Do Household Characteristics Really Matter? A Meta-Analysis on the Determinants of Households' Energy-Efficiency Investments

Henningsen, Geraldine and Wiese, Catharina

Danish Competition Agency, Danish Ministry of the Environment

2019

Do Household Characteristics Really Matter? A Meta-Analysis on the Determinants of Households' Energy-Efficiency Investments

Géraldine Henningsen[a,*], Catharina Wiese[b]

[a]*Danish Competition Agency, Carl-Jacobsensvej 35, 2500 Valby, Denmark*
[b]*Danish Ministry of the Environment, Børsgade 4, 1215 Copenhagen, Denmark*

Abstract

Most environmental policies that aim to encourage households to invest in more climate-friendly technologies and retrofits, e.g., solar panels, electric cars, or attic insulation, are broadly targeted and do not take households' individual investment behaviour into account. Scholars have, therefore, emphasised the need to account for household heterogeneity in policy design in order to ensure effective and efficient policy outcomes. However, such a policy design requires the existence of easily accessible household characteristics, which can reliably and consistently explain households' investment behaviour in a variety of investment scenarios. Using the vast empirical literature on the determinants of households' investments in energy-efficient home improvements as a case study, we conduct a meta-analysis to: (i) determine the magnitude of the effects of easily accessible household characteristics, and; (ii) test the stability of these effects under a variety of circumstances. We integrate the empirical results from 63 publications that investigate the impact of socio-economic characteristics on households' energy-efficiency investments and examine potential model- and sample-specific factors to explain the variation in the estimated effects. Our findings for the household characteristics: income, age, education, household size, and home ownership, show that significant effects only exist for some of these characteristics, with income and home ownership showing the greatest impact. Furthermore, the results confirm a strong situational component in the effect of these household characteristics on households' investment decisions, which challenges the practicality of a tailored policy design.

JEL classification: Q40, D12, D04

Keywords: Household heterogeneity, Environmental policy, Climate, Meta analysis

1. Introduction

Policy interventions to encourage households to invest in climate-friendly and energy-efficient technologies and home-improvements are usually broadly targeted. Thus, they provide similar incentives for the majority of households. However, households are not identical but are instead heterogeneous in many respects. Therefore, they face different barriers to investment (Allcott and Greenstone, 2012), such as imperfect information, liquidity constraints, or split incentives, which discourage them from investing in new technology or engaging in retrofitting that would be privately and socially profitable (e.g., Jaffe and Stavins, 1994; Gillingham et al., 2009).

To properly address potential investment barriers, scholars have, therefore, emphasised the need to design targeted policies that account for household heterogeneity (e.g., Stern, 1992; Allcott and Greenstone, 2012; Gillingham and Palmer, 2013; Allcott et al., 2014). The intuition is straightforward: if only a subset of households fails to adopt profitable investment options and, therefore, stands to gain from a policy intervention, specifically targeting these households will be more effective and eventually more cost-effective than targeting all households.

However, despite the emphasised need to design targeted policies, it remains unclear whether systematic and exploitable patterns in households' investment behaviour exist. Although observable investment decisions show considerable heterogeneity (e.g., Newell and Siikamäki, 2013, 2015), households' individual investment barriers are difficult and costly to detect. Thus, in order to realistically consider household heterogeneity in policy

*Corresponding author
Email addresses: geraldine.henningsen@gmail.com (Géraldine Henningsen), catharina.wiese@posteo.de (Catharina Wiese)

design, the existence of observable variables that are easily accessible for policy makers or policy modellers and that can consistently and reliably explain households' heterogeneous investment decisions is a basic prerequisite.

To investigate the existence of such variables, we conduct a meta-analysis based on the large number of empirical studies that analyse the effect of socio-economic characteristics on households' investments in climate-friendly and energy-efficient technologies and retrofitting (e.g., Ameli and Brandt, 2015; Aravena et al., 2016; Mills and Schleich, 2010a, 2012; Smiley, 1979; Trotta, 2018a).[1] By integrating the results from 63 individual studies with a total of 167 different regression results, we investigate the existence of systematic and stable patterns across the following five standard characteristics: income, age, education, household size, and home-ownership status as determinants of households' investment behaviour. Furthermore, we compare the empirical effects of the five variables with five hypotheses that are derived from a simple micro-economic investment model in order to assess the alignment of the empirical results with economic theory. We use these results to determine whether standard household characteristics can significantly and consistently explain the heterogeneity in households' investment behaviour, so that policy makers and policy modellers can use these characteristics as proxies to incorporate household heterogeneity in policy design. Our analysis is, to the best of our knowledge, the first to approach this question systematically.

The article is structured as follows: section 2 describes the theoretical investment model and formulates the hypotheses; section 3 introduces our analysis, discusses the search for relevant literature, and presents the empirical findings; section 4 discusses these findings with respect to potential limitations and compares them to our theoretical hypotheses; finally, section 5 concludes. Due to methodological constraints or limitations on data availability, we had to dismiss studies that empirically analyse the effect of socio-economic characteristics on households' energy-efficiency investments. A detailed overview of these studies is provided in table A.12 in AppendixA.1.

[1] We subsequently gather all investments in climate-friendly and energy-efficient technological and retrofitting home improvements under the term 'investments in energy-efficiency'.

2. Model and Hypotheses Formulation

To set a theoretical framework for the analysis of the empirical results, we define a simple investment model such as suggested by Allcott and Greenstone (2017). Households can improve the climate impact of their home by investing in portable or non-portable assets, e.g., energy-efficient appliances, building envelope renovations, or solar panels.

