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Adoption of retrofit measures among home-owners 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.

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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. In Germany for instance, the Energy-Efficient Refurbishment program administered by the KfW (Bank for Reconstruction) currently offers homeowners loans of up to €100,000 with favorable interest rates (0.75%) for financing measures aimed at saving energy and reducing CO_2 emissions in the existing residential building stock. Similarly, the Home Energy Efficiency Program in Scotland (HEEPS) offers homeowners interest-free loans of up to £10,000 for implementing energy efficiency measures. 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 such 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 and Vance, 2009; 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 are just as likely to 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 study a 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., 2016), 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), 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 high-cost energy-efficient technologies for households with poor access to capital – an external barrier to energy efficiency. To the best of our knowledge, this proposition has not been tested empirically. Previous empirical studies have 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 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 describes the data, the econometric models and the variables employed in our empirical analyses. Then, section 3 presents and discusses the findings. Finally, section 4 concludes and provides policy implications.

2 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.

2.1 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).

2.2 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 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.

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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 GBP. The amounts reported in the descriptive statistics in Appendix Table A 1 use the converted rates (Euro equivalent).

2 The data from this survey has been used in several other analyses of household adoption of energy-efficient technologies. Schleich et al. (2019) explore the role of standard time discounting, risk aversion, loss aversion and present bias on the adoption of light emitting diodes (LEDs), energy-efficient appliances and retrofit measures. Olsthoorn et al. (2019) analyze the adoption of low-energy houses, and Schleich (2019) focuses on the role of income on the take-up of LEDs and energy-efficient appliances for households in general and of retrofit measures for homeowners. While the specification of the retrofit adoption equations is similar, none of these studies have looked at the role of debt aversion on the take-up of energy-efficient technologies. In addition, they did not explore the factors related with debt aversion or access to capital.

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, 2010a, 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.

2.3 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 A 1 in the Appendix reports the country-specific descriptive statistics of the dependent variables and the covariates.

2.3.1 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 A 1 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 A 1, 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%).

2.3.2 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 which enter the *retrofit adoption model*. 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 *CapitalAccess*, which is constructed from a one-item scale asking respondents to rate their access to capital. While typically correlated with 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 A 1 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, *CapitalAccess* 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[3]. 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 A 1 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 now turn to the remaining covariates. Most empirical studies find income to be positively related with the adoption of energy-efficient technologies (e.g. Michelsen and Madlener, 2012; Ameli and Brandt, 2015; Trotta, 2018; 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; Mills and Schleich 2009; 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 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.

3 Cronbach's α takes on the value of 0.75 suggesting satisfactory internal consistency of the items.

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.

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*.

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 respondent lives in the center of a major town or in a suburban town.		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

Label	Description	Retrofit adoption model	Target group model
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

3 Results and Discussion

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

3.1 Results for retrofit adoption model

Results for the *retrofit adoption model* appear in Table 2 using observations from all countries[4]. 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. For non-linear models such as the Probit model, the marginal effects of the covariates depend on the values of all

4 To test for collinearity variance-inflation factors (VIFs) were calculated. The highest VIF for any variable is 2.24, and thus below the critical value of 10 typically used as a benchmark in the empirical literature. Thus, the covariates in the retrofit adoption model are not highly inter-correlated.

covariates[5]. We first note that the findings for the Probit and the LPM model are very similar[6]. 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 $p<0.01$. 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.

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5 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.

6 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.

Table 2: Probit model and LPM results 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

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 net 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 (2016), 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. 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. 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.

Table A 2 in the Appendix presents the findings of estimating the retrofit adoption model for individual countries[7],[8]. 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 A 2 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. The coefficient associated with *CapitalAccess* in Table A 2 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.

3.2 Results for target group model

In the *target group model*, belonging to the group of 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[9]. 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[10]. Hence, the findings appear robust to estimating the model as a Probit or as an LPM model. Second, except for the

7 To this end, we calculated and z-scored CapitalAccess, DebtAversion, Energycosts, and Environmental_ID at the level of individual countries.

8 To save space, Table A 2 reports the findings for the LPM only. Probit model results are virtually identical.

9 For the target group model, the highest VIF for any variable is 2.16. Thus, the estimation results do not appear to suffer from collinearity.

10 Estimating the target group model as a Logit model leads to virtually the same findings as those reported in Table 3.

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. Lower income households may therefore be expected to more likely respond to soft loan offers for retrofit measures than higher income households. Similarly, *Education* is negatively related with being a non-debt-averse individual with limited access to capital. The findings for *Age* suggest that younger homeowners are more likely to be non-debt averse and at the same time also have limited access to capital in all countries. Next, *Males* tend to be more likely to be non-debt averse and at the same time also have limited access. 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.

Table 3: Probit model and LPM results 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

c	Probit	LPM
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

Appendix Table A 3 documents the findings of the *target group model* for individual countries. Since the findings for the LPM and Probit models are very similar, Table A 3 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.

