and for retrofit measures in existing buildings, giving priority to young couples, large families, and households with disabled persons.

In Poland, since 2009, the thermo-modernization and repairs fund subsidizes 20% of a loan taken out for retrofit or renewable heating measures in existing buildings (capped at 16% of expenses or twice the amount of expected annual energy cost savings). Since 2018, the anti-smog Clean Air Program provides co-financing for retrofit and renewable heating measures for owners of existing single-family houses. For the construction and purchase of new buildings exceeding energy efficiency standards, since 2013, the government also offers subsidized loans. These support programs are ongoing.

In Romania an ongoing thermal rehabilitation program initiated in 2006 provides government-backed guarantees of bank loans taken out by owners of existing single-family houses for retrofit measures and heating upgrades.

In Spain, the PAREER-CRECE program supports retrofit measures and replacements of heating systems for existing buildings through direct grants. In addition, the program also foresees loans for up to 90% of the eligible costs not covered by the grant. PAREER-CRECE started in 2013 and ended in 2016. Since 2018, PAREER-II provides similar support as PAREER-CRECE. PAREER-II is scheduled to end in 2020.

In Sweden, since 2008, homeowners are entitled to a tax deduction of labor costs for installing energy efficiency measures. Currently, this rate is 30%, up to a maximum amount of SEK 50,000 (ca. € 4818) per year. In 2008, Sweden introduced credit guarantees for loans taken out for new construction and conversion work, allowing homeowners to obtain further mortgages from commercial banks. The guarantee covers up to 90% of the value of the building.

In the United Kingdom, the ongoing Home Energy Efficiency Program in Scotland (HEEPS) was launched in 2013 and offers homeowners interest-free loans of up to £10,000 (ca. €11,000) for implementing energy efficiency measures. In Northern Ireland, the ongoing Better Energy Homes Scheme (BEH) which come into force in 2009, provides grants for retrofit measures and upgrades of heating systems of up to £10,000 (ca. €11,000). In addition, since 2014 the Affordable Warmth Scheme offers grants targeting low-income households who are considered energy poor. In particular, the Boiler Replacement scheme offers grants of up to £1,000 (ca. €1,100) for low-income households with a boiler that is at least 15 years old.

In summary, among the countries in our study, the UK relies most heavily on EEOS to meet its energy efficiency targets providing government-sponsored subsidies for low-income households in Scotland and Northern Ireland only. In comparison, France, Italy, Spain and Poland use a mix of EEOS and publicly funded measures, and Germany, Romania, and Sweden do not employ EEOS at all. For the entire EU, EEOS are estimated to have achieved about one third of all energy savings (European Commission, 2019) between 2014 and 2017, but effectiveness differed across countries. In particular, EEOS are considered to have been more effective in the UK than in other countries (e.g. ENSPOL, 2015; Fawcett et al., 2019; Trotta et al., 2018). Surveying the energy efficiency support measures in EU countries, Rosenow et al. (2017) find that grants are the most popular instrument used, arguably because they are easy to design and administer. In comparison, loan programs are somewhat less frequent, and focus on energy efficiency measures which are more complex and have high upfront costs. Loan schemes also tend to be less costly to public budgets than grants or tax exemptions and they leverage more additional private funds per public funds spent (e.g. IEA, 2012). In light of the significant investments required in the buildings sector to meet ambitious energy and climate targets, Rosenow et al. (2017) call for a shift in support measures from grants towards loans. However, debt-averse homeowners may undermine the effectiveness of such a shift.

3 Methodology and Data

Our empirical analysis relies on data from a multi-country survey and involves estimating two types of econometric models. First, the *retrofit adoption model* explores whether debt aversion affects the likelihood to adopt retrofit measures. Second, the *target group model* is used to identify the socio-economic characteristics of homeowners who are most likely to respond to energy efficiency support policies involving loans.

The remainder of this section describes the survey, the models and the dependent and explanatory variables used in the econometric analyses.

3.1 Survey

The empirical analyses rely on a dataset collected within a larger online survey collected in summer 2016 through the household panel of Ipsos GmbH. The original dataset includes roughly 15,000 responses from households in France, Germany, Italy, Poland, Romania, Spain, Sweden, and the United Kingdom; in each of these countries, the samples were recruited via quota sampling to be representative of the country's population on the criteria of age (between 18 and 65 years), gender, and geographic distribution. Initial screening questions on household decision-making ensured that all survey participants were involved in decisions for utilities, heating, and household appliances. Following recommended practice (Brislin, 1970), the surveys were translated through native speakers into the target languages before being translated back into English. This procedure allowed to control for differences across countries due to language.

The general survey focused on energy-efficient technology adoption, dwelling characteristics, and individual characteristics including attitudes, personality traits, and socio-demographic information. In particular, the survey included items eliciting attitudes towards taking up debts and asked respondents to rate their access to capital.

All monetary amounts (e.g., for income categories) were presented in the respondents' national currency[1]. Since our analysis focuses on investments in retrofit measures, we only used the subset of respondents who were homeowners; as a consequence, the final sample used in this paper consists of 6630 homeowners, with the following distribution across countries: France (n=787), Germany (n=594), Italy (n=1037), Poland (n=898), Romania (n=927), Spain (n=814), Sweden (n=566), and the United Kingdom (n=1007)[2]. Sample sizes are somewhat smaller for countries where the home ownership rate is lower (Germany), or where the original survey sample was smaller (Sweden).