Let $\theta_{ij} = (e_{ij}, \xi_{ij}, c_{ij}, \mathcal{T}_{ij})'$ be a vector, where $i = 1, \ldots, \mathcal{I}$ is the household index, and $j \in \mathcal{J}_i$ indicates a specific climate friendly investment from the set of all feasible investment measures, $\mathcal{J}_i$, available to household i. e_{ij} is the expected monetary present day value (PDV) of eventual energy savings of the investment; ξ_{ij} is the expected PDV of the monetised non-monetary benefits of the investment (e.g., better indoor climate, warm glow, etc.); c_{ij} are the monetary costs of the investment and $\mathcal{T}_{ij}$ are the expected monetised non-monetary costs (e.g., due to disruptive and time-consuming construction work). We set up the following expected utility function:

$$E(U(y_i, e_{i0}, \mathcal{B}_{i0}, \Theta_i, \mathbf{I}_i)) = y_i - e_{i0} + \mathcal{B}_{i0} + \sum_{j \in \mathcal{J}_i} I_{ij}(e_{ij} + \xi_{ij} - c_{ij} - \mathcal{T}_{ij}), \qquad (1)$$

where y_i is household income, a proxy for wealth[2]; e_{i0} is the PDV of the expenditures of the future baseline energy consumption without investments; $\mathcal{B}_{i0}$ are the monetised non-monetary benefits of the status quo; $\Theta_i = \{\theta_{ij}; j \in \mathcal{J}_i\}$ is the set of costs and benefits of all energy-efficient measures available to household i; I_{ij} is a dummy variable indicating whether household i adopts investment option j, and $\mathbf{I}_i = \{I_{ij}; j \in \mathcal{J}_i\}$.[3]

These variables, except for y_i and I_{ij}, are usually unobserved latent variables. Therefore, we suggest expressing them through functions that depend on the following five observable household characteristics: income, y_i, age, a_i, education, d_i, household size,

[2]We expect overall wealth to be more relevant than income. However, because data on wealth is rarely included in empirical studies, we do not include it in our model.

[3]We assume that all potential investments in set $\mathcal{J}_i$ are independent. Consequently, some energy-efficient measures are package solutions, when their conservation effect depends on the combination of several investments, e.g., a household with two potential investments A and B has three options: 'A', 'B', or 'A and B'.

z_i, and the household's ownership status, o_i, which indicates whether a household owns or rents its home. The expected utility function extends to:

$$
\begin{aligned}
E(U(y_i, e_{i0}, \mathcal{B}_{i0}, \Theta_i, \mathbf{I}_i)) = y_i - e_{i0}(y_i, a_i, d_i, z_i, o_i) + \mathcal{B}_{i0}(y_i, a_i, d_i, z_i, o_i) \\
+ \sum_{j \in \mathcal{J}_i} I_{ij}(e_{ij}(y_i, a_i, d_i, z_i, o_i) + \xi_{ij}(y_i, a_i, d_i, z_i, o_i) \\
- c_{ij}(y_i, a_i, d_i, z_i, o_i) - \mathcal{T}_{ij}(y_i, a_i, d_i, z_i, o_i))
\end{aligned} \tag{2}
$$

Drawing on this function, equation (3) shows the effect of adopting investment j on the expected utility of household i:

$$
\begin{aligned}
\lambda_{ij}(\cdot) = e_{ij}(y_i, a_i, d_i, z_i, o_i) + \xi_{ij}(y_i, a_i, d_i, z_i, o_i) \\
- c_{ij}(y_i, a_i, d_i, z_i, o_i) - \mathcal{T}_{ij}(y_i, a_i, d_i, z_i, o_i),
\end{aligned} \tag{3}
$$

where $\lambda_{ij} = E(U(\cdot) \mid I_{ij} = 1) - E(U(\cdot) \mid I_{ij} = 0)$, which in our simple investment model corresponds to the net present value (NPV) of investment j. The NPV depends on the monetary and non-monetary costs and benefits, which we assume are functions of heterogeneous household characteristics. Thus, income, age, education, household size and ownership status determine whether λ_{ij} is positive, negative, or neutral and, therefore, whether it affects households' propensity to invest. In the following, we formulate hypotheses considering how each of the five household characteristics affects λ_{ij} and the propensity to invest. The hypotheses serve as benchmarks in the evaluation of our empirical results in section 4.

2.1. Income

Hypothesis 1 *The higher the income, the higher the propensity for the household to invest. This effect increases with the capital intensity of the investment.*

Irrespective of the income level, most households stand to benefit from improving the energy-efficiency of their home, either through monetary savings, e_{ij}, or non-monetary benefits, ξ_{ij}. Thus, the main effect of income is determined on the cost side. Although pure purchasing costs are likely to be the same for all households, capital costs may vary considerably between income groups. High income households have better access to capital and might face lower interest rates than low income households because the former own more assets, which can be used as collateral. Thus, monetary costs c_{ij} are expected to be lower for high income households than for low income households. This effect is reinforced the larger the investment sum associated with an energy-efficiency measure. On the other hand, households with a higher income face higher opportunity costs connected to the time spent implementing the measure, which might increase the non-monetary costs $\mathcal{T}_{ij}$ for these households. This will particularly affect time-intensive investments.

2.2. Age

Hypothesis 2 *The effect of age on a household's propensity to invest is ambiguous for capital-intensive investments with long amortisation periods.*

On the one hand, increasing age reduces the value of investment benefits because elder household heads have a shorter time horizon to accumulate the benefits. Thus, the PDV of monetary, e_{ij}, and non-monetary benefits, ξ_{ij}, decreases with age, which lowers the propensity to invest for elder household heads.[4] A longer expected amortisation period of an investment reinforces this effect.

