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ORIGINAL ARTICLE

Social norms, pro-environmental identity, and finances: what motivates households to participate in energy efficiency programs?

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Abstract Municipal governments, often in collaboration with utilities, have implemented a range of energy efficiency programs to encourage homeowners and businesses to adopt energy efficiency upgrades. Energy efficiency holds promise to reduce energy consumption, reduce greenhouse gas emissions, improve public health, and reduce energy bills. However, these programs often suffer from poor participation and have typically had limited success. In this analysis, we use novel data to understand the relationship between social norms, pro-environmental identity, and household finances to understand program participation and retrofit decision-making. We find that the variables that predict retrofit decision-making do not explain a household's initial decision to contact an energy efficiency program. We suggest that the processes that drive households to contact energy efficiency programs—a necessary first step in improving energy efficiency—are different from the processes that explain why households decide to upgrade their homes.

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Introduction

Dietz et al. (2009), estimated that a combination of behavioral change and adoption of energy efficient technologies in the home could reduce total U.S. emissions by 7%. A large body of research has considered why people upgrade their homes—rooftop solar PV systems are one example that has received considerable attention. Households adopt solar systems in part because of pressure from social norms and the perceived expectations of neighborhoods (Allcott, 2011; Curtius et al., 2018), financial considerations (Langheim et al., 2014), concern for the environment (Schelly, 2010), and interest in new technologies (Palm, 2020). We know comparatively less about decision-making regarding other types of home upgrades, especially those that are less conspicuous than home solar installations.

In this paper, we integrate diverse strands of literature to evaluate what drives households' decisions to participate in energy efficiency programs and upgrade their home energy systems. Specifically, we ask how a combination of social norms, debt aversion, and pro-environmental identity (described further below) explain participation in a municipal energy efficiency program and, ultimately, household's decisions to upgrade their homes.

Background

Social norms

Social norms are unwritten, informal rules that are typically taken for granted yet govern behavior within a given social context. Social norms are emergent and are not easily manipulated by researchers, but several studies have documented efforts to shift social norms around energy consumption (Idahosa & Akotey, 2021). One of the most high-profile efforts to influence social norms around energy consumption was the OPOWER experiment, in which households were provided an informational treatment about the energy consumption of homes similar to theirs (Allcott, 2011; Horne & Kennedy, 2021; Schultz et al., 2007). Informational treatments are meant to create social norms about energy consumption and have likely reduced energy usage (Abrahamse & Steg, 2013; Harries et al., 2013).

These types of social norms are typically called *descriptive norms* because they provide a description of the typical behavior of others. Descriptive social norms do not define a behavior as good or bad—rather, descriptive social norms simply refer to the prevalence of a behavior. The implicit assumption of descriptive norm interventions is that, at least with regard to energy practices, people will feel normative pressure to reduce their energy usage to align with their neighbors or similar households. That is, descriptive social norm interventions establish a benchmark for what is typical or normal (Cialdini, 2007; Gerber & Rogers, 2009).

Injunctive social norms are those that we are all expected to follow and will receive a punishment or sanction for violating said norm. That is, injunctive social norms are perceived social pressures to perform (or not perform) certain behaviors—and the perception that failure to comply will result in some type of social punishment. Complying is perceived to have some type of social reward. Perceived punishments or rewards can range from very minor or quite severe—for some injunctive norms, the reward is no more than a sense of approval or endorsements from neighbors or peers. Some scholars use the term "personal norms" to refer to an internalized feeling of moral obligation to perform a task (Kleinschafer et al., 2021; Shi et al., 2019; Van der Werff et al., 2019).

Social norms are emergent and change over time. For instance, social norms around rooftop solar shift as more homes in a neighborhood or region adopt rooftop solar—through peer effects, installing solar begins to be seen as a normal and desirable decision the more households that adopt (Curtius et al., 2018; Scheller et al., 2022). Social norms are related to some energy efficiency decisions, such as the intention to purchase energy efficiency light bulbs (Bergquist & Nilsson, 2019), electric vehicles (Coffman et al., 2017; Jansson et al., 2017; Tran et al., 2012), and energy efficient appliances (Dieu-Hang et al., 2017).

Pro-environmental identity

Being environmentally conscious and behaving accordingly is often rooted in identity. That is, some people see themselves as a person who cares about the environment and feel that is important to engage in behaviors with environmental benefits (Whitmarsh and O'Neill, 2010). This pro-environmental identity is likely rooted in values that are formed during childhood and adolescence and unlikely to shift substantially over the life course (Van der Werff et al., 2014; Wang et al., 2021; Zeiske et al., 2021).

Several studies, notably most of which have been conducted in Europe, have linked pro-environmental identity to energy conservation behaviors or the adoption of energy efficiency technologies. Tu et al. (2021) evaluated survey data from eight European nations and found that pro-environmental identity was associated with more positive perceptions of smart meter technologies. Pro-environmental identity increases intentions to purchase energy efficient lightbulbs, cars, and household appliances (Berman Caggiano et al., 2021). In a Swedish sample, pro-environmental identity was associated with interest in and participation in a smart meter technologies (Van der Werff & Steg, 2016) and, using data from the Netherlands, Van der Werff et al. (2013) report that pro-environmental identity is related to a range of environmental behaviors, including the purchase of energy efficient light bulbs (see also Carfora et al., 2017; Dermody et al., 2015; Grębosz-Krawczyk et al., 2021). In addition to behaviors, pro-environmental identity is linked to support for energy efficiency policies (Faure et al., 2022). We are aware of no studies that link pro-environmental identity to household energy efficiency in the U.S.

We extend this work in new directions. First, a large portion of the literature relies upon self-reported behavioral intentions, interest in energy efficiency technologies, or similar measures that may not necessarily align with actual behavior. Further, studies tend to concentrate on specific technologies (e.g., smart meters)—a drawback of this approach is that not all homes may be candidates for the same technology. We build upon prior work using survey data by using validated energy efficiency program participation data. In the next section, we describe several factors that are likely related to energy efficiency upgrade decisions and that were investigated in this work.

Awareness of consequences

Awareness of consequences is the recognition of the positive or negative impacts of performing or not performing a behavior (Ryan & Spash, 2012; Stern et al., 1993). Awareness of consequences implicitly involves an ascription of responsibility, in which the individual decision maker assumes that their action will have some impact (De Groot & Steg, 2008; Lorenzoni et al., 2007; Van der Werff et al., 2013).

The awareness of consequences construct has been widely studied, with very consistent results across studies conducted at different time periods, for different outcome variables, and in varying political and social contexts. These include energy conservation behaviors in China (Al Mamun et al., 2022), Tunisia (Ibtissem, 2010), Vietnam (Duong, 2023), Kuwait (Alomari, 2021), and the Netherlands (Abrahamse & Steg, 2009) and intention to purchase energy efficient appliances, electric cars, or install solar panels in multiple contexts (e.g., Awais et al., 2022; He & Zhan, 2018; Klöckner et al., 2013; Wittenberg et al., 2018; Zhao et al., 2019). We adapt vetted measures to capture awareness of consequences, described further below.

Debt aversion and household finances

Fundamentally, energy efficiency upgrades are financial decisions. Households invest in energy upgrades in part because they hope that it may reduce their utility bills or provide other savings, in addition to other motivations (Alipour et al., 2020; Klöckner et al., 2013; Palm, 2020). To pay for upgrades, households rely upon some combination of cash payments, loans, and rebates.

Using a sample from eight European countries, Schleich et al. (2021) find that debt aversion is negatively associated with retrofit decisions, net of a range of controls. Households that are averse to taking on additional debt are less likely to update their homes, but debt aversion does not provide a full picture of the financial status of a household. Extending this literature, we argue that households, even those of a similar income, may find themselves in very different financial situations with regard to savings and overall financial satisfaction. We extend the prior research on debt aversion by assessing a household's financial status, particularly the nature of a household's savings.