3.2 Econometric models

The first econometric model (*retrofit adoption model*) regresses the adoption of retrofit measures on a set of covariates which includes, among others, proxies for access to capital and debt aversion. In particular, we include an interaction term of access to capital and debt attitudes to test whether debt-averse homeowners with poor access to capital are less likely to have adopted retrofit measures than non-debt-averse homeowners with poor access to capital. The second model (*target group model*) is used to identify the socio-economic characteristics of the target group of energy efficiency support policies involving soft loans (homeowners with poor access to capital who are most likely to

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1 We used the following (real) conversion rates from Euro amounts into the national currency (of 1 June 2016): Poland 1€ = 4.391 PLN; Romania 1€ = 4.52 RON, Sweden 1€ = 9.272 SEK, and UK 1€ = 0.775 £. The amounts reported in the descriptive statistics in Appendix Table A1 use the converted rates (Euro equivalent).

2 In the context of energy-efficient technology adoption, data from this survey has been used to study the role of time preferences, risk aversion and loss aversion (Schleich et al., 2019), the adoption of low-energy houses (Olsthoorn et al., 2019), and the role of homeowner income. None of these studies have looked at the role of debt aversion or the factors related with debt aversion or access to capital.

respond to these policies). To do so, we first identify homeowners with poor access to the capital market who are not debt averse. Then, we use the model to see the factors that determine the socio-economic characteristics of those who do belong to this group.

For both models, the dependent variable is dichotomous. Models with a dichotomous dependent variable are typically estimated via binary response models. We therefore employ a Probit model. However, Probit models (as well as Logit models) make strong assumptions about the distribution of error terms in the assumed underlying structural model. If these assumptions do not hold, the parameter estimates may be substantially biased. As suggested by Wooldridge (2002, p. 455), we also estimate our models as linear probability models (LPMs) via ordinary least squares (OLS). LPMs result in unbiased estimates of the coefficients, but they do not constrain the predicted value to range between zero and one, unlike in binary response models. In addition, OLS estimation imposes heteroscedasticity. To address the second drawback, we estimate the LPMs using heteroscedasticity-consistent robust standard error estimates (see also Angrist, 2001).

Following the empirical literature employing multi-country surveys (e.g., Mills and Schleich, 2010, 2012; Ameli and Brandt, 2015; Krishnamurthy and Kriström, 2015; Schleich et al., 2019) we aggregate observations across countries and use country dummies to reflect differences across countries. As a robustness check, we also estimate a *retrofit adoption model* and a *target group model* for each individual country.

3.3 Variables

First, we describe how the dependent variables were constructed for the *retrofit adoption model* and for the *target group model*. Then, we describe the sets of covariates used in these models. Table A1 in the Appendix reports the country-specific descriptive statistics of the dependent variables and the covariates.

3.3.1 Dependent variables

The dependent variable for the *retrofit adoption model* was constructed from participants' self-reported adoption decisions on retrofit measures. The dichotomous dependent variable takes on the value of one if the respondent household had implemented at least one of the following retrofit measures in the previous ten years: insulation of roof or ceiling, insulation of exterior walls, insulation of basement, installation of double-glazed windows, or installation of triple-glazed windows. Otherwise, the dependent variable was set to zero. The descriptive statistics in Appendix Table A1 show that the share of homeowners who reported to have adopted a retrofit measure amounts to 55% for the entire sample, and ranges from about 40% for Spain and Sweden to 64% for Germany and 83% for Romania.

The dependent variable for the *target group model* was constructed from the proxies reflecting households' access to capital markets and individuals' debt attitudes (for further details see 2.3.2). If the proxy for access to capital was below the country median in our sample and the proxy for debt attitudes was above the country median in our sample (reflecting lower debt aversion than the median respondent in a particular country), the dependent variable takes on the value of one. For all other cases, the dependent variable was set equal to zero. Hence, respondents for whom the dependent variable is equal to one are the interesting ones when offering low-interest loan programs for retrofit measures: they are in the targeted group of households with poor access to capital and are also likely to respond positively to these programs. As reported in Appendix Table A1, the share of this group of homeowners in the sample is 22%. It is highest for Romania (27%), Spain (27%), and Italy (26%), and lowest for the United Kingdom (17%), Germany (19%) and Poland (21%).

3.3.2 Covariates

In addition to proxies reflecting homeowner access to capital and debt aversion, the set of covariates used in the multivariate analyses have typically been included in empirical studies of household adoption of energy-efficient technologies and reflect household socio-economic information, dwelling characteristics, and individual attitudes. This rich set of covariates is meant to help identify the effects of debt aversion and access to capital on the adoption of retrofit measures. Table 1 summarizes how those covariates are defined. Table 1 also indicates if a variable is included in the *retrofit adoption model* and/or in the *target group model*. We first present the covariates that enter the *retrofit adoption model*.

Access to capital and debt aversion

As explained earlier, homeowner access to credit may affect the adoption of capital-intensive energy efficiency measures. Indeed, using the same dataset, Schleich at al. (2019) find a positive correlation between a household's subjective assessment of its access to the capital market and stated adoption of retrofit measures. Similar to Schleich et al. (2019), our analysis includes *CapitalAcces*s, which is constructed from a one-item scale asking respondents to rate their access to capital. While typically correlated with household disposable income, homeowner access to capital is more general, and is expected to also depend on other assets possessed by the household such as bonds, or real estate property. Appendix Table A1 suggests that stated access to capital is highest in Sweden, the United Kingdom and Germany, and lowest in Romania, Italy, and Spain. To simplify the interpretation of the results, *CapitalAcces*s is transformed into its z-score before entering the econometric analysis. For z-scored variables, a one unit change corresponds to a change by one standard deviation.