On the other hand, increasing age reduces both monetary and non-monetary costs. Considering monetary costs, c_{ij}, increasing age decreases credit constraints (Jappelli, 1990; Lyons, 2003) and the capital costs of elder households, as elder households will, on average, own more assets than younger household heads.[5] Again, larger investment sums reinforce this effect. Considering the non-monetary costs, $\mathcal{T}_{ij}$, we expect that the share of labour income to total income decreases for most households with increasing

[4]For simplicity, we assume a common discount rate across all households.

[5]This assumption is only valid until a certain age, after which capital costs eventually increase sharply because lenders evaluate the risk of giving loans to elderly households as high.

age (Aaronson et al., 2014). Elder household heads will, on average, have *ceteris paribus* (e.g., for a given total income) a lower marginal income from labour and, consequently, they have lower opportunity costs of leisure time. Thus, the higher the household head's age, the lower the costs linked to lost leisure time as a consequence of time-intensive investments.

2.3. Education

Hypothesis 3 *The higher the educational attainment, the higher a household's propensity to invest. This effect increases with the expected amortisation period of the investment.*

Empirical analyses find a significant and negative effect of higher educational attainment on the discount rate that an investing individual applies to future benefits (Harrison et al., 2002). In other words, individuals with a longer education are, on average, more patient and, hence, more willing to wait for future benefits. Thus, we expect that the higher the educational attainment, the higher the assigned present day value of future monetary, e_{ij}, and non-monetary benefits, ξ_{ij}, and consequently, the higher the household's propensity to invest. This effect is reinforced the longer the amortisation period of the investment.

2.4. Household size

Hypothesis 4 *The effect of household size on the propensity to invest is ambiguous for capital-intensive investments, but positive for less capital-intensive investments.*

Household size is primarily a control variable and, therefore, it impacts the propensity to invest through other variables. On the one hand, a larger household size correlates, *ceteris paribus*, with greater demand for energy services. If these energy services are provided more efficiently after an investment, larger households benefit over-proportionally through larger energy savings. This effect increases the propensity of the household to invest. On the other hand, a larger household size means, *ceteris paribus*, a lower per capita income, which eventually translates into higher costs of financing capital-intensive investments and, thus, a lower propensity to invest. Thus, for capital-intensive investments, this lower propensity to invest may cancel out the higher propensity due to the larger benefits, and overall results in an ambiguous net-effect of the variable.

2.5. Home ownership

Hypothesis 5 *Home ownership increases a household's propensity to invest. This effect reinforces with the capital intensity of the investment.*

Renting is commonly considered a barrier to investments within the home due to the challenge of allocating costs and benefits between property owners and tenants (Jaffe and Stavins, 1994). The barrier is strongest for capital-intensive investments. Whilst households that own and live in their home would gain all monetary, e_{ij}, and non-monetary benefits, ξ_{ij}, of an investment, tenants do not benefit from, e.g., the increase in real-estate value resulting from a home improvement. Thus, they are unable to reap the full benefits of the investment. We, therefore, expect the propensity to invest to be lower for households that rent compared to those that own. This argumentation becomes less strong when considering minor investments in, e.g., energy-efficient appliances or light bulbs. The costs and benefits of minor investments are most likely the same for owners and renters.

3. Analysis

3.1. Literature Search

To identify relevant publications, we screened the literature for empirical studies that analyse the determinants of households' energy efficiency investment decisions both under market conditions and as a reaction to policies in either an authentic or in an experimental (hypothetical) setting. We focused our search on the following three broad categories: real market behaviour, stated preference studies—mainly choice experiments—, and policy evaluations, and used the following keywords: 'energy efficiency', 'energy efficiency investment', 'energy efficiency households', and 'determinants energy efficiency investments' in the literature databases: Google Scholar, Scopus, EconStor, and EconPapers. We included all studies that investigated investment decisions regarding minor investments, e.g., light bulbs, thermostats, or smaller insulation or weatherisation projects, medium investments, e.g., water heaters or appliances, and major investments, e.g., building insulation, solar panels, heating systems, or windows and doors. For each identified and relevant study, we also conducted a forward and backward citation search in all four databases to identify further relevant publications that had not come up in our initial search. In order to generate a comprehensive sample, we included both peer reviewed and grey literature in our search (Stanley, 2001). The search was conducted during 2017 and 2018.

We screened all studies that contained relevant empirical analyses for household characteristics that are both frequently used and easily accessible to modellers and policy makers. The studies included a multitude of different household characteristics as covariates, of which the most frequently used were: income, age, education, household size, and home ownership. Other frequently included characteristics were race and number of children living in the household, whilst variables such as household debt, employment status, and gender were used infrequently. Environmental attitudes and political affiliation are often included covariates—especially in the political science and psychological literature. However, as these household characteristics are normally not easily accessible to policy modellers and policy makers as they require extensive surveying, we did not include them in our meta-analysis. Given these results, we focused on the following five household characteristics: income, age of household head, education of household head, household size, and home ownership.

From the potentially relevant literature, we selected publications that fulfilled the following criteria:

- present empirical results of the determinants of private households' investment choices in energy efficiency,

- contain at least one of the five selected household characteristics as a covariate,

i.e., the publications included in our analysis present empirical results that allow inference about the propensity of households to invest in measures that would improve the households' energy efficiency.

We found a total of 104 relevant publications that matched the two criteria (a more detailed overview of all 104 publications can be found in the online appendix of this article). However, we had to discard 41 publications because of insurmountable methodological differences or an absence of vital statistical information, which meant that extracting comparable effect measures was impossible.