Methods

Data collection

The current research is part of a larger study evaluating energy efficiency decision-making with a focus on an energy efficiency program sponsored by the city of Fort Collins, CO. This program, called Epic Homes, was designed to guide households through the process of receiving an energy assessment (at no or reduced cost), to locating contractors and financing, to filing for any relevant rebates. After a professional audit, participating households were provided with a report that detailed potential improvements to their homes and associated energy saving estimates and included a list of vetted contractors and their contact information to perform the work. The program also aided with locating financing and filing for rebates. The city and its municipal utility advertised the program.

Fort Collins sits about 45 miles north of Denver, CO, in the Front Range metropolitan area that includes several other medium-sized cities (Fort Collins at 170,000 people, Loveland at 77,000, Wellington and Windsor with a combined population of 42,000). Fort Collins hosts a large public university, several hospitals, and a diverse array of firms of various sizes in the technology, engineering, and energy sectors. The city has an aggressive climate mitigation plan and has actively encouraged renewable energy and energy efficiency for several years. Our results may be most applicable to other cities with similar characteristics but may not be as applicable to highly different metropolitan areas (e.g., large cities in the Southern U.S.). Many of the studies that most inform our work were conducted in Europe, so applying similar constructs to the U.S. context is warranted.

After IRB approval, we implemented a mixed-mode (e.g., multiple types of data collection) strategy for data collection. The city of Fort Collins provided email addresses for program participants ($n=1683$), 310 of which were duplicates, and 136 were undeliverable (we were only able to repair 3 of the undeliverable email addresses). To create a group of non-participants, we contracted with Marketing Systems Group (MSG), a provider of sampling services. MSG provided 3321 email addresses believed to be associated with Fort Collins addresses; of these, 89 were duplicates, and 269 were undeliverable. MSG explained that their internal procedures could filter out many renters. We hosted an online survey on the Qualtrics platform, and we screened all respondents for age (i.e., over 18 years) and residence in the city of Fort Collins.

Nine-hundred and seventy-four respondents began the email survey, although fifty did not proceed beyond the screening question—that is, they did not answer a single question and just clicked on the link. Another 13 were disqualified by the screening question. Like our experience conducting other studies in this region, a non-trivial portion of respondents (about 50) answered most of the questions in the main portion of the survey but skipped demographic questions. We next implemented a hybrid push-to-web/drop-off pick-up mode by distributing the survey link to households via a door hanger. The door hanger strategy produced very modest results ($n=33$). For the final model of data collection, we conducted a mailing of 4329 push-to-web cards ($n=109$). More details about the data collection can be found in Mayer and Carter (2023).

Some 600 respondents answered most of the questions, although the regression models below use slightly less data ($n=523$). Using 911 as the number of surveys that respondents began (the total number of respondents who navigated to the survey minus those that did not answer the screening question or were not eligible), the completion rate was 65.8%. Using a highly restrictive response rate calculation (AAPOR 1), the response rate was 9.37%—this estimate is consistent with our other research in the region. AAPOR definition 1 assumes that all non-responders were eligible to complete the survey; there are other less restrictive ways to calculate response rates that would have produced a higher estimate.

In the next section, we present the variables used in our analysis. We conducted factor analysis on some items and discuss these procedures below. We then proceed to the results of binary logistic regression models for program participation and performing a retrofit and provide effect size measures in the form of average marginal effects.

Dependent variables

We use two different dependent variables. The first captures whether the household participated in the energy efficiency program—for this variable, participation is defined broadly as contacting the program and expressing interest in an energy efficiency upgrade. Administrative records provided by the city of Fort Collins indicated that 58% of our initial sample, or 456 households, participated in the program. However, due to missing data from incomplete surveys (as described above, many respondents did not navigate beyond the first question), the number of valid cases used in the regression models below is much lower. We asked respondents if they had received an energy assessment and report and followed up by asking if they had made any changes in their home based upon the report. Thus, our second dependent variable is an indicator of whether the household followed any of the recommendations of the report, where 0 = did not make any changes to their home, and 1 = made a retrofit. Tables 1 and 2 provide the distribution of these variables disaggregated by each predictor. Appendix Figs 2, 3, 4 and Tables 5, 6 and 7 shows the distribution of the key predictor variables and the associated factor analyses, when applicable.

Personal and social norms

To capture norms, we adapted a series of questions used by Abrahamse and Steg (2009) and many others (e.g., Fang et al., 2017; Gholamrezai et al., 2021; Groh & Ziegler, 2022). For social norms, we used the following questions: "Many of my relatives or friends would adopt or have already adopted solutions for improving the energy efficiency of their homes," "Many of my neighbors would adopt or have already adopted solutions for improving the energy efficiency

Table 1 Descriptive statistics by program participation

	Participation		
	No	Yes	Total
Categorical variables (%)			
Non-emergency repair			
% from all others	39.11	28.11	32.52
% from savings	60.89	71.89	67.48
Emergency repair			
% from all others	40.57	30.89	34.75
% from savings	59.43	69.11	65.25
Rainy day funds			
% no	20.8	12.54	15.82
%yes	79.2	87.46	84.18
Ideology			
Conservative (%)	22.32	13.94	17.33
Independent (%)	20.54	17.58	18.77
Liberal (%)	57.14	68.48	63.9
College graduate			
% no	17.47	12.5	14.49
%yes	82.53	87.5	85.51
Race			
% non-white	9.87	5.67	7.35
% white	90.13	94.33	92.65
Female			
% non-female	36.79	63.21	57.17
% female	45.98	54.02	42.83
Continuous variables (means)			
Social norms	2.65	2.42	2.51
Pro-environmental identity	4.42	4.58	4.52
Debt aversion	0.21	0.38	0.31
Debt acceptance	1.19	1.3	1.25
Awareness of consequences	3.86	4.03	3.96

$N = 523$

Table 2 Descriptive statistics by retrofit

	Retrofit		
	No	Yes	Total
Categorical variables (%)			
Non-emergency repair			
% from all others	37.24	24.79	32.52
% from savings	62.76	75.21	67.48
Emergency repair			
% from all others	38.58	28.45	34.75
% from savings	61.42	71.55	65.25
Rainy day funds			
% no	18.44	11.71	15.82
%yes	81.56	88.29	84.18
Ideology			
Conservative (%)	21.41	10.8	17.33
Independent (%)	20.53	15.96	18.77
Liberal (%)	58.06	73.24	63.9
College graduate			
% no	17.8	9.13	14.49
% yes	82.2	90.87	85.51
Race			
% non-white	8.14	6.07	7.35
% white	91.86	93.93	92.65
Female			
% non-female	61.54	38.46	57.17
% female	61.16	38.84	42.83
Continuous variables (means)			
Social norms	2.63	2.33	2.51
Pro-environmental identity	4.38	4.73	4.51
Debt aversion	0.24	0.43	0.31
Debt acceptance	1.21	1.32	1.25
Awareness of consequences	3.87	4.11	3.96

$N = 523$

of their homes," "Most of the people important to me would approve if I improve the energy efficiency of my home," and "Most of my neighbors would approve if I improve the energy efficiency of my home." These items use a 5-category Likert-type scale. For *personal* norms, we used the following question: "I feel good about myself if I invest in improving energy efficiency in my home."