To capture individuals' attitudes towards debts, we employ a seven-item rating scale, which is described in more detail in Table 1. *DebtAversion* is calculated as the unweighted sum of the seven items. With a Cronbach's alpha of 0.75, the items appear to be internally consistency and adding them up seems appropriate. Items (i) to (iv) (see Table 1) were slightly adjusted from Walters et al. (2019); items (v) to (vii) were developed for the purpose of this study. Thus, higher values of *DebtAversion* correspond to higher aversion. Appendix Table A1 reports the highest values of *DebtAversion* for Germany and France, and the lowest for Italy and Sweden. The z-score of *DebtAversion* is employed in the econometric analyses. In the retrofit adoption equation, we also include the interaction of the z-scores of *CapitalAccess* and *DebtAversion.* Because we anticipate debt-averse individuals with good access to capital to be less likely to have adopted retrofit measures than non-debt-averse individuals with good access to capital, we expect the coefficient associated with this interaction term to be negative. We next turn to the remaining covariates.

Socio-demographic characteristics

Most empirical studies find household disposable income to be positively related with the adoption of energy-efficient technologies (e.g. Michelsen and Madlener, 2012; Ameli and Brandt, 2015; Trotta, 2018b; Schleich, 2019). Similarly, individuals with higher levels of education are typically more likely to have adopted energy-efficient technologies (e.g. di Maria et al. 2010; Michelsen and Madlener 2012; Ramos et al. 2015). However, Bruderer Enzler et al. (2014) and, using the same dataset as in the present study, Schleich et al. (2019) found a negative correlation with education for retrofit measures. Our set of covariates includes *Income* and *Education* to capture the effects of household disposable income and education levels in the implementation of retrofit measures. *Education* enters the regression equations as a dummy, reflecting whether individual education level is equal to or above the country median in survey sample. We also include respondent *Age*. The empirical evidence on the relation between energy-efficient technology adoption and age is rather mixed. Michelsen and Madlener (2012) conclude that age is negatively related with investments in pellet-fired boilers. Similarly, Ramos et al. (2015) find the propensity to invest in low-energy ovens, double-glazing and light bulbs to be lower in households with more senior citizens. The findings by Ameli and Brandt (2015) suggest that older people are less likely to have adopted heat pumps, but they are more likely to have adopted light bulbs, heat thermostats, thermal insulation and energy-efficient windows. Finally, based on the same dataset as in the present study, for half the countries, Schleich (2019) finds a positive relation between age and the implementation of retrofit measures.

Attitudes towards energy costs and the environment

Higher energy costs are typically associated with a lower propensity to invest in energy efficiency (e.g., Nair et al., 2010; Houde, 2018; Cohen et al., 2017; Olsthoorn et al., 2019). We therefore include a measure reflecting participants' attitudes towards energy costs when investing in retrofit measures, *Energycosts*. In the econometric analyses, we use the z-score of *Energycosts*.

Pro-environmental attitudes are typically positively related with the adoption of energy-efficient technologies (e.g., di Maria et al., 2010; Mills and Schleich, 2014; Ramos et al., 2015; Schleich, 2019). We employ *Environmental_ID* to capture environmental attitudes. *Environmental_ID* is measured via four items which were adapted from Whitmarsh and O'Neill (2010). *Environmental_ID* was calculated as the average of the four items described in detail in Table 1. Our econometric analyses use the z-score of *Environmental_ID*.

Dwelling characteristics

The set of covariates for the *retrofit adoption model* refers to the dwelling of the household. *Detached* is a dummy variable which captures differences in the likelihood for retrofit measures being implemented in detached versus non-detached houses. Findings based on the same dataset suggest that detached houses are more likely to be low-energy houses (Olsthoorn et al., 2019) and to have energy efficiency measures implemented (Schleich et al., 2019). Finally, *BuildingAge* is assumed to reflect the effect of building age on the uptake of retrofit measures. Typically, older buildings are associated with a higher take-up of retrofit measures (e.g., Schleich et al., 2019).

The set of covariates for the *target group model* includes *income*, *education*, and *age*. In addition, we also allow having children (*children*) and living in an urban versus non-urban area (*urban*) to be related with belonging to the target group of respondents who are both capital constrained and non-debt averse, and hence likely to respond to policies involving low-interest loans for implementing retrofit measures.

Table 1: Description of covariates.

Label	Description	Retrofit adoption model	Target group model
CapitalAccess†	Subjective assessment of a household's access to capital. Constructed using the responses to the following question (1= very poor access to 5= very good access): "How would you categorize your access to loans/credits/capital?"	x	
DebtAversion†	Subjective assessment of a respondent's debt aversion. Constructed using the responses to the following questions (1= very much like me to 6= not at all like me): "Please rate the following statements: (i) If I have debts, I like to pay them as soon as possible; (ii) If I have debts, I prefer to delay paying them if possible, even if it means paying more in total; (iii) If I have debts, it makes me feel uncomfortable; (iv) If I have debts, it doesn't bother me; (v) I dislike borrowing money; (vi) I feel OK borrowing money for 'essential' purchases e.g. Cars, appliances, mortgage; (vii) I enjoy being able to borrow money to buy things I like, and to pay for things I cannot afford." To construct *DebtAversion*, we subtracted the score from 7 for questions (i), (iii), and (v).	x	
Income	Household annual income (after taxes) in 1000 Euro (using midpoint of eleven categories, and the lower bound of the highest category).	x	x
Education	Dummy = 1 if level equal to or higher than country median in survey. Considered levels: no degree or certificate/trade or vocational certificate /high school or equivalent/higher education.	x	x
Age	Respondent age in years.	x	x
Children	Dummy = 1 if children below 18 years of age are living in the household.		x
Energycosts†	Score calculated from participant stated importance of energy costs when investing in insulation measures (1= played no role to 5= very important).	x	
Male	Dummy =1 if respondent reported to be male.		x
Environmental_ ID†	Score reflecting environmental identity. 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."	x	
Detached	Dummy = 1 if house is detached.	x	
BuildingAge	Age of the building calculated by subtracting the midpoint year (of the selected category describing when the dwelling was built) from the year of the survey (i.e. 2016). These categories are < 1920, 1921-1944, 1945-1959, 1960-1969, 1970-1979, 1980-1989, 1990-1999, 2000-2009, > 2009; for the first and last category, we used the upper and lower limit respectively.	x	
Urban	Dummy = 1, if respondent lives in the center of a major town or in a suburban town.		x

† Variable enters the regression equations as z-score;

4 Results

We first present the results for the *retrofit adoption model*, and then for the *target group model*.