The empirical analyses reported in the identified publications differ significantly in terms of their methodological approaches, which in some cases prevents a direct comparison of the regression coefficients.[6] The main empirical approaches used in the 104 publications include: pairwise correlations between energy efficiency investments and household characteristics (three publications), the regression of factor loadings, derived from multiple energy efficiency investments, on household characteristics (three publications), the regression of investment sums or tax rebates on household characteristics (12 publications), and the impact of household characteristics on a household's likelihood to invest in energy efficiency (83 publications). Only the latter approach provided a sufficient number of comparable observations that could be included in our meta-analysis (79 publications in total). All other empirical approaches failed to provide the critical number of comparable observations to support reliable results in a meta-analysis.

Where standard errors, p-values, or t-values were missing in the publication, i.e., the significance of the coefficient estimate was only indicated by asterisks, we calculated the standard errors of the coefficient estimates at the thresholds as defined by the published asterisks (e.g., by assuming a p-value of 0.05 for two asterisks or if indicated otherwise in the study by the corresponding p-value) and assumed a default p-value of 0.5 for sta-

[6] E.g., the magnitude of regression coefficients from studies where the endogenous variable is continuous is incomparable to the magnitude of regression coefficients from studies where the endogenous variable is binary or categorical.

tistically insignificant coefficient estimates. Using this approach will in almost all cases create standard errors for the coefficient estimates that are upwards biased, hence, they will reflect the additional insecurity connected to the respective observation in the subsequent meta-analysis. In order to test whether our default choice of 0.5 for insignificant coefficient estimates had any impact on our results, we ran a sensitivity analysis setting the default p-value to $\{0.2, 0.4, 0.5, 0.7, 0.9\}$, respectively. The impact was negligible (at the fourth decimal) and, hence, we proceeded with a default p-value of 0.5 for statistically insignificant coefficient estimates.

Where vital summary statistics were missing in the publication, we first contacted the authors of the study. If summary statistics were not provided by the authors, we tried to find approximate estimates for the missing variable means through secondary statistics, assuming that the study used a representative sample from the population of interest. However, despite our efforts, we had to discard another 16 studies from the meta-analysis due to missing summary statistics, so that our final sample comprises 63 publications with a total of 167 regression results.

If a publication included several estimations, we refrained from calculating the mean effect of the variable of interest across all included estimations, and instead included all the estimation results that were either based on different samples or sub-samples, or addressed different choice categories, e.g., insulating the roof and purchasing solar panels. Following Houtven et al. (2017) we later accounted for the panel structure of our data by using cluster robust standard errors.

Table 1 gives an overview of all publications that have been included in our meta-analysis. Furthermore, in order to preserve the relevant results from all excluded studies, we generated Table A.12 (see appendix), which only compares the direction of the effects of the variables of interest on households' propensity to invest in energy efficiency. Although a mere effect-counting study cannot provide the same in-depth analysis as a meta-analysis, we argue that the results, nevertheless, may be important additional indicators for the quantification of the overall effect of the five household characteristics on the propensity to invest.

Table 1: Publications included in the meta-analysis

Publications		
Abeliotis et al. (2011)	Alberini et al. (2014)	Allen et al. (2015)
Ameli and Brandt (2015)	Andor et al. (2016)	Aravena et al. (2016)
Baldini et al. (2018)	Blasch et al. (2017a)	Blasch et al. (2017b)
Bollinger and Gillingham (2012)	Braun (2011)	Brechling and Smith (1994)
Burlinson (2017)	Brounen et al. (2013)	Cirman et al. (2013)
Collins and Curtis (2017)	Das et al. (2018)	Datta and Filippini (2016)
Dato (2018)	Dieu-Hang et al. (2017)	Di Maria et al. (2010)
Durham et al. (1988)	Bruderer Enzler et al. (2014)	Fujii and Mak (1984)
Frondel and Vance (2013)	Gamtessa (2013)	Gans (2012)
Gillingham et al. (2012)	Gillingham and Tsvetanov (2018)	Hamilton et al. (2016)
Hasset and Metcalf (1995)	McCoy and Lyons (2017)	Jakob (2007)
Johnson-Carroll et al. (1987)	Kesternich (2010)	Ledesma-Rodriguez (2014)
Leicester and Stoye (2013)	Martínez-Espiñeira et al. (2014)	Meier and Tode (2015)
Michelsen and Madlener (2012)	Mills and Schleich (2009)	Mills and Schleich (2010a)
Mills and Schleich (2010b)	Mills and Schleich (2012)	Murray and Mills (2011)
Nauleau (2014)	Newell and Siikamäki (2015)	Neveu and Sherlock (2016)
Noonan et al. (2015)	Palmer et al. (2015)	Pon and Alberini (2012)
Qiu et al. (2014)	Ramos et al. (2016)	Sahari (2017)
Sardianou (2007)	Scasny and Urban (2009)	Schleich et al. (2017)
Schwarz et al. (2014)	Trotta (2018b)	Trotta (2018a)
Tsvetanov and Segerson (2014)	Walsh (1989)	Welsch and Kühling (2009)

3.2. Extraction of effect measures and moderator variables

Our meta-analysis focusses on adoption studies where the dependent variable is either binary or (ordered) categorical. However, even within this group of publications, a multitude of different estimation methods have been applied. Our sample comprises studies that use linear probability models, binary logistic regression models, binary probit regression models, ordered probit regression models, multivariate probit regression models, multinomial logistic regression models, or OLS in combination with a dependent variable that varies between 0 and 1 (e.g., shares). Overall, the majority of the analyses are based on micro data at the household level, whilst some analyses are based on locally aggregated data (e.g., at the ZIP code level). These methodological differences prevent a direct comparison of the coefficient estimates from different analyses. Furthermore, differences in the measurement units of continuous covariates (e.g., income measured in \$1000 or \$10,000) and different encodings of categorical or interval-coded covariates (e.g., three income categories versus six income categories) aggravate this problem.