Next, we estimated a factor analysis on a polychoric correlation matrix using the iterated principal factors method for extraction. This produced a single factor solution with an eigenvalue of 2.614, with all variable loading in excess of 0.7 on the first factor—the first factor accounted for 79% of the inter-item variation (Appendix Table 5). Although these questions were meant to capture two distinct but related constructs—social norms and personal norms—the factor analysis implies that a single dimension underlies these items. We calculated a factor score that we use as a predictor in Model 2, Table 3, and Model 2, Table 4.

Pro-environmental identity

We use an established indicator of pro-environmental identity (Van der Werff et al., 2013; Wang et al., 2021) that has been adapted for studies of energy behaviors and decision-making (Tu et al., 2021). To

Table 3 Results of binary logistic regression models for program participation

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	b (se)	*b* (se)	*b* (se)	*b* (se)	*b* (se)	*b* (se)	*b* (se)
Social norms		−0.043					
		(0.131)					
Pro-environmental identity			0.184				
			(0.121)				
Debt aversion				0.130			
				(0.092)			
Debt acceptance				0.196			
				(0.134)			
Rainy day					0.474	0.492	
					(0.262)	(0.264)	
Non-emergency repair					0.246		
					(0.206)		
Emergency repair						0.156	
						(0.205)	
Awareness of consequences							0.319
							(0.218)
Female	−0.445 *	−0.446 *	−0.441 *	−0.407 *	−0.431 *	−0.422 *	−0.451 *
	(0.184)	(0.184)	(0.184)	(0.186)	(0.188)	(0.188)	(0.184)
Ideology (ref. conservative)							
Independent	0.136	0.112	0.063	0.114	0.158	0.167	−0.032
	(0.301)	(0.310)	(0.306)	(0.303)	(0.307)	(0.308)	(0.323)
Liberal	0.557 *	0.515	0.439	0.519 *	0.580 *	0.599 *	0.301
	(0.255)	(0.285)	(0.266)	(0.256)	(0.258)	(0.259)	(0.309)
College	0.431	0.422	0.377	0.425	0.204	0.224	0.402
	(0.275)	(0.276)	(0.278)	(0.277)	(0.289)	(0.287)	(0.276)
AIC	701.283	703.176	700.954	700.095	684.196	683.922	701.117
BIC	722.581	728.733	726.511	729.912	713.878	713.590	726.674

$N = 523$, ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 4 Binary logistic regression models for home retrofits

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	b (se)	*b* (se)	*b* (se)	*b* (se)	*b* (se)	*b* (se)	*b* (se)
Social norms		−0.379 **					
		(0.146)					
Pro-environmental identity			0.276 *				
			(0.125)				
Debt aversion				0.141			
				(0.090)			
Debt acceptance				0.171			
				(0.144)			
Rainy day					0.384	0.400	
					(0.285)	(0.287)	
Non-emergency repair					0.360		
					(0.213)		
Emergency repair						0.246	
						(0.210)	
Awareness of consequences							0.662 *
							(0.267)
Female	−0.058	−0.066	−0.052	−0.010	−0.013	0.005	−0.060
	(0.186)	(0.187)	(0.187)	(0.189)	(0.189)	(0.190)	(0.187)
Ideology (ref. conservative)							
Independent	0.252	0.044	0.142	0.220	0.332	0.361	−0.075
	(0.336)	(0.348)	(0.341)	(0.338)	(0.340)	(0.343)	(0.362)
Liberal	0.760 **	0.409	0.589 *	0.716 *	0.777 **	0.819 **	0.276
	(0.282)	(0.311)	(0.292)	(0.283)	(0.284)	(0.287)	(0.335)
College	0.772 *	0.700 *	0.695 *	0.769 *	0.597	0.621	0.718 *
	(0.323)	(0.326)	(0.326)	(0.325)	(0.332)	(0.330)	(0.326)
AIC	687.196	682.098	684.243	686.243	676.140	675.170	682.409
BIC	708.494	707.656	709.800	716.060	705.822	704.839	707.966

$N = 523$, $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

evaluate the dimensionality of these items, we again turned to factor analysis using a polychoric correlation matrix and the iterated principal factors method for extraction (Holgado-Tello et al., 2010; Kiwanuka et al., 2022). The factor analysis produced an eigenvalue of 3.315 for the first factor, with all variables loading above 0.4, implying a single factor solution (Appendix Table 6). We use the resulting factor score as a predictor in the third model in Table 3 and 4.

Debt aversion

We borrow a series of questions from Schleich et al. (2021) to capture aversion to debt. Respondents were asked to rate if the following statements described them: "If I have debts, I like pay them as soon as possible," "If I have debts, I prefer to delay paying them if possible, even if it means paying more in total," "If I have debts, it makes me feel uncomfortable," "If I have debts, it doesn't bother me," "I dislike borrowing money," "I feel OK borrowing money for essential purchases e.g. Cars, appliances, mortgage, "I enjoy being able to borrow money to buy things I like, and to pay for things I cannot afford."

Like our prior constructs, we estimated a polychoric correlation matrix and extracted factors using the iterated principal factors method with a varimax rotation. Our factor analysis suggested a two-factor solution, although the first item ("If I have debts, I like to pay them") did not load strongly on any factor and the second to last item ("I feel OK borrowing money for essential purchases e.g. Cars, appliances, mortgage") was the only variable that loaded on the third factor. Our results may diverge from Schleich et al. (2021) for a few reasons. First, they tallied the items and used Cronbach's alpha to assess their inter-item reliability—factor analysis is a more flexible method of dimension reduction that sometimes reveals additional complexity. Further, Schleich et al., 2021 data comes from Sweden and our somewhat different results may reflect cultural differences between the U.S. and Sweden. We elected to retain two factors, the first of which corresponds to debt aversion, and the second of which responds to debt acceptance. These factor scores were used in Model 3, Table 3, and Model 3, Table 4.

Financial status

To gauge the financial status of households beyond their aversion or acceptance to debt, we also asked the following question: "Have you set aside emergency or rainy day funds that would cover your expenses for 3 months, in case of sickness, job loss, economic downturn, or other emergencies?"—respondents could answer "yes" or "no."

We developed a few unique questions to further assess the ability of a household to pay for an energy retrofit. We asked: "Imagine that your home needs a $2000 repair to fix a problem. The problem is not an emergency but needed to keep your home in good working order and avoid future problems. How would you pay for this repair?" with the following response categories: "I would ask my landlord to do it," "I would not make the repair," "I would pay for it with savings," "I would borrow money from friends or family," "I would take out a loan," "I would charge it to my credit card," or an "other" category.[1] We recoded this variable into two categories (0 = all other categories, 1 = I would pay for it with savings).

We followed this question but specified that it was an emergency repair, using the same response categories: "Imagine that your home needs a $2000 emergency repair. How would you pay for this repair?" Again, we recoded this variable such that 0 = all other categories and 1 = savings. These predictors were used as predictors in Models 4 and 5 in Table 3 and 4.

Awareness of consequences

From prior research, we adopted an awareness of consequences scale tailored to energy (e.g., (De Groot & Steg, 2008; Ryan & Spash, 2012). Respondents answered the following questions using a give item Likert-type scale: "Using renewable energy is good for the environment," "Improving the energy efficiency of my home is good for the environment," and "Improving the energy efficiency of my home is good for the health of my family." Our factor analysis of a polychoric correlation matrix strongly pointed to a single factor solution (eigenvalue = 2.352, 90% of variance accounted for, factor loadings all more than 0.8). We estimated an awareness of consequences factor score to use in our analysis. We entered this

[1] Forty-eight respondents chose the "other" category, but those responses cannot be reduced into fewer categories in any logical way. Two stated that they would use a HELOC or home equity loan, some provided ambiguous responses (e.g., "I would work it out") and one stated "none of your business.".

variable as a predictor in the seventh model for each outcome. In Table 1 and 2, we provide descriptive statistics for the variables, disaggregated by program participation (Table 1) and whether the home made a retrofit (Table 2).