4.1 Results for retrofit adoption model

Results for the *retrofit adoption model* appear in Table 2 using observations from all countries. To test for collinearity, variance-inflation factors (VIFs) were calculated and are reported in Table A6 in the Appendix. The highest VIF for any variable is 2.24, and thus below the critical values of 5 or 10 often used as benchmarks in the empirical literature. The covariates in the retrofit adoption model are therefore not highly inter-correlated. To save space, the findings for the country dummies do not appear in Table 2. To allow for a meaningful interpretation of the Probit model results, Table 2 reports the average marginal effects and, for the dichotomous variables, the discrete probability effects. Appendix Table A2 shows the coefficients of the Probit model together with several goodness-of-fit measures. The goodness-of-fit tests show satisfactory goodness-of-fit. For non-linear models such as the Probit model, the marginal effects of the covariates depend on the values of all covariates. As pointed out by Ai and Norton (2003) and further elaborated by Greene (2010), the coefficient of the interaction term in the structural model does not reflect the true estimated interaction effect. To calculate the marginal effect for *z_DebtAversion X z_CapitalAccess*, we compare the discrete probability effects of *z_DebtAversion* when *z_CapitalAccess takes* on the value of one rather than zero. We recall that for z-scored variables, the mean is zero, and a change by one unit corresponds to an increase by one standard deviation.

We first note that the findings for the Probit and the LPM model are very similar. As an additional robustness check, we estimated the retrofit adoption model as a Logit model.

The results of the Logit model are almost identical to those presented in Table 2 for the Probit model and the LPM. Hence, the findings appear robust to whether the *retrofit adoption model* is estimated as a binary response model or a LPM. In addition, all coefficients are statistically significant, typically at $p<0.01$.

Access to capital and debt aversion

The finding for *CapitalAccess* suggests that for the average homeowner in our sample, propensity to have adopted at least one retrofit measure in the ten years prior to when the survey was conducted increases by 3.6 percentage points when *CapitalAccess* increases by one unit. Since *CapitalAccess* enters the regression equation as a z-value, an increase in one unit corresponds to an increase in one standard deviation. The findings for *CapitalAccess* in Table 2 are generally quite similar to those found with essentially the same dataset by Schleich et al. (2019), who find an average marginal effect of 3.1 percentage points in their aggregate model for all countries.

Next, we find that *DebtAversion* is negatively related with retrofit adoption -- independent of whether the household has good or poor access to capital. Thus, even households with good access to capital do not want to run into debts to finance investment in retrofit measures. For the average homeowner in our sample, an increase of *DebtAversion* by one standard deviation corresponds to a decrease in retrofit adoption by 1.7 percentage points.

Next, the coefficient associated with the interaction term of *CapitalAccess* and *DebtAversion* is negative. Thus, the likelihood to have adopted a retrofit measure is lower for debt-averse homeowners with poor access to capital compared to non-debt-averse individuals with poor access to capital. In other words, the negative effect of debt aversion on the adoption of retrofit measures appears to be stronger when access to capital is poor. This result is consistent with indirect evidence by Trotta (2018a), who finds homeowners in the UK who took out a mortgage, and hence are unlikely to be debt averse or may have better access to capital, to be more likely to have adopted retrofit measures in the past.

More generally, previous empirical literature has linked energy efficiency technology adoption with behavioral biases such loss aversion (e.g. Blasch and Daminato, 2020; Heutel, 2019; Schleich et al., 2019) and present bias and myopia (e.g., Cohen et al., 2017; Schleich et al., 2019). Likewise, adoption of energy efficient technologies has been found to be related with preferences such as pro-environmental preferences (e.g. di Maria et al., 2010; Ramos et al., 2015), social preferences (e.g. Schleich et al., 2019), standard time discounting (e.g., Newell and Siikamäki 2015; Schleich et al., 2019) or aversion towards risk (e.g., Farsi, 2010; Qiu et al., 2014). The framework of Schleich et al. (2016), for example, classifies behavioral biases and preferences as internal barriers to energy efficiency because they are internal to the decision maker - unlike external barriers such as lack of access to capital, the landlord tenant problem, or transaction costs. Our findings for the *retrofit adoption model* suggest that debt aversion appears to be an internal barrier to the adoption of retrofit measures.

Table 2: Probit model and LPM results (average marginal effects) *for retrofit adoption model* (all countries).