To overcome the problem of comparability, we use the **R** (R Core Team, 2018) package urbin (Henningsen and Henningsen, 2018a,b) to calculate semi-elasticities for continuous covariates, $\epsilon_k = \dfrac{\partial P(Y=1|X=x)}{\partial x_k} \cdot x_k$, and effects for each category of categorical or interval-coded covariates, $E_k = P(Y=1|X=x, x_k=1) - P(Y=1|X=x, x_k=0)$, at the sample means of the respective study samples. In cases where categorical or interval-coded covariates are grouped in different ways or where the base category differs, we used package urbin to unify the number of categories, interval-bounds, and base categories across all studies. Furthermore, we used urbin to calculate the semi-elasticities from categorical or interval-coded covariates and effects from continuous covariates in order to unify the effect measures across all studies. Finally, we used urbin to redress results from ordered probit regression models and multinomial logistic regression models into results from regression models with a binary response variable. To derive approximate standard errors for the calculated semi-elastisticities and effects that could be used as weighting factors in the meta-analysis, we followed the approach described in Henningsen and Henningsen (2018b) and implemented in urbin.[7]

Next to the effect measures, we also extract a number of moderator variables from the publications (see table 2 for details). Because our effect measures are, in most cases, only a sub-set of the covariates that explain a household's likelihood of investing in energy efficiency, the variance in our effect measures may be the result of either the characteristics of the respective sample and/or the model specification that was chosen by the analyst. To take these different influences into account, we extract two

[7]The online-appendix to this publication provides a detailed description of the modifications and calculations performed on the coefficient estimates, sample means, and standard errors of each included publication.

Table 2: Variable names and definitions

Name	Definition
Effect measures:	
elaIncome	Semi-elasticity of continuous income variable
effAgeMid/Old	Effect of interval coded variable age, where the base category is 18–35 years, the medium category is 36–50 years, and the senior category is 51–80 years.
effEdu	Effect of categorical variable education, where the base category is 'below university/college' and the second category is 'some university/college or higher'.
elaHZ	Semi-elasticity of variable household size.
effOwn	Effect of binary variable home-ownership, where the base category is 'no ownership'.
Moderator variables:	
year	Year of publication.
sampleZ	Number of observations in study.
nCov	Number of covariates in study.
share	Share of adopters in sample.
country	Country where study was conducted, with 0 = multiple OECD countries, 1 = Canada, 2 = USA, 3 = Ireland, 4 = UK, 5 = Germany, 6 = Southern Europe, 7 = Central Europe, 8 = Northern Europe.
experiment	Categorical variable of whether the study has been conducted as an experiment (field and hypothetical), with the base category 'no experiment'.
investment	Categorical variable describing the size of the investment, with the base category 'minor investment', comprising smaller investments such as light bulbs or programmable thermostats, the second category 'medium investment', comprising medium-sized investments such as appliances or boilers, and category 'major investment', comprising large investments such as retrofits or solar panels.
house	Categorical variable indicating whether the regression model includes covariates that describe the building.
social	Categorical variable indicating whether the regression model includes covariates that describe the social status of a household or attitudinal variables.
politic	Categorical variable indicating whether the regression model includes covariates that describe the political orientation of the household.
price	Categorical variable indicating whether the regression model includes covariates that describe energy prices or price levels.
temp	Categorical variable indicating whether the regression model includes heating degree days or other climatic variables.

Table 3: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
year	167	2011	7.64	1983	2010	2016	2018
sampleZ	167	38,273.00	296,365.50	50	1,107.5	15,031.5	3,817,392
nCov	167	21.67	9.66	5	14	28	43
share	167	0.39	0.28	0.00	0.12	0.63	0.95
country = 1	167	0.08	0.27	0	0	0	1
country = 2	167	0.23	0.42	0	0	0	1
country = 3	167	0.08	0.27	0	0	0	1
country = 4	167	0.14	0.35	0	0	0	1
country = 5	167	0.14	0.35	0	0	0	1
country = 6	167	0.11	0.31	0	0	0	1
country = 7	167	0.10	0.30	0	0	0	1
country = 8	167	0.02	0.15	0	0	0	1
experiment = 1	167	0.18	0.39	0	0	0	1
investment = 1	167	0.26	0.44	0	0	1	1
investment = 2	167	0.61	0.49	0	0	1	1
house = 1	167	0.75	0.43	0	1	1	1
social = 1	167	0.62	0.49	0	0	1	1
politic = 1	167	0.03	0.17	0	0	0	1
price = 1	167	0.25	0.44	0	0	0.5	1
temp = 1	167	0.17	0.38	0	0	0	1

groups of moderator variables: moderator variables that describe the sample (year, share, country, experiment, and investment) and moderator variables that serve as proxies for the model specification (degrees of freedom, house, politic, price, and temp). Table 3 provides the summary statistics for the moderator variables. It reveals that our sample is biased towards more recent data sets. Furthermore, the sample size of the studies varies considerably, which reflects the broad type of publications included in our meta analysis that range from small choice experiments to studies with data sets covering millions of households over several countries.