Results

Both of our indicators are binary. Binary logistic regression is a well-established approach to model the effect of a series of predictors on a binary outcome. Our data presented an additional complication. Three constructs—pro-environmental identity, social norms, and awareness of consequences—were highly collinear (variance inflation factors (VIFs) and were 8.14, 12.12, and 27.58, respectively). We suspect that this degree of collinearity would bias our results towards the null, and perhaps mask important effects. We opt to estimate unique models for each one of these constructs and compare Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) across models to determine which variable provides the best fit. We start with a "controls only" model, and then estimate models separately for social norms, debt aversion and acceptance, and awareness of consequences. We conclude with a series of robustness checks.[2]

Table 3 provides the binary logistic regression results for the program participation outcome—that is, did the household contact the program, or not. We begin with Model 2, which adds social norms to the demographic variables from Model 1. Social norms are not statistically significant, and the AIC and BIC statistics are both larger, implying that the inclusion of the social norm factor score has worsened model fit. In Model 3, we drop social norms and add in the factor score for pro-environmental identity, which is not statistically significant and, according to the BIC statistic, has not improved model fit. In Model 4, we place pro-environmental identity with the factor scores for debt aversion and debt acceptance, which again are not statistically significant. In Model 5, we drop the indicators for debt aversion and debt acceptance and add the variables for rainy day funds and non-emergency repairs—as with prior predictors, these are not statistically significant. Model 6 replaces non-emergency repair with our variable for emergency repair. Consistent with prior models, it is not statistically significant. Finally, in Model 7, we add in the variable for awareness of consequences, which is not significant and, compared to Model 1, does not result in an improved AIC and BIC statistic.

Overall, our results imply that many known predictors of energy efficiency upgrade decisions or environmental behaviors do not predict whether the household contacted the energy efficiency program. There is a consistent effect of female sex wherein females are more apt to state that their household contacted the program, and in some models, there is evidence of differences between liberals and conservatives. We return to these findings in the discussion.

Table 4 provides the results of the binary logistic regression models for home retrofits—that is, did the household follow any of the guidelines of their energy audit report and make upgrades. In Model 2, we add the factor score for social norms to the demographics-only specification from Model 1 and find that it improves model fit (both the AIC and BIC have decreased), and it is statistically significant ($b = -0.378$, $p < 0.05$). In Model 3, pro-environmental identity emerges as statistically significant, and the inclusion of this variable has decreased the AIC but increased the BIC over Model 1, providing mixed evidence of improved model fit. In Model 4, we add in the scales for debt aversion and debt acceptance, neither of which approach statistical significance. In the next model (Model 5), we drop these variables for the rainy-day funds and emergency funds indicators, which are also not statistically significant, and do not improve model fit over Model 1. Finally, we find a statistically significant effect of awareness of consequences in Model 7. Our survey also included questions about specific types of retrofits, we provide modelling results for these questions in Appendix 5.

Average marginal effects

Binary logistic regression models such as those we estimate in this analysis produce coefficients that are not readily interpretable. For this reason, many methodologists recommend using average marginal effects, probabilities,

[2] We do not include race in our models because of the lack of variability in this data. A strong majority of the sample is white, in line with the demographics of Fort Collins, CO.

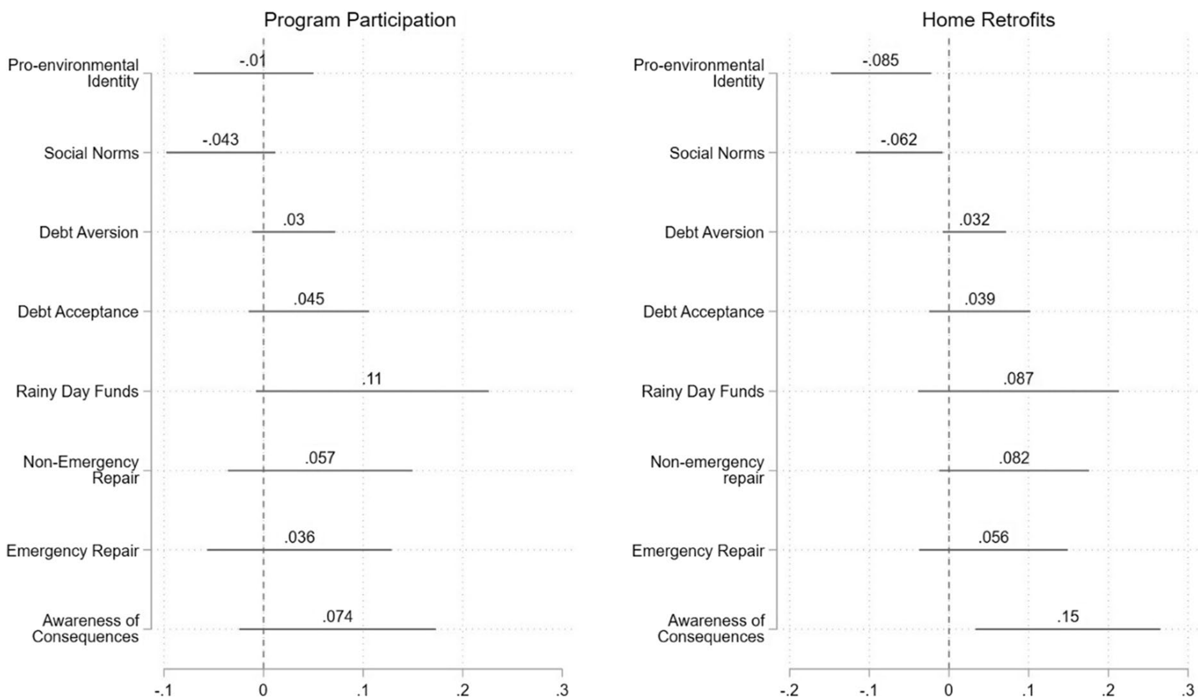

Fig. 1 Average marginal effects for predictor variables with 95% confidence intervals. Note: estimates derived from Table 2 and 3

or similar statistics to render modelling results more intuitive (Brambor et al., 2006; Howell-Moroney, 2023; Mood, 2010). In Fig. 1, we provide average marginal effects (AMEs) derived from the coefficients reported in Table 3 and 4. AMEs are advantageous because of their straightforward interpretation on the probability scale. For instance, the AME of −0.085 for "Energy Saving Identity" under "Home Retrofits" indicates that the probability of performing a retrofit decreases by 0.085 (or 8.5 percentage points) for every one unit increase in the Energy Saving Identity scale. Notably, awareness of consequences has perhaps the most substantial effect on home retrofit decisions (AME = 0.15). Given that the awareness of consequences scale has a range of almost 4 (i.e., the difference between the highest and lowest score), the total effect could be as large as some 0.6. That is, the difference probability of performing a home retrofit between a person who had no awareness of consequences and one who had the highest awareness is roughly 0.6, implying that awareness of consequences is among the more powerful predictors.

Robustness checks

We also performed a series of robustness checks that we provide in appendices. Many of the predictors identified in the prior literature on energy efficiency and environmental behaviors were not statistically significant in our models, but our sample size is smaller than some other studies, some of which have thousands of observations. In Appendix Tables 8, 9 and 10 and Figs 6, 7, we provide a series of simulations wherein we doubled the size of our sample repeatedly and re-ran the models. We find that debt aversion, debt acceptance, and social norms become statistically significant predictors of program participation with more data, but pro-environmental identity does not become statistically significant even with vast increases in the number of cases. For retrofit decisions (i.e., the dependent variable used in Table 4), we find that a doubling of the sample size renders all predictors statistically significant. Thus, some of the divergence between our work and prior research occurs because those studies have used much larger samples and hence were able to detect statistical significance of the results.