	Probit	LPM
CapitalAccess †	0.036***	0.036***
	(0.000)	(0.000)
DebtAversion	-0.017***	-0.017***
	(0.002)	(0.004)
DebtAversion†	-0.021***	-0.021***
X CapitalAccess†	(0.000)	(0.000)
Income	0.001***	0.001***
	(0.001)	(0.001)
Education	-0.025**	-0.024*
	(0.047)	(0.058)
Age	0.001***	0.001***
	(0.005)	(0.005)
Energycosts†	0.031***	0.032***
	(0.000)	(0.000)
*Environmental_*	0.062***	0.062***
ID†	(0.000)	(0.000)
Detached	0.081***	0.082***
	(0.000)	(0.000)
BuildingAge	0.001***	0.001***
	(0.000)	(0.000)
Constant		0.475***
		(0.000)
Country dummies	YES	YES
Wald $\chi^2(17)$	810.01***	
N	6630	6630
R^2		0.127

p-values (robust) in parentheses; *** p<0.01, ** p<0.05, * p<0.1; † z-score of the variable was used;

Socio-demographic characteristics

We now turn to the findings for the remaining covariates in the *retrofit adoption model*. In line with the thrust of the literature, we find higher *Income* to be associated with a higher likelihood to have adopted a retrofit measure. On average, an increase in household annual disposable income by 1000 Euro corresponds to an increase in the likelihood to have adopted a retrofit measure by 0.1 percentage points. Unlike most previous studies, yet similar to Bruderer Enzler et al. (2014) and Schleich et al. (2019), homeowners with higher education are less likely to have implemented retrofit measures. Schleich et al. (2019) speculate that better educated homeowners reside in better insulated dwellings. Similar to the findings by Ameli and Brandt (2015), and Schleich (2019), *Age* is positively related with implementing retrofit measures. Older individuals have been found to be more patient (e.g. Tanaka et al., 2010). Hence, older individuals discount future energy cost savings of retrofit measures less and accept longer payback times, therefore implying a positive relation between age and the adoption of retrofit measures.

Attitudes towards energy costs and the environment

Generally, and in line with the literature, the more homeowners value energy costs when investing in retrofit measures, the more likely they are to have adopted retrofit measures. An increase in *Energycosts* by one standard deviation increases the likelihood that the average homeowner in the sample had implemented a retrofit measure by around three percentage points. In line with the thrust of the empirical literature, we find a higher environmental identity to be associated with a higher adoption of retrofit measures. If *Environmental_ID* increases by one standard deviation, the likelihood that the average homeowner household had implemented a retrofit measure rises by about six percentage points.

Dwelling characteristics

Consistent with previous studies using this dataset, we find that *Detached* houses are more likely to have undergone retrofit measures. For the average homeowner in the sample, the likelihood to have invested in a retrofit measures is about eight percentage points higher for a household living in a detached house rather than a non-detached house. Because fewer parties are involved in the decision-making, it may be less complicated to realize retrofit measures in detached houses. Finally, the relation between *BuildingAge* and retrofit measures is positive and statistically significant. One additional year of building age raises the retrofit rate by about 0.1 percentage points for the average homeowner household in the sample. We conjecture that newer dwellings have lower retrofit needs because they are already equipped with good insulation measures.

Results for country-specific models

Table A3 in the Appendix presents the findings of estimating the retrofit adoption model for individual countries, using z-scores *for CapitalAccess*, *DebtAversion*, *Energycosts*, and *Environmental_ID* at the level of individual countries. Individual country models allow the coefficients to differ across countries, yet they suffer from lower degrees of freedom, because the sample sizes are much smaller than in the eight-country model. We will briefly summarize the findings of Table A3 which are related to the focus of our paper, i.e., the role of debt aversion and access to capital for household adoption of retrofit measures. To save space, Table A3 reports the findings for the LPM only. The Probit model results are virtually identical. The coefficient associated with *CapitalAccess* in Table A3 is positive for all countries, and statistically significant in four of the eight countries in the sample. For Germany and Poland the coefficient is just shy of being statistically significant at conventional levels. Similarly, *DebtAversion* is statistically significantly and negatively related with household adoption of retrofit measures in four countries. Finally, the coefficient associated with the interaction term of *CapitalAccess* and *DebtAversion* is negative and statistically significant in three countries. For Romania and Sweden it is just shy of being statistically significant at conventional levels. We further note that rejecting a null hypothesis does not imply that an effect is absent. We therefore conclude that in general, the findings for the individual country models are consistent with those presented in Table 2 where observations from all countries were aggregated.

4.2 Results for target group model

In the *target group model*, belonging to the group of non-debt-averse homeowners with low access to capital is regressed on socio-economic variables. Findings appear in Table 3 for both the Probit and the LPM model. Table A6 in the Appendix shows the VIFs for all variables included in the target group model. The highest VIF for any variable is 2.16. Thus, the estimation results do not appear to suffer from collinearity. The coefficients of the Probit model appear in Appendix Table A4. The goodness-of-fit tests suggest that the model fits the data well. For the Probit model, Table 3 reports the average marginal effects and for the dichotomous variables the discrete probability effects. We first note that the findings for the Probit and the LPM model are virtually identical. We also note that estimating the target group model as a Logit model leads to virtually the same findings as those reported in Table 3. Hence, the findings appear robust to estimating the model as a Probit, as a Logit, or as an LPM model. Second, except for the coefficient associated with *Urban*, all coefficients turn out to be statistically significant at least at $p<0.1$.

Accordingly, on average, homeowners with lower *Income* are more likely to be non-debt-averse homeowners with limited access to capital. Intuitively, finding low-income homeowners to have limited access to capital not surprising. The second criteria for belonging to the target group, i.e. low debt aversion, allows for interesting policy implications: households with lower disposable income may be expected to more likely respond to soft loan offers for retrofit measures than households with higher disposable income. The likelihood of belonging to the target group is 0.2 percentage point higher for homeowners with below-median income disposable income compared to homeowners with above-median disposable income. Thus, the size effect of *Income* is rather small. Note, however that this finding is somewhat at odds with recent results from Lim et al. (2019), who find that, for students, income is negatively related to aversion to take on educational debt. *Education* is negatively related with being a non-debt-averse individual with limited access to capital. Similar to *Income,* finding lower educated homeowners to be capital constrained is in line with intuition. Regarding debt aversion, these findings are supported by Lim et al. (2019), who find that less educated individuals are more likely to be averse to taking on educational debt. The size effect of *Education* is an order of magnitude larger than for *Income* but still relatively small. The findings for *Age* suggest that older homeowners are more likely to be non-debt averse and at the same time also have limited access to capital. An additional year of age increases the likelihood of belonging to the target group by 0.2 percentage points. This result is in line with Lim et al. (2019) who find that older respondents are less likely to be averse to educational debt. Next, *Males* tend to be more likely to be non-debt averse and at the same time also have limited access to capital, but the size effect is about 3 percentage points only. This finding is supported by George et al.'s (2018) large scale study who find that women who have experienced negative macroeconomic events tend to be less debt tolerant than men with the same experiences. Finally, having *Children* or living in an *Urban* environment appear positively related with belonging to the group of non-debt-averse individuals with limited access to capital. Yet, the coefficient associated with *Urban* is just shy of being statistically significant at conventional levels.