The average study in our sample includes 22 covariates, with the largest model specification including as many as 43 covariates. This raises the question of the degree to which the results from such analyses are hampered by multicollinearity. Although multicollinearity generally does not generate any bias in the estimates, it, nevertheless, creates imprecise estimates, which are overly sensitive to changes in the model specification.[8]

[8]In order to test for the impact of the number of covariates on the size of the calculated standard errors of our effect measures, we regressed the standard errors from all six effect measures on 'nCov' and 'sampleZ'. However, none of the estimation models was statistically significant and, therefore, we conclude that this problem is negligible in our sample.

Finally, Table 3 shows that the distribution over the shares of adopters in each study is right-skewed. This finding is not surprising given the fact that most studies in our sample look at major investments, for which the uptake is generally low.

3.3. Results

Table 4: Unweighted mean effects, mean effects weighted with standard error, mean effects weighted with sample size

	Mean	Std. Err.	z	p-value	CI Lower	CI Upper
Income unweighted	0.02962	0.02158	1.37233	0.16996	-0.01268	0.07192
Income weighted	0.01025	0.00784	1.30691	0.19124	-0.00512	0.02563
Income sample size	0.02946	0.00886	3.32539	**0.00088**	0.01210	0.04682
AgeMid unweighted	-0.01086	0.05515	-0.19698	0.84385	-0.11895	0.09722
AgeMid weighted	0.00267	0.00900	0.29646	0.76688	-0.01498	0.02032
AgeMid sample size	-0.00959	0.01184	-0.81008	0.41789	-0.03279	0.01361
AgeOld unweighted	-0.00705	0.08149	-0.08655	0.93103	-0.16677	0.15266
AgeOld weighted	0.00424	0.01188	0.35725	0.72091	-0.01904	0.02753
AgeOld sample size	-0.00668	0.01491	-0.44817	0.65403	-0.03591	0.02255
Edu unweighted	0.02351	0.03919	0.59983	0.54862	-0.05330	0.10031
Edu weighted	0.00294	0.00929	0.31645	0.75166	-0.01526	0.02114
Edu sample size	0.01794	0.00712	2.52024	**0.01173**	0.00399	0.03189
HZ unweighted	0.03319	0.05205	0.63759	0.52374	-0.06883	0.13521
HZ weighted	0.00273	0.00829	0.32948	0.74179	-0.01351	0.01897
HZ sample size	0.03027	0.01437	2.10646	**0.03516**	0.00211	0.05844
Own unweighted	0.03445	0.03631	0.94887	0.34269	-0.03671	0.10562
Own weighted	0.02356	0.01281	1.83863	0.06597	-0.00155	0.04867
Own sample size	0.03505	0.00862	4.06793	**0.00005**	0.01816	0.05193

Table 4 provides an overview of the mean effects of all six effect measures (Income, AgeMid, AgeOld, Edu, HZ, and Own). We calculated the unweighted arithmetic mean, $\bar{\theta} = \sum_i \frac{\theta_i}{m}$, where θ_i is the effect measure of the ith regression result and m is the total number of results included. We also calculate the weighted mean, $\bar{\theta} = \frac{\sum_i w_i \theta_i}{\sum_i w_i}$ where—as it is standard—the weights w_i are the inverse of the standard errors of the effect measures. Using **R** package metafor (Viechtbauer, 2010), we calculate the weighted means by means of a random effects model. Given that our effect measures stem from studies that significantly differ in their model specifications, we cannot rule out that our effect measures are in fact drawn from different populations (Becker and Wu, 2007). Contrary to a simple weighted mean (the fixed effect model), which assumes that all effect measures are drawn from the same target population with one mean $\bar{\theta}$ and, hence, assume that each effect measure can be described by $\theta_i = \bar{\theta} + \epsilon_i$, the random effects estimator assumes that effect measures are samples from different populations whose respective population means are distributed around a grand mean $\bar{\theta}$. Hence, the random effects model assumes that each effect measure can be described by $\theta_i = \bar{\theta} + \phi_i + \epsilon_i$, where ϕ_i depicts the difference between the grand mean $\bar{\theta}$ and the true mean of the population from which the effect measure was sampled. The random effects model allows, therefore, unconditional inference by assuming that the sample of studies is a random sample from a larger population of all possible studies (Viechtbauer, 2010; Borenstein et al., 2010).

Following Houtven et al. (2017), we also calculate the mean effects using the study sample sizes, sampleZ, of the respective estimates as weights. Whilst Houtven et al. (2017) apply this approach because of non-reported standard errors of the effect measures, our reason to apply it is different and is due to the non-linearity of the estimation models used in most of our studies.

We use a binary probit regression model to exemplify the problem that arises from this non-linearity. Figure 1 plots the Gaussian link function of the probit regression model. The Gaussian link function, defining the probability of adoption $P(Y = 1|X = x) = \Phi(\mathbf{X}'\beta)$, is the cumulative density function of a standard normal distribution. However, as the semi-elasticity, our effect measure, from a probit regression model is calculated as $\frac{\partial P(Y = 1|\mathbf{X} = \mathbf{x})}{\partial x_k} \cdot x_k = \phi(\mathbf{x}'\beta)x_k\beta_k$, the size of the semi-elasticity will *ceteris paribus* be influenced by the value of the probability density function $\phi(\mathbf{x}'\beta)$, which in turn is determined by the probability of an average household in the sample adopting the energy efficiency measure. E.g., in a case where the probability of adoption for the average household is 0.5, the derivative of the cumulated density function at this point corresponds to the peak value of the probability density function. Hence, the value of the probability density function that is used to calculate the semi-elasticity will be large, whilst if the average household in the sample has a rather small or rather large likelihood of adopting a measure, the corresponding value on the probability density function will