As an additional robustness check, we conducted a multiverse analysis. The logic of this approach is that any researcher chooses to report one model that comes from a wide universe of potential model specifications. The multiverse approach involves estimating hundreds, sometimes even thousands, of alternative model specifications with different control variables, or even functional form transformations and higher order interaction terms. In our application, we re-estimated the models from Table 3 and 4 with varying combinations of predictors, and we plot the coefficients of the predictor of interest across model specifications. We also calculate the percentage of models in which the predictor of interest is statistically significant and wherein the sign of the coefficient has the same direction (i.e., positive or negative). Appendix Tables 8, 9 and 10 and Figs 6, 7, shows a relative robustness for the program participation results—the effects that are statistically significant are consistently so in the multiverse of models. For the retrofit decision, we find that social norms, pro-environmental identity, and awareness of consequences are uniquely robust and consistent predictors.

Discussion

The purpose of this paper was to extend prior research on energy efficiency program participation using several known predictors. We considered a comprehensive energy efficiency program for households in Fort Collins, CO, using original survey data.

We found that many well-documented predictors of environmental behaviors and energy efficiency upgrade decisions did not predict a household's decision to make the initial contact with the program. Social norms, pro-environmental identity, awareness of consequences, and debt aversion had statistically null effects and did not improve model fit. Although we respect than many analysts would prefer to see large, statistically significant findings, our perspective is that these null results are informative (Abadie, 2020). The bulk of the literature considers outcomes such as the decision to install a specific home retrofit, and there is a related literature on environmental behaviors that employs similar constructs. However, there is much less work on the *initial decision* to contact and energy efficiency program. We suggest that this decision may be different enough from other decisions, such as the choice to upgrade a home, that it may require its own model. That is, the factors that predict contact with an energy efficiency program may not be the same as those that predict the likelihood of making a retrofit. Given that contacting a program is often the first step towards energy efficiency, more research on what drives homes to contact programs is warranted.

For instance, we found that social norms have a null effect (i.e., an effect that is not statistically significant) on the initial step of contacting the energy efficiency program. This null finding could have emerged because there is a cognitive disconnect between the program and energy efficiency and social norms in the minds of our respondents. Perhaps they did not recognize that it was a program that could address their concerns regarding energy efficiency, even if it was advertised as such. That is, although households may have faced some pressure from social norms to improve their energy efficiency, they may not have recognized that the Epic Homes program was a route to do so.

Or perhaps there were other barriers that kept households from contacting the programs that are simply not well understood at this point. Qualitative research with candidate households who elect not to participate should be conducted in the future.

The muted effects of our financial variables deserve further discussion. Energy efficiency upgrades involve cost–benefit calculations for households, and some households may need loans to pay for them. However, we found that debt aversion, debt acceptance, and our variables for savings had null effects in all our models, including those that were focused on whether the household follow any of the guidelines of their energy audit report and make upgrades. These effects may have been statistically significant in a larger sample (as we demonstrated in series of simulations wherein we doubled the size of our sample repeatedly and re-ran the models), but even so, the effect sizes are not large in practical terms (see Appendix Figs 2, 3, 4 and Tables 5, 6 and 7). We can only offer informed speculations on this surprising finding. For one, Fort Collins, CO, has relatively expensive housing stock and our sample skews more affluent—many of our respondents may have had significant home equity that could effectively fund upgrades. Perhaps for this reason, norms and identity variables tend to be more powerful influences while financial variables have less of an effect. Further, some research identifies a conflict between intrinsic (e.g., social norms and identity) motivations and extrinsic (i.e., cost savings) motivations for energy efficiency (Pellerano et al., 2017) and non-monetary incentives are likely stronger motivators of energy saving behaviors (Mi et al., 2021). Perhaps a similar dynamic was at play in our work, wherein our sample was more motivated by extrinsic factors and non-monetary concerns. Notably, pro-environmental identity also does not approach statistical significance, even at large sample sizes.

As with all research, the current study has both strengths and weaknesses. A strength of this study is the breadth of constructs that we were able to measure, and our usage of two different dependent variables provides a more complete picture of energy efficiency program participation. We employed several constructs that had mostly been used in European research and had not been applied to the U.S. We did not model how the upgrades that households chose to implement coincided with their reports or did not. That is, did households follow all the recommendations, or only some, and why did they choose some over others? These questions can be answered with follow up research.

Conclusion and policy implications

This study has multiple implications that should be of interest to policymakers. For one, we found that factors like social norms and pro-environmental identity do not meaningfully predict whether a household contacted the energy efficiency program. This implies that program promoters cannot rely heavily upon social norms or appealing to pro-environmental identity to encourage households to take the initial step of contacting the program, although these variables may be useful to encourage interested households to complete the program. One possibility to improve program participation is to connect candidate households—that is, homes that are in need of energy efficiency upgrades—to energy counseling services, rather than waiting for homes to contact energy efficiency programs (Murto et al., 2019).

Appendix 1. Descriptive statistics and factor analysis

Social norms

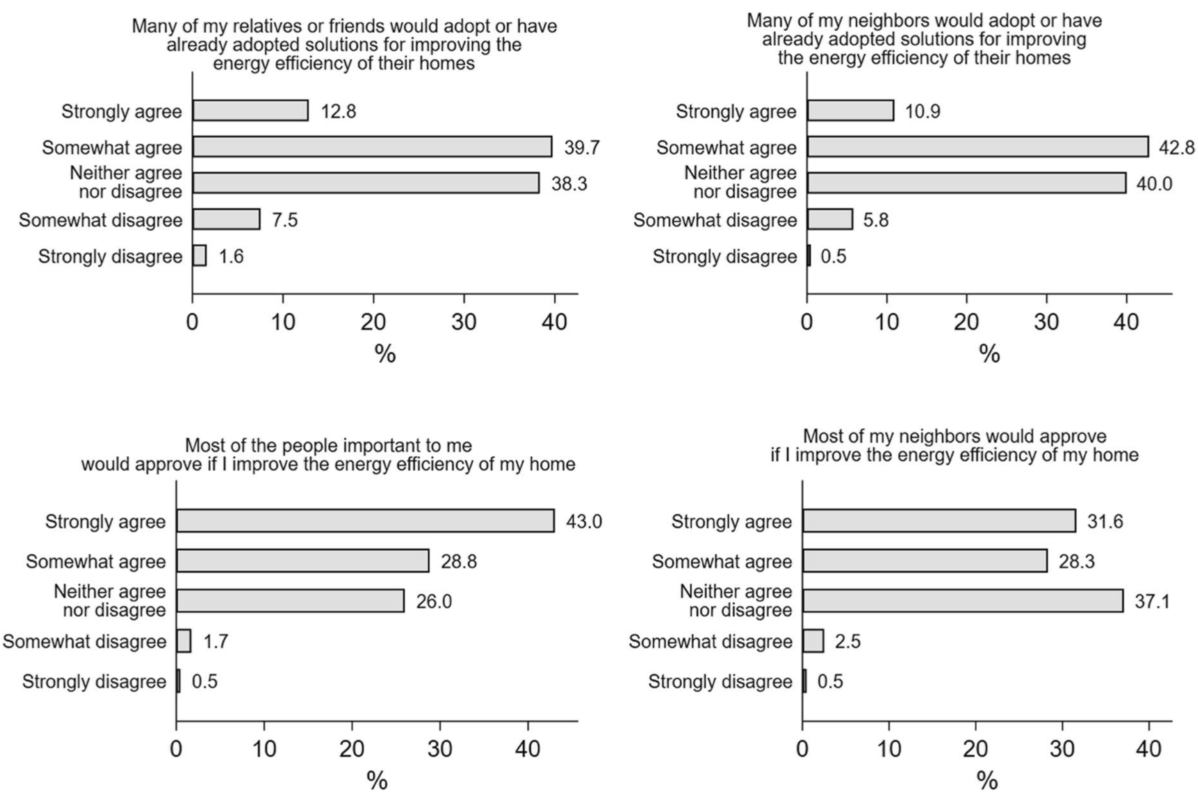

Fig. 2 Distribution of social norms questions

Table 5 Factor analysis for social norms

	Factor 1	Factor 2
Many of my relatives or friends would adopt or have already adopted solutions for improving the energy efficiency of their homes	0.723	0.384
Many of my neighbors would adopt or have already adopted solutions for improving the energy efficiency of their homes	0.762	0.344
Most of the people important to me would approve if I improve the energy efficiency of my home	0.862	
Most of my neighbors would approve if I improve the energy efficiency of my home	0.876	−0.326
Eigenvalue	2.614	0.459
Variance	0.792	0.139