Thus, while socio-demographic factors are generally correlated with belonging to the target group of non-debt averse homeowners with limited access to capital, their size effects are relatively small. Arguably, other factors, not included in our set of covariates, may have larger size effects. These could include factors such a financial literacy or trust in government.

Table 3: Probit model and LPM results (average marginal effects) for *target group model* (all countries).

c	Probit	LPM
Income	-0.002***	-0.002***
	(0.000)	(0.000)
Education	-0.033**	-0.035***
	(0.003)	(0.002)
Age	-0.002***	-0.002***
	(0.000)	(0.000)
Male†	0.027***	0.028***
	(0.007	(0.006)
Children	0.021*	0.021*
	(0.065)	(0.076)
Urban	0.014	0.014
	(0.018)	(0.017)
Constant		0.383
		(0.293)
Country dummies	YES	YES
R^2		0.02
Wald $\chi^2(6)$	187.45***	
N	6630	6630

p-values (robust) in parentheses; *** p<0.01,
** p<0.05, * p<0.1;

Results for country-specific models

Appendix Table A5 documents the findings of the *target group model* for individual countries. Since the findings for the LPM and Probit models are very similar, Table A5 only reports the findings for the LPM to save space. In general, findings are consistent with those presented in Table 3. In particular, the coefficients associated with *Income* and *Age* are negative and statistically significant for most of the eight countries in the sample. The coefficient related with *Education* is negative for all but one country, statistically significant for two countries, and almost statistically significant (i.e., p<0.2) in three countries. For the remaining variables, the findings appear somewhat more heterogeneous.

5 Conclusions and Policy Implications

To help achieve climate and energy efficiency targets, many countries offer low-interest loans to private homeowners to spur the implementation of retrofit measures such as building insulation or double and triple glazing of windows in the residential building sector. Yet, private homeowners may fail to respond to attractive loan offerings because they intrinsically dislike being in debt. Thus, debt aversion may be an internal barrier to energy efficiency if these households need external funding to finance capital-intensive energy efficiency measures. This paper provides a first empirical analysis of the relation between debt aversion and energy-efficient technology adoption. To this end, we employ a demographically representative household survey implemented simultaneously among about 6600 homeowners in France, Germany, Italy, Poland, Romania, Spain, Sweden, and the United Kingdom. In particular, we econometrically analyze the adoption of retrofit measures by homeowners, allowing debt aversion (i.e., an internal barrier to adoption) to interact with household stated access to capital (i.e., an external barrier to adoption). The findings from estimating this retrofit adoption equation suggest that debt-averse homeowners are generally less likely to have implemented retrofit measures in the past, independent of whether they have good or poor access to capital. Thus, debt aversion appears to be an internal barrier to the adoption of retrofit measures. In addition, our findings provide evidence that retrofit adoption for debt-averse homeowners with poor access to capital is lower than for less debt-averse homeowners with poor access to capital. This finding has important policy implications. It suggests that offering soft loans to help finance retrofit measures to debt-averse homeowners may not be an effective policy. In particular, a potential shift in support measures from grants towards loans, which has been suggested for the financing of complex and comprehensive retrofit measures (Rosenow et al., 2017) may result in lower energy savings than expected.

Instead, these soft loans should be targeted at homeowners who suffer from poor access to capital, but are not debt averse. We find that this target group may account for a substantial share of all homeowners. Using country medians for debt aversion and access to capital as criteria, this group accounts for 22% of all homeowners in our sample. This share ranges between 17% and 27% across countries. Results from additional econometric analyses suggest that younger homeowners with less formal education living in households with lower disposable income were generally more likely to belong to this target group. Other household characteristics such as having children, or living in an urban environment appear to be less systematically related with belonging to this group across countries. Thus, targeting soft loans at younger homeowners with low education and low household disposable income may be particularly effective for speeding up the adoption of retrofit measures. Of course, limiting support to this target group may prove difficult in practice. In addition, prior to their implementation, such policies should undergo cost-benefit analyses.

Our findings also have implications for model-based assessments of policy interventions. Typically, energy-economic models employ implicit discount rates to govern household investments decisions, with higher implicit discount rates implying lower investments in energy efficiency (e.g., Steinbach and Staniaszek, 2015). Effective policy interventions essentially lower the implicit discount rates. Our findings therefore add to the empirical evidence suggesting that the adjustment in the implicit discount rates should account for heterogeneity in household response to policy interventions (e.g., Gerarden et al., 2017; Schleich et al., 2016). In particular, for soft loans, our findings offer some evidence that debt-averse homeowners are unlikely to respond to these interventions. For these households, the implicit discount rates should not be adjusted; else, the model-based evaluations are likely to overstate the effectiveness of soft loan programs.