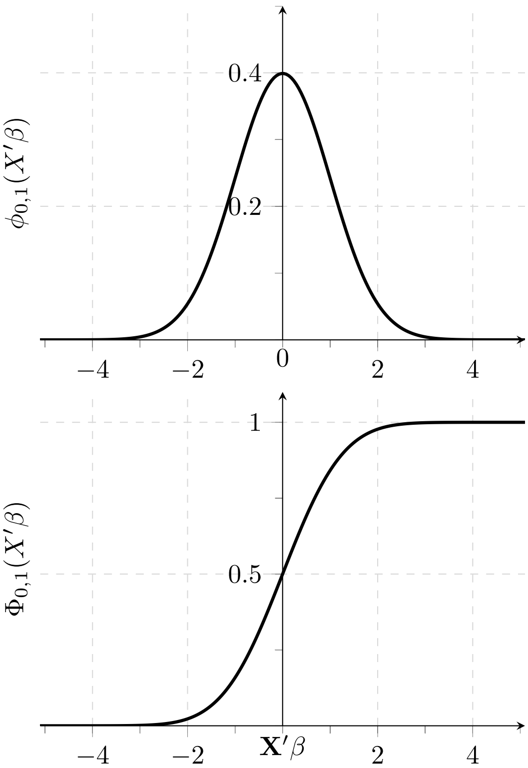

Figure 1: Cumulative and probability density function of a normal distribution

be small and, hence, all things equal, the corresponding semi-elasticity and its standard errors will be closer to zero.

One could argue that this characteristic of the semi-elasticities compromises the comparability of the effect measures across different samples and that all semi-elasticities should instead be calculated at the mode of their respective probability density functions. We argue that, as we are interested in the effect measure of the *average* household from each study, this approach would no longer represent the true mean effect of our sample, but would grossly overestimate the mean semi-elasticity.

However, in order to overcome the problem that smaller semi-elasticities *ceteris paribus* correspond with smaller standard errors, we chose to include a more neutral weighting factor, sample size, in our analysis. The effect of this choice becomes apparent in table 4, where the mean effects weighted by sample size are considerably larger than the mean effect weighted by the inverse standard error. In order to account for the influence of the adoption share on the corresponding semi-elasticities, we, therefore, included the adoption shares as an additional moderator variable in our analyses.

Tables 5 to 10 report the results of the weighted least squares estimations for all six effect measures, where we follow the standard approach of using the inverted standard errors of the effect measures.[9] We estimate four different model specifications: specification one only includes sample-related moderator variables, the second specification only includes model-related moderator variables, which in fact are of little interest for the analyses and only serve as control variables, whilst the third and fourth specifications estimate the full model.

Unlike meta-analyses based on experimental studies, which mainly test differences in the mean effects between different treatment groups, our sample is based on regression analyses with many different combinations of covariates. As discussed in the previous

[9]One could argue that as all six effect measures might be correlated, it would be appropriate to estimate a system of equations. However, the equation set up does not imply an apparent correlation of the error terms, which would necessitate such a step. Also, not taking an eventual correlation of the error terms into account will, at most, result in less efficient estimates and, hence, to more conservative results, but will not lead to biased results.

Table 5: Moderator analyses for effect 'Income'

	Dependent variable: elaIncome			
	(1)	(2)	(3)	(4)
year	−.001***		−.001**	−.001**
	(.0003)		(.0003)	(.0005)
country = 1	−.004		.048*	.038
	(.017)		(.025)	(.029)
country = 2	−.015*		.029	.033
	(.009)		(.028)	(.028)
country = 3	−.003		.006	.013
	(.014)		(.021)	(.023)
country = 4	−.009		.020	.014
	(.010)		(.019)	(.021)
country = 5	−.013		.026	.034
	(.012)		(.031)	(.030)
country = 6	.026**		.060**	.059**
	(.013)		(.029)	(.029)
country = 7	.003		.029	.031
	(.011)		(.019)	(.019)
country = 8	−.014		.044	.052
	(.010)		(.040)	(.039)
experiment	−.010		−.031	−.031
	(.014)		(.020)	(.022)
investment = 1	.008		−.002	−.003
	(.012)		(.013)	(.014)
investment 2	.003		.004	−.0002
	(.011)		(.012)	(.012)
share	.107***		.136***	.157***
	(.035)		(.047)	(.044)
share2	−.101**		−.123**	−.137***
	(.040)		(.049)	(.051)
log(df)		−.002		.002
		(.003)		(.005)
df			−0.00000***	
			(0.00000)	
house		−.013	−.030*	−.029*
		(.011)	(.015)	(.015)
social		.006	.023	.028*
		(.007)	(.016)	(.016)
politic		−.022	.059	−.004
		(.023)	(.037)	(.029)
Price		.010	.010	.003
		(.007)	(.013)	(.012)
temp		.004	−.009	−.017
		(.010)	(.016)	(.015)
constant	2.008***	.035	1.602**	2.217**
	(.571)	(.028)	(.672)	(.898)
Observations	135	135	135	135
R^2	.228	.045	.302	.284
Adjusted R^2	.138	.0003	.180	.158
Residual Std. Error	.368 (df = 120)	.396 (df = 128)	.359 (df = 114)	.364 (df = 114)
F Statistic	2.531*** (df = 14; 120)	1.008 (df = 6; 128)	2.466*** (df = 20; 114)	2.256*** (df = 20; 114)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: Moderator analyses for effect 'AgeMid'