Factor loadings below 0.3 deleted from the table

Pro-environmental identity

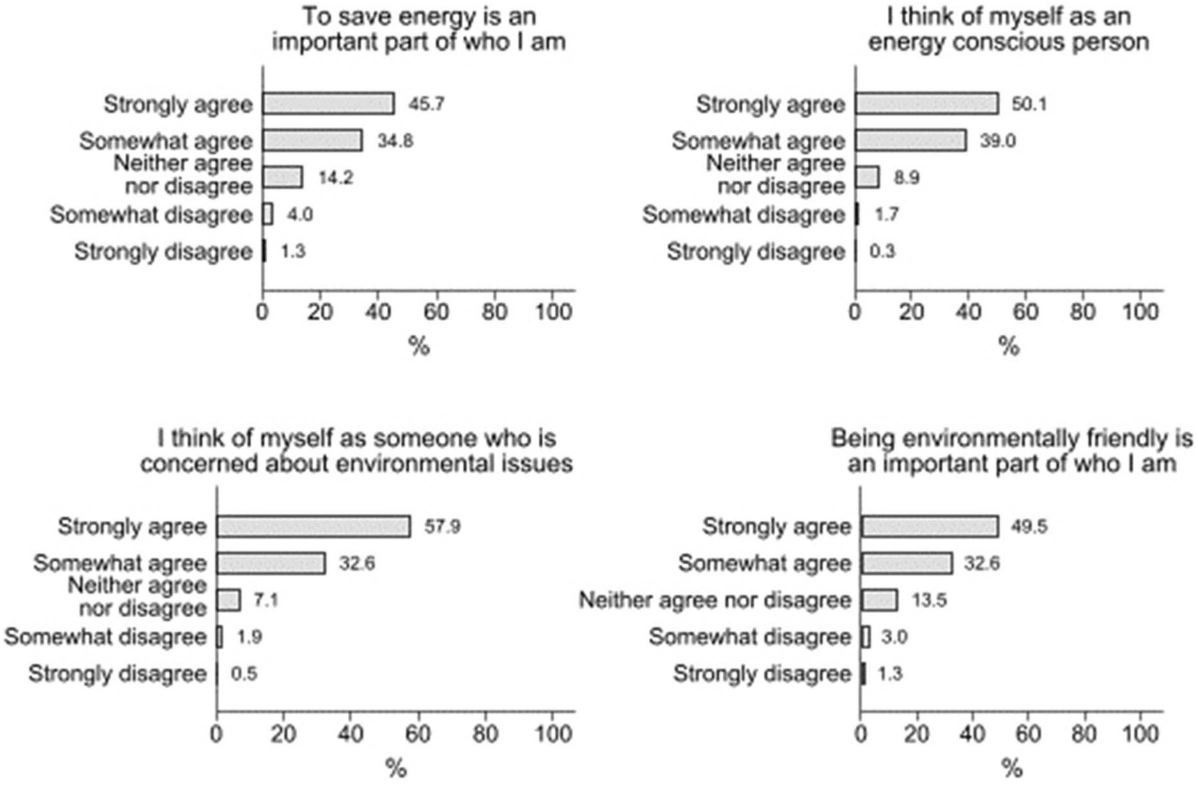

Fig. 3 Distribution of pro-environmental identity items

Table 6 Factor analysis for pro-environmental identity

	Factor 1	Factor 2
To save energy is an important part of who I am	0.892	
I think of myself as an energy conscious person	0.885	
I think of myself as someone who is concerned about environmental issues	0.918	
Being environmentally friendly is an important part of who I am	0.945	
Eigenvalue	3.315	0.211
Variance	0.926	0.059

Factor loadings below 0.3 deleted from the table. $N = 523$

Debt aversion and debt acceptance

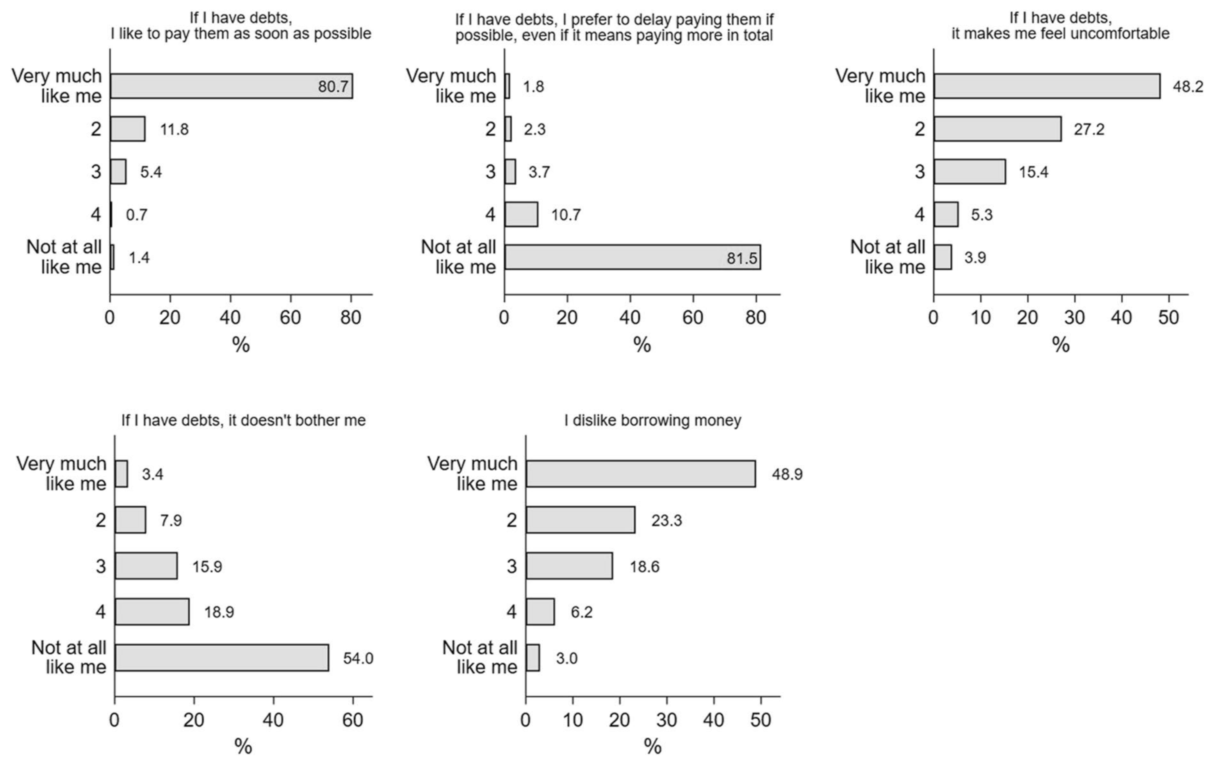

Fig. 4 Distribution of debt acceptance and debt aversion items

Table 7 Factor analysis for debt acceptance and debt aversion items

	Factor 1	Factor 2	Factor 3
If I have debts, I like pay them as soon as possible		−0.869	
If I have debts, I prefer to delay paying them if possible, even if it means paying more in total		0.795	
If I have debts, it makes me feel uncomfortable	0.910		
If I have debts, it doesn't bother me	−0.815		
I dislike borrowing money	0.481		−0.448
I feel OK borrowing money for essential purchases (e.g. cars, appliances, mortgage)			0.638
I enjoy being able to borrow money to buy things I like, and to pay for things I cannot afford		0.422	
Eigenvalue	1.885	1.711	0.744
variance explained	0.403	0.366	0.159