Future research may explore whether our findings for the relation of debt aversion and the adoption of retrofit measures also hold for other investments with high up-front costs such as zero net energy or energy plus buildings or photovoltaic installations. Likewise, since the effects of debt aversion may differ across countries, future research could further explore the factors explaining these differences. Similarly, it may be particularly interesting to explore the effects of debt aversion on the acceptance of soft loan programs for energy technologies in emerging and developing countries. Ideally, rather than relying on Likert scales to capture debt aversion, future empirical analyses should employ incentivized experiments similar to the multiple price list experiments developed to elicit time and risk preferences (Holt and Laury, 2002; Coller and Williams, 1999). Finally, it may be worth further investigating which factors explain belonging to the target group of non-debt-averse homeowners with limited access to capital. The results could be used to better target homeowners most likely to respond to soft loan programs for energy efficiency investments.

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Appendix: Descriptive statistics

Table A1: Descriptive statistics (means and standard deviations).

	All countries	FR	DE	IT	PL	RO	ES	SE	UK
Retrofit	0.55	0.64	0.44	0.44	0.64	0.83	0.40	0.41	0.53
	(0.50)	(0.48)	(0.50)	(0.50)	(0.48)	(0.38)	(0.49)	(0.49)	(0.50)
Target group	0.22	0.22	0.19	0.26	0.21	0.27	0.27	0.22	0.17
	(0.42)	(0.41)	(0.39)	(0.44)	(0.41)	(0.44)	(0.44)	(0.42)	(0.37)
Income	31.59	34.30	42.93	30.38	14.25	10.16	28.17	50.08	51.62
	(24.21)	(20.10)	(20.59)	(17.98)	(9.38)	(9.77)	(17.32)	(25.54)	(28.50)
Education	0.64)	0.59	0.52	0.81	0.51	0.67	0.55	0.89	0.60
	(0.48)	(0.49)	(0.50)	(0.40)	(0.50)	(0.47)	(0.50)	(0.32)	(0.49)
Age	43.01	45.61	44.89	44.32	39.73	37.92	44.36	45.28	43.74
	(12.89)	(13.42)	(13.12)	(12.95)	(12.16)	(10.37)	(12.68)	(12.99)	(13.28)
Male	0.52	0.51	0.53	0.51	0.52	0.54	0.52	0.54	0.50
	(.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Children	0.611	0.67	0.62	0.61	0.63	0.58	0.66	0.64	0.51
	(0.49)	(0.47)	(0.49)	(0.49)	(0.48)	(0.49)	(0.47)	(0.48)	(0.50)
CapitalAccess†	3.51	3.39	3.71	3.19	3.52	3.13	3.29	4.11	3.99
	(1.21)	(1.15)	(1.12)	(1.22)	(1.15)	(1.24)	(1.17)	(1.20)	(1.05)
DebtAverson	33.28	33.86	34.08	32.11	33.53	33.52	33.45	32.70	33.31
	(5.99)	(5.35)	(6.25)	(5.72)	(6.34)	(6.03)	(6.17)	(5.02)	(6.40)
Energycosts†	4.24	4.19	4.23	4.34	4.32	4.48	4.05	4.04	4.13
	(0.78)	(0.70)	(0.76)	(0.66)	(0.73)	(0.68)	(0.94)	(0.87)	(0.80)
Environmental_ID†	14.76	15.12	14.34	15.63	14.83	15.08	15.35	13.04	13.98
	(3.23)	(2.87)	(3.34)	(2.89)	(3.11)	(3.14)	(3.10)	(3.42)	(3.36)
Detached	0.39	0.60	0.50	0.33	0.34	0.33	0.31	0.57	0.30
	(0.49)	(0.49)	(0.50)	(0.47)	(0.47)	(0.47)	(0.46)	(0.50)	(0.46)
BuildingAge	48.83	54.74	50.29	45.14	45.72	41.00	38.96	54.84	61.76
	(23.42)	(26.97)	(24.72)	(20.85)	(22.07)	(15.54)	(18.04)	(22.51)	(25.69)
Urban	0.58	0.43	0.40	0.66	0.57	0.66	0.67	0.50	0.61
	0.49	(0.50)	(0.49)	(0.47)	(0.50)	(0.47)	(0.47)	(0.50)	(0.49)
N	6630	787	594	1,037	898	927	814	566	1,007

† z-score of the variable was used;

Table A2: Probit model results for *retrofit adoption model* (all countries).

	Probit
CapitalAccess †	0.102***
	(0.000)
DebtAversion	-0.050***
	(0.003)
DebtAversion† X *CapitalAccess*†	-0.056***
	(0.000)
Income	0.003***
	(0.001)
Education	0.071**
	(0.047)
Age	0.0026**
	(0.043)
Energycosts†	0.088***
	(0.000)
Environmental_ ID†	0.175***
	(0.000)
Detached	0.229***
	(0.000)
BuildingAge	0.003***
	(0.000)
Constant	-0.080
	(0.401)
Country dummies	YES
McFadden's Pseudo R^2	0.099
Wald $\chi^2(17)$	810.01***
Hosmer-Lemeshow $\chi^2(8)$	3.79
Share of correct predictions	65.49%
N	6630

p-values (robust) in parentheses; *** p<0.01, ** p<0.05, * p<0.1; † z-score of the variable was used;

Table A3: LPM results for *retrofit adoption model* (individual countries).