4 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. Previous empirical literature has linked energy efficiency technology adoption with attitudes such as environmental or social preferences, standard time discounting, aversion towards risk and losses, or present bias. 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 energy efficiency) to interact with household stated access to capital (i.e., an external barrier to energy efficiency). 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 does appear to be an internal barrier to energy efficiency. To our knowledge, this is the first effort to document this effect. 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 suggest that offering soft loans to help finance retrofit measures to debt-averse homeowners may not be an effective policy. 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 lower income households 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 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.

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References

Alberini, A., Bigano, A., Boeri, M., 2014. Looking for free riding: energy efficiency incentives and Italian homeowners. Energy Efficiency 7, 571–590. https://doi.org/10.1007/s12053-013-9241-7.

Ai, C., Norton, E.C. (2003). Interaction terms in logit and probit models. Economic Letters, 80, 123–129. https://doi.org/10.1016/S0165-1765(03)00032-6.

Ameli, N., Brandt, N., 2015. Determinants of households' investment in energy efficiency and renewables: evidence from the OECD survey on household environmental behavior and attitudes. Environmental Research Letters 10, 44015. http://dx.doi.org/10.1088/1748-9326/10/4/044015.

Angrist, J. D., 2001. Estimation of Limited Dependent Variable Models with Dummy Endogenous Regressors: Simple Strategies for Empirical Practice. Journal of Business & Economic Statistics 19 (1), 2-16.

Boomhower, J., Davis, L.W., 2014. A credible approach for measuring inframarginal participation in energy efficiency programs. Journal of Public Economics 113, 67–79. https://doi.org/10.1016/j.jpubeco.2014.03.009.

Brislin, R.W., 1970. Back translation for cross-cultural research. Journal of Cross-Cultural Psychology 1(3), 185–216. https://doi.org/10.1177/135910457000100301.

Bruderer Enzler, H., Diekmann, A., Meyer, R., 2014. Subjective discount rates in the general population and their predictive power for energy saving behavior. Energy Policy 65, 524–540. http://dx.doi.org/10.1016/j.enpol.2013.10.049.

Cohen, F., Glachant, M., Söderberg, M., 2017. Consumer myopia, imperfect competition and the energy efficiency gap: Evidence from the UK refrigerator market. European Economic Review 93, 1-23. http://dx.doi.org/10.1016/j.euroecorev.2017.01.004.

Di Maria, C., Ferreira, S., Lazarova, E., 2010. Shedding light on the light bulb puzzle: the role of attitudes and perceptions in the adoption of energy efficient light bulbs. Scottish Journal of Political Economy 57, 48–67. http://dx.doi.org/10.1111/j.1467-9485.2009.00506.x.

Eckel, C.C., Johnson, C., Montmarquette, C., Rojas,C., 2007. Debt aversion and the demand for loans for post secondary education. Public Finance Review35, 233–262. http://dx.doi.org/10.1177/1091142106292774.

Farsi, M., 2010. Risk aversion and willingness to pay for energy efficient systems in rental apartments. Energy Policy 38, 3078–3088. http://dx.doi.org/10.1016/j.enpol.2010.01.048.

Field, E., 2009. Educational debt burden and career choice: evidence from a financial aid experiment at NYU law school. American Economic Journal: Applied Economics1, 1–21. http://dx.doi.org/10.1257/app.1.1.1.

Gerarden,T., Newell, R.G., Stavins, R.N., 2017. Assessing the energy-efficiency gap. Journal of Economic Literature 55 (4)1486-1525. http://dx.doi.org/10.1257/jel.20161360.

Greene, W., 2010. Testing hypotheses about interaction terms in nonlinear models. Economic Letters, 107, 291–296. DOI: 10.1016/j.econlet.2010.02.014.

Grösche, P., 2010. Housing, energy cost, and the poor: counteracting effects in Germany's Housing allowance program. Energy Policy 38 (1), 93–98. http://dx.doi.org/10.1016/j.enpol.2009.08.056.

Heutel, G., 2019. Prospect theory and energy efficiency. Journal of Environmental Economics and Management 96, 236-254. https://doi.org/10.1016/j.jeem.2019.06.005.

Houde, S., 2018. How Consumers Respond to Product Certification and the Value of Energy Information The RAND Journal of Economics 49 (2), 453-477.

Joskow, P.L., Marron, D.B., 1992. What does a Negawatt really cost? Evidence from utility conservation programs. The Energy Journal 13, 41–74. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol13-No4-3.

Krishnamurthy, C.K.B., Kriström, B., 2015. How large is the owner-renter divide in energy efficient technology? Evidence from an OECD cross-section. The Energy Journal 36(4), 85-104. https://doi.org/10.5547/01956574.36.4.ckri.

Loughran, D.S., Kulick, J., 2004. Demand-side management and energy efficiency in the United States. The Energy Journal 25 (1), 19-43. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol25-No1-2.

Malm, E., 1996. An actions-based estimate of the free rider fraction in electric utility DSM programs. The Energy Journal 17 (3), 41-48. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol17-No3-3.

Marchand, R.D., Koh, S.C.L., Morris, J.C., 2015. Delivering energy efficiency and carbon reduction schemes in England: lessons from Green Deal pioneer places. Energy Policy 84, 96–106.