Factor loadings below 0.3 deleted from the table. $N = 523$

Appendix 2. Average marginal effects for specific retrofits

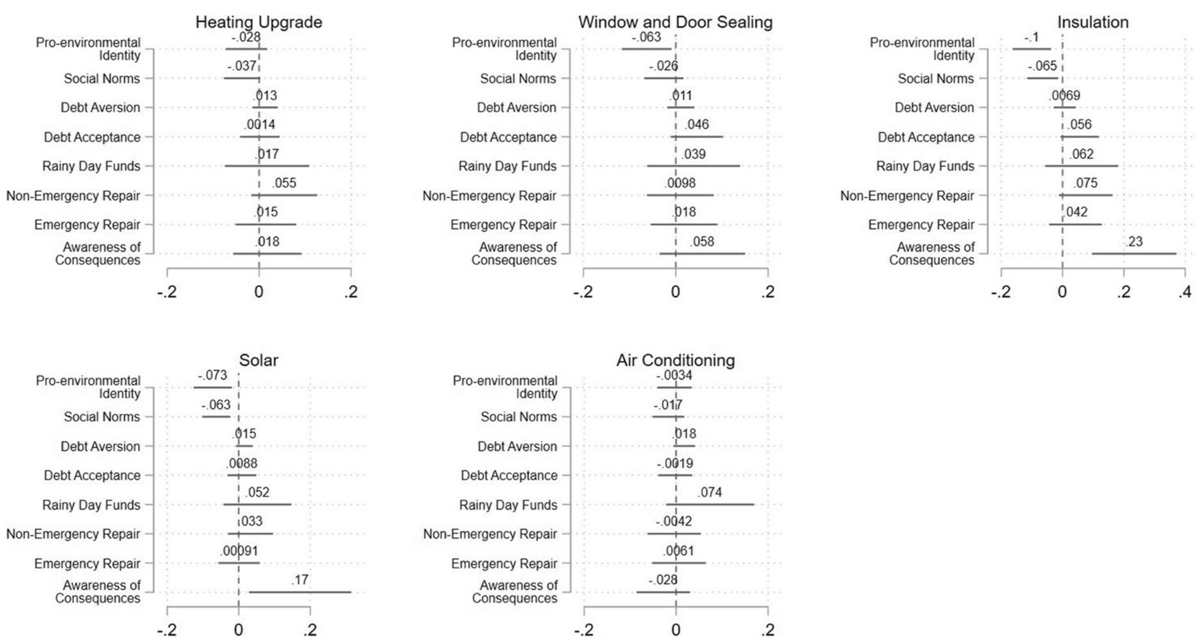

Fig. 5 Average marginal effects for specific retrofits. Note: dependent variables are coded 0,1. Estimates were derived by re-running the regression model specifications from Table 2 and 3 with each outcome

We also asked respondents to report on what upgrades they made to their home. Response categories included: rooftop solar, heating upgrades, air conditioning upgrades, window and door sealing, and insulation. The question also included and "other" category and the option for respondents to write their "other" retrofit into a text box. The responses for the "other" category were too different from each other to be grouped effectively and hence we did not use the data for the "other" response category.

We estimated a series of binary logistic regression models for each outcome, using the model specifications from Table 2 and 3 (that is, the same combination of predictor variables). For each model, we calculated average marginal effects for the predictor of interest, like our approach in the main text. We provide these average marginal effects in Fig. 5 above. Overall, our results imply that, for many specific retrofits, the predictors are not statistically significant and have substantively small effects. However, awareness of consequences does predict improvements in insulation and the adoption of rooftop solar.

Appendix 3. Robustness checks

As shown in our regression models, some variables that were statistically significant in other papers (using other data, of course) were not consistently statistically significant in our models. Yet, compared to some work, our sample sizes are smaller. For instance, pro-environmental identity was statistically significant in multiple papers (e.g., Gatersleben et al., 2014; Schleich et al., 2021; Whitmarsh and O'Neill, 2010). To determine if a difference in sample size explains the divergence between our work and prior research, we conducted a series of simulations wherein we increased the size of our dataset by duplicating observations and then re-running the models in Table 3 and 4 for both the participation and the retrofit dependent variables. Appendix Table 8 shows the results of these simulations. The simulations suggest that, for program participation, pro-environmental identity was not statistically significant even when the sample size is much larger. The null effect is robust to a larger sample size. On the other hand, our indicator for emergency repair would cross the alpha = 0.05 threshold at three times the current sample size (i.e., roughly 1800 cases) while the indicator for emergency repair would only become statistically significant at n*7. Overall, the simulations for program participation imply that our results may diverge from other studies because these studies used larger samples that contributed to smaller standard errors and smaller p values.

The second panel of the table shows sample size simulations for the retrofit outcome variable. For this variable, most of the predictors of interest were statistically significant, so the results of the simulations are perhaps less substantively interesting. Still, in the interest of transparency, we present these results.

Table 8 Sample size simulations

Participation									
	n*2	n*3	n*4	n*5	n*6	n*7	n*8	n*9	n*10
Social norms	0.031	0.008	0.002	0.001	0.000	0.000	0.000	0.000	0.000
Pro-environmental identity	0.643	0.571	0.513	0.464	0.423	0.387	0.355	0.326	0.301
Debt aversion	0.046	0.015	0.005	0.002	0.001	0.000	0.000	0.000	0.000
Debt acceptance	0.039	0.011	0.004	0.001	0.000	0.000	0.000	0.000	0.000
Rainy day	0.011	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Non-emergency repair	0.091	0.039	0.017	0.008	0.003	0.002	0.001	0.000	0.000
Emergency repair	0.282	0.188	0.128	0.089	0.062	0.044	0.031	0.022	0.016
Awareness of consequences	0.038	0.011	0.003	0.001	0.000	0.000	0.000	0.000	0.000
	n*2	n*3	n*4	n*5	n*6	n*7	n*8	n*9	n*10
Made changes									
Social norms	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pro-environmental identity	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Debt aversion	0.000	0.007	0.002	0.000	0.000	0.000	0.000	0.000	0.000
Debt acceptance	0.002	0.040	0.018	0.008	0.004	0.002	0.001	0.000	0.000
Rainy day	0.000	0.020	0.007	0.003	0.001	0.000	0.000	0.000	0.000
Non-emergency repair	0.000	0.003	0.001	0.000	0.000	0.000	0.000	0.000	0.000
Emergency repair	0.002	0.042	0.019	0.009	0.004	0.002	0.001	0.000	0.000
Awareness of consequences	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 9 Konfound analysis

	Participation	Made change	
Social norms	22.42%	Social norms	11.01%
Pro-environmental identity	83.34%	Pro-environmental identity	24.32%
Debt aversion	28.23%	Debt aversion	20.52%
Debt acceptance	25.70%	Debt acceptance	39.54%
Rainy day	7.94%	Rainy day	31.42%
Non-emergency repair	39.26%	Non-emergency repair	14.18%
Emergency repair	61.27%	Emergency repair	40.33%
Awareness of consequences	25.46%	Awareness of consequences	20.67%

Konfound analysis

Next, we turn to the konfound method. In the current application, konfound estimates the degree of measurement error (e.g., replaced with a case with no effect, or with an effect) that would be required to invalidate an inference—that is, to render a statistically significant effect non-significant (at alpha = 0.05) and to change a non-significant effect to statistically significant (Frank & Xu, 2017; Frank et al., 2013; Xu et al., 2019). Appendix Table 9 shows the percentage of cases that would have to be measured with error to change the inference. These estimates are derived from the regression models presented in Table 3 and 4.