	FR	DE	IT	PL	RO	ES	SE	UK
CapitalAccess †	0.042**	0.036	0.043**	0.027	0.027**	0.047***	0.009	0.020
	(0.016)	(0.109)	(0.010)	(0.129)	(0.034)	(0.008)	(0.663)	(0.229)
DebtAversion	-0.036**	-0.051***	0.006	-0.002	-0.005	-0.052***	-0.048**	0.011
	(0.027)	(0.010)	(0.688)	(0.884)	(0.680)	(0.003)	(0.022)	(0.479)
DebtAversion†	-0.035**	0.013	-0.040***	-0.018	-0.017	-0.033**	-0.024	-0.015
X CapitalAccess†	(0.029)	(0.539)	(0.009)	(0.303)	(0.132)	(0.044)	(0.199)	(0.287)
Income	0.000	0.002**	0.001	0.003	0.002*	0.002**	0.002**	0.001
	(0.910)	(0.034)	(0.146)	(0.108)	(0.093)	(0.028)	(0.039)	(0.323)
Education	-0.038	-0.096**	0.033	-0.007	-0.042	0.058	-0.025	-0.081**
	(0.267)	(0.020)	(0.397)	(0.825)	(0.110)	(0.107)	(0.696)	(0.013)
Age	0.002*	-0.001	-0.000	0.003**	0.002**	0.000	-0.002	0.002*
	(0.089)	(0.398)	(0.905)	(0.049)	(0.045)	(0.814)	(0.266)	(0.094)
Energycosts†	0.053***	0.057**	0.003	0.034*	0.028*	0.021	0.005	0.036**
	(0.003)	(0.012)	(0.848)	(0.065)	(0.061)	(0.214)	(0.792)	(0.026)
*Environmental_*	0.035*	0.048**	0.078***	0.056***	0.040***	0.087***	0.081***	0.070***
ID†	(0.056)	(0.022)	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)
Detached	0.151***	0.079**	0.067**	0.032	0.016	0.103***	0.125***	0.107***
	(0.000)	(0.048)	(0.040)	(0.344)	(0.546)	(0.005)	(0.004)	(0.002)
BuildingAge	0.003***	0.005***	0.001	-0.000	-0.002*	0.001	0.002**	-0.000
	(0.000)	(0.000)	(0.264)	(0.719)	(0.095)	(0.458)	(0.038)	(0.508)
Constant	0.332***	0.181*	0.310***	0.497***	0.797***	0.232***	0.246**	0.454***
	(0.000)	(0.063)	(0.000)	(0.000)	(0.000)	(0.004)	(0.027)	(0.000)
N	787	594	1,037	898	927	814	566	1,007
R^2	0.093	0.113	0.050	0.048	0.048	0.088	0.076	0.062

p-values (robust) in parentheses; *** p<0.01, ** p<0.05, * p<0.1; † z-score of the variable was used;

Table A4: Probit model results for *target group model* (all countries).

c	Probit
Income	-0.008***
	(0.000)
Education	-0.114***
	(0.003)
Age	-0.009***
	(0.000)
Male†	0.094***
	(0.008)
Children	0.073*
	(0.067)
Urban	0.049
	(0.179)
Constant	-0.202**
	(0.027)
Country dummies	YES
McFadden's Pseudo R^2	0.028
Wald $\chi^2(6)$	187.45***
Hosmer-Lemeshow $\chi^2(8)$	5.36
Share of correct predictions	77.59%
N	6630

p-values (robust) in parentheses; *** p<0.01, ** p<0.05, * p<0.1;

Table A5: LPM results for *target group model* (individual countries).

	FR	DE	IT	PL	RO	ES	SE	UK
Income	-0.001**	-0.004***	-0.003***	-0.005***	-0.002	-0.003***	-0.001	-0.001
	(0.043)	(0.000)	(0.000)	(0.000)	(0.215)	(0.000)	(0.104)	(0.130)
Education	-0.006	0.042	-0.001	-0.045	-0.046	-0.086**	-0.087	-0.064**
	(0.852)	(0.211)	(0.969)	(0.112)	(0.151)	(0.011)	(0.140)	(0.010)
Age	-0.001	-0.003*	-0.000	-0.003**	0.003	-0.004***	-0.006***	-0.005***
	(0.288)	(0.066)	(0.906)	(0.035)	(0.118)	(0.003)	(0.000)	(0.000)
Male†	0.054*	0.004	0.009	0.033	0.015	0.056*	-0.006	0.023
	(0.066)	(0.902)	(0.753)	(0.222)	(0.617)	(0.067)	(0.872)	(0.341)
Children	0.008	0.018	0.002	-0.029	0.057*	0.019	0.075*	0.022
	(0.827)	(0.616)	(0.940)	(0.380)	(0.099)	(0.610)	(0.070)	(0.376)
Urban	-0.025	0.028	-0.020	0.021	0.018	0.076**	0.005	-0.001
	(0.412)	(0.399)	(0.500)	(0.440)	(0.550)	(0.017)	(0.887)	(0.958)
Constant	0.307***	0.414***	0.364***	0.399***	0.164***	0.501***	0.579***	0.424***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)
R^2	0.011	0.041	0.016	0.031	0.017	0.051	0.040	0.031
N	787	594	1,037	898	927	814	566	1,007

p-values (robust) in parentheses; *** p<0.01, ** p<0.05, * p<0.1;

Table A6: Variance inflation factors (VIFs) for *retrofit adoption model* and *target group model* (all countries).

	Retrofit adoption	Target group
CapitalAccess †	1.21	
DebtAversion†	1.05	
DebtAversion X CapitalAccess†	1.04	
Energycosts†	1.18	
Environmental_ ID†	1.20	
Income	1.71	1.64
Education	1.13	1.13
Age	1.08	1.28
Male		1.01
Children		1.24
Urban		1.05
BuildingAge	1.12	
Detached	1.06	
Germany	1.64	1.62
Italy	2.09	2.02
Poland	2.09	2.02
Romania	2.24	2.16
Spain	1.90	1.83
Sweden	1.70	1.64
United Kingdom	2.15	2.07
Mean VIF	1.50	1.60

† z-score of the variable was used