Meissner, T., 2016. Intertemporal consumption and debt aversion: an experimental study. Experimental Economics 19 (2), 281–298. https://doi.org/10.1007/s10683-015-9437-0.

Michelsen, C.C., Madlener, R., 2012. Homeowners' preferences for adopting innovative residential heating systems: A discrete choice analysis for Germany. Energy Economics 34, 1271–1283. https://doi.org/10.1016/j.eneco.2012.06.009.

Mills, B.F., Schleich, J., 2010a. What's driving energy efficient appliance label awareness and purchase propensity? Energy Policy 38, 814–825. https://doi.org/10.1016/j.enpol.2009.10.028.

Nair, G., Gustavsson, L., Mahapatra, K., 2010. Factors influencing energy efficiency investments in existing Swedish residential buildings. Energy Policy 38, 2956–2963. https://doi.org/10.1016/j.enpol.2010.01.033.

Nauleau, M.L., 2014. Free-riding on tax credits for home insulation in France: An econometric assessment using panel data. Energy Economics 46, 78-92. https://doi.org/10.1016/j.eneco.2014.08.011.

Newell, R.G., Siikamaki, J. V, 2015. Individual time preferences and energy efficiency. American Economic Review 105, 196–200. http://dx.doi.org/10.1257/aer.p20151010.

Olsthoorn, M., Schleich, J., Faure, C., 2019: Exploring the diffusion of low energy houses: An empirical study in the European Union. Energy Policy 129, 1382-1393. https://doi.org/10.1016/j.enpol.2019.03.043.

Olsthoorn, M., Schleich, J., Gassmann, X., Faure, C., 2017. Free riding and rebates for residential energy efficiency upgrades: A multi-country contingent valuation experiment. Energy Economics 68, 33-44. https://doi.org/10.1016/j.eneco.2018.01.007.

Qiu, Y., Colson, G., Grebitus, C., 2014. Risk preferences and purchase of energy-efficient technologies in the residential sector. Ecological Economics 107, 216–229. http://dx.doi.org/10.1016/j.ecolecon.2014.09.002.

Ramos, A., Labandeira, X., Löschel, A. (2015). Pro-Environmental Households and Energy Efficiency in Spain. Environmental and Resource Economics, 63, 367–393.

Rosenow, J.; Galvin, R. (2014). Evaluating the evaluations: evidence from energy efficiency programmes in Germany and the UK. Energy & Buildings 74, 655-662.

Schleich, J., Gassmann, X., Meissner, T., Faure, C., 2016. Making the implicit explicit: A look inside the implicit discount rate. Energy Policy 97, 321-331. http://dx.doi.org/10.1016/j.enpol.2016.07.044.

Schleich, J., Gassmann, X., Meissner, T., Faure, C., 2019. A large-scale test of the effects of time discounting, risk aversion, loss aversion and present bias on household adoption of energy efficient technologies. Energy Economics 80, 377–393.

Schleich, J. 2019. Energy efficient technology adoption in low-income households in the European Union – What is the evidence? Energy Policy 125, 196–206. https://doi.org/10.1016/j.enpol.2018.10.061.

Steinbach, J., Staniaszek, D. 2015. Discount rates in energy system analysis. Fraunhofer ISI, Building Performance Institute Europe (BPIE): Karlsruhe, Germany.

Tanaka, T., Camerer, C.F., Nguyen, Q., 2010. Risk and time preferences: Linking experimental and household survey data from Vietnam. American Economic Review 100, 557–571. http://dx.doi.org/10.1257/aer.100.1.557.

Trotta, G., 2018. Factors affecting energy-saving behaviors and energy efficiency investments in British households. Energy Policy 114, 529-539.

Walters, D., J., Erner, C., Fox, C. R., Scholten, M., Read, D., 2019. Debt Aversion: Anomalous in the lab, advantageous in practice. Mimeo.

Whitmarsh, L., O'Neill, S., 2010. Green identity, green living? The role of pro-environmental self-identity in determining consistency across diverse pro-environmental behaviours. Journal of Environmental Psychology 30, 305–314. http://dx.doi.org/10.1016/j.jenvp.2010.01.00.

Wooldridge, J., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press. 2nd edition.

Appendix: Descriptive statistics

Table A 1: 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
	33.28	(1.15)	(1.12)	(1.22)	(1.15)	(1.24)	(1.17)	(1.20)	(1.05)
DebtAverson	4.24	33.86	34.08	32.11	33.53	33.52	33.45	32.70	33.31
	14.76	(5.35)	(6.25)	(5.72)	(6.34)	(6.03)	(6.17)	(5.02)	(6.40)
Energycosts†	3.51	4.19	4.23	4.34	4.32	4.48	4.05	4.04	4.13
	33.28	(0.70)	(0.76)	(0.66)	(0.73)	(0.68)	(0.94)	(0.87)	(0.80)
Environmental_ ID†	4.24	15.12	14.34	15.63	14.83	15.08	15.35	13.04	13.98
	14.76	(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 A 2: 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
R2	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 A 3: 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

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