For program participation, we find that social norms (which were not statistically significant) could become significant with a relatively small amount of measurement error, but the effect of pro-environmental identity could only be statistically significant if a strong majority of the cases were measured with error (83.34%)—a scenario that is dubious. The non-significant effect of rainy day funds is comparatively less robust (7.94%). Overall, the konfound analysis for program participation implies that some predictors are less robust than others, although most inferences would require a non-trivial amount of measurement error to change the inference.

For retrofits, social norms were statistically significant but not highly robust (11.01%) while pro-environmental identity was somewhat more robust (24.32%). Non-emergency repairs, which were not statistically significant, also exhibit a relatively low level of robustness to measurement error (14.18%) while awareness of consequences was slightly more robust (20.67%).

Multiverse analysis

Appendix Table 10 provides the percentage of multiverse models wherein the predictor of interest takes the same sign (i.e., positive or negative) and is statistically significant. As we noted in the main text, the nulls effects reported in Table 3 appear to be robust. That is, they do not change to non-null under alternative model specifications, and our reported models do not appear to be unusual outlier models wherein the effects are not statistically significant. Appendix Fig. 6 provides a graphical distribution of the multiverse of coefficients, and a dashed line to represent the coefficient reported in Table 3. Appendix Fig. 7 suggests that pro-environmental identity, social norms, and awareness of consequences are highly robust and exhibit strong sign stability. Further, most of the non-significant predictors from Table 4 are rarely significant in a multiverse of models.

Table 10 Results of multiverse analysis

	% statistically significant	% sign stability
Program participant		
Energy saving identity	0	100
Social norms	50	100
Debt aversion	25	100
Debt acceptance	0	100
Rainy day savings	63	100
Emergency repair	0	100
Savings repair	19	100
Awareness of consequences	50	100
Retrofit		
Energy saving identity	100	100
Social norms	100	100
Debt aversion	25	100
Debt acceptance	0	100
Rainy day savings	25	100
Emergency repair	13	100
Savings repair	63	100
Awareness of consequences	100	100

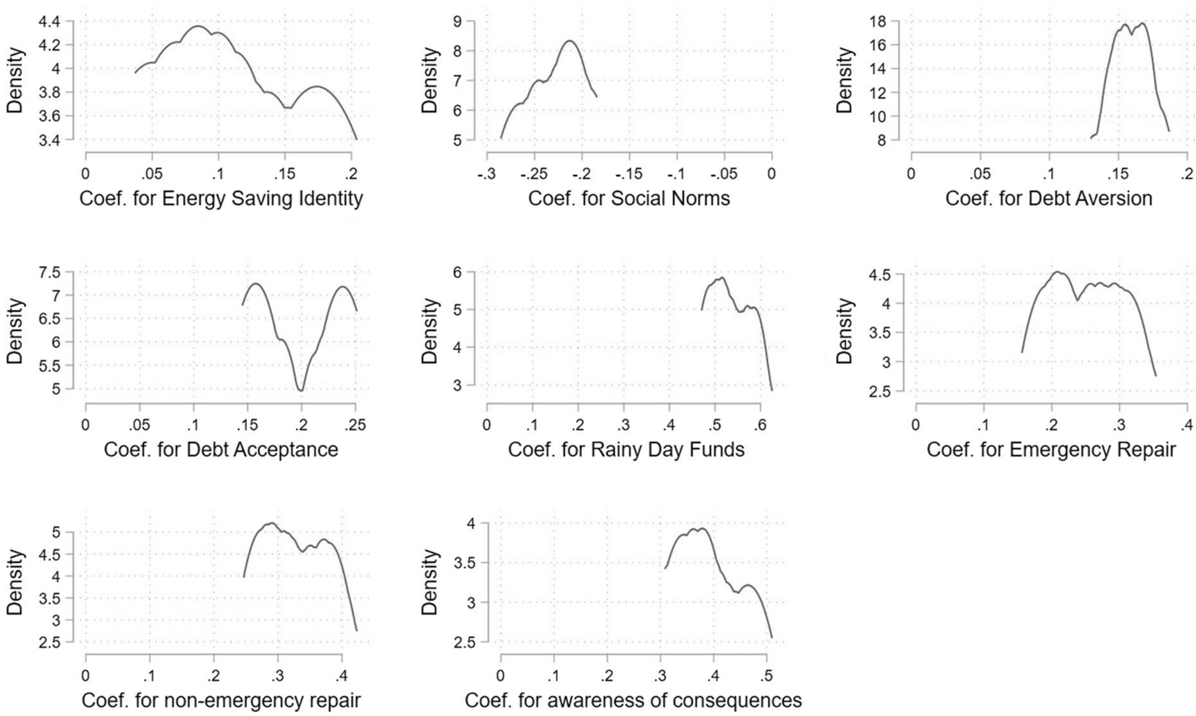

Fig. 6 Distribution of the multiverse coefficients for program participation

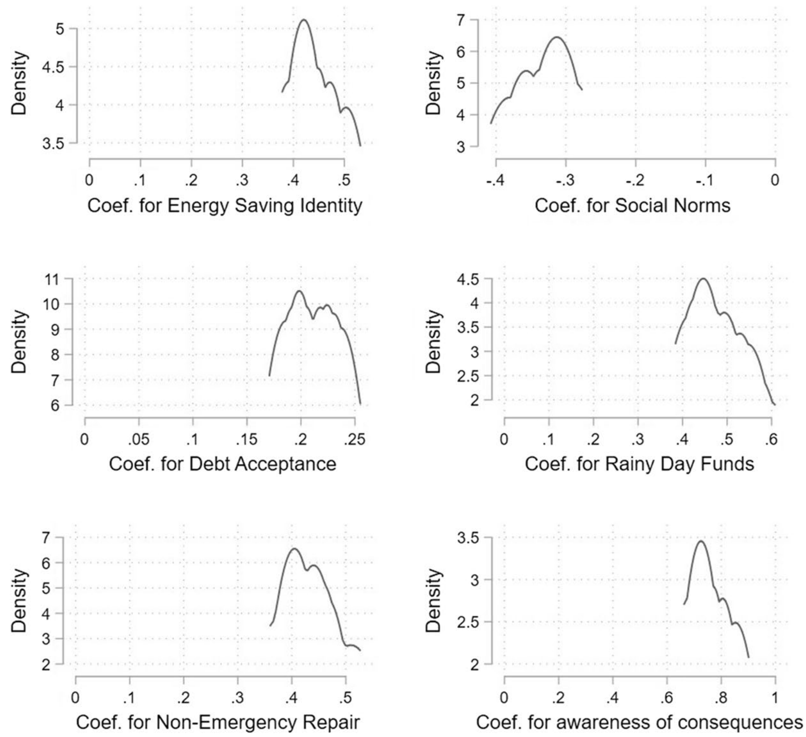

Fig. 7 Distribution of multiverse coefficients for retrofit

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Declarations

Conflict of interest The authors declare no competing interests.

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