	Dependent variable: effAgeMid			
	(1)	(2)	(3)	(4)
year	.001		.001	.0004
	(.001)		(.001)	(.001)
country = 1	.004		.019	.025
	(.040)		(.023)	(.021)
country = 2	−.005		.072***	.069***
	(.023)		(.020)	(.021)
country = 3	−.041***		−.034	−.036
	(.014)		(.023)	(.024)
country = 4	−.012		.035	.008
	(.014)		(.024)	(.017)
country = 5	.002		.051***	.048***
	(.019)		(.017)	(.018)
country = 6	.014		.069***	.069***
	(.020)		(.024)	(.025)
country = 7	−.017		.005	.004
	(.036)		(.025)	(.025)
country = 8	−.018		.116***	.115***
	(.015)		(.032)	(.032)
experiment	−.020		−.035	−.040*
	(.037)		(.024)	(.023)
investment = 1	.004		−.010	−.006
	(.016)		(.017)	(.015)
investment 2	−.001		−.005	−.004
	(.008)		(.007)	(.006)
share	−.019		−.060	−.070*
	(.066)		(.042)	(.040)
share2	.054		.066	.083*
	(.065)		(.054)	(.050)
log(df)		.0003		−.004
		(.003)		(.004)
df			−0.00000**	
			(0.00000)	
house		−.027***	−.017	−.019
		(.006)	(.013)	(.013)
social		−.0001	.048***	.049***
		(.007)	(.017)	(.017)
politic		−.132***	−.166***	−.165***
		(.008)	(.016)	(.016)
Price		.002	.014	.008
		(.008)	(.021)	(.019)
temp		−.006	−.074***	−.076***
		(.007)	(.021)	(.021)
constant	−2.120	.024	−2.189	−.720
	(2.138)	(.026)	(1.830)	(1.254)
Observations	96	96	96	96
R^2	.139	.220	.447	.434
Adjusted R^2	−.010	.167	.299	.283
Residual Std. Error	.311 (df = 81)	.282 (df = 89)	.259 (df = 75)	.262 (df = 75)
F Statistic	.932 (df = 14; 81)	4.176*** (df = 6; 89)	3.029*** (df = 20; 75)	2.872*** (df = 20; 75)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Moderator analyses for effect 'AgeOld'

	Dependent variable: effAgeOld			
	(1)	(2)	(3)	(4)
year	.002		.001	.001
	(.002)		(.002)	(.001)
country = 1	.003		.017	.022
	(.075)		(.053)	(.051)
country = 2	−.012		.136***	.129***
	(.046)		(.035)	(.038)
country = 3	−.089***		−.072	−.076
	(.031)		(.050)	(.051)
country = 4	−.039*		.030	.005
	(.023)		(.032)	(.028)
country = 5	.006		.113***	.107***
	(.041)		(.032)	(.033)
country = 6	−.031		.035	.026
	(.047)		(.070)	(.075)
country = 7	−.042		.003	−.001
	(.071)		(.054)	(.055)
country = 8	−.045		.198***	.195***
	(.041)		(.038)	(.040)
experiment	−.035		−.050	−.054
	(.069)		(.049)	(.050)
investment = 1	−.005		−.039	−.035
	(.027)		(.027)	(.025)
investment 2	−.005		−.006	−.005
	(.012)		(.011)	(.010)
share	.037		−.108	−.121
	(.144)		(.121)	(.119)
share2	.043		.115	.132
	(.140)		(.124)	(.123)
log(df)		.001		−.006
		(.006)		(.008)
df			−0.00000	
			(0.00000)	
house		−.061***	−.043	−.045
		(.015)	(.029)	(.028)
social		.007	.097***	.097***
		(.019)	(.026)	(.027)
politic		−.223***	−.278***	−.277***
		(.019)	(.040)	(.039)
Price		.010	.041	.037
		(.013)	(.031)	(.030)
temp		−.020	−.142***	−.141***
		(.017)	(.033)	(.035)
constant	−3.780	.047	−2.865	−1.439
	(4.611)	(.058)	(3.123)	(2.667)
Observations	96	96	96	96
R^2	.155	.237	.449	.445
Adjusted R^2	.009	.186	.303	.297
Residual Std. Error	.427 (df = 81)	.387 (df = 89)	.358 (df = 75)	.360 (df = 75)
F Statistic	1.064 (df = 14; 81)	4.608*** (df = 6; 89)	3.061*** (df = 20; 75)	3.010*** (df = 20; 75)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: Moderator analyses for effect 'Edu'

	Dependent variable: effEdu			
	(1)	(2)	(3)	(4)
year	−.004*		−.003***	−.004***
	(.002)		(.001)	(.001)
country = 1	−.004		.009	.011
	(.036)		(.029)	(.027)
country = 2	−.025		.009	−.002
	(.037)		(.034)	(.031)
country = 3	−.009		.020	−.015
	(.035)		(.031)	(.029)
country = 4	−.031		.053	.036
	(.036)		(.043)	(.040)
country = 5	−.039		−.040	−.052*
	(.038)		(.031)	(.030)
country = 6	−.010		.027	.005
	(.037)		(.033)	(.030)
country = 7	.041		.040	.019
	(.050)		(.030)	(.030)
country = 8	−.004		−.033	−.026
	(.035)		(.031)	(.028)
experiment	−.010		.001	−.019
	(.015)		(.022)	(.020)
investment = 1	−.032		−.029	−.034
	(.021)		(.022)	(.025)
investment 2	−.023		−.025	−.031
	(.018)		(.020)	(.023)
share	.128***		.069	.072
	(.041)		(.049)	(.047)
share2	−.160***		−.127**	−.128**
	(.051)		(.050)	(.051)
log(df)		−.007***		−.015**
		(.002)		(.007)
df			−0.00000**	
			(0.00000)	
house		−.018	−.061***	−.054***
		(.017)	(.019)	(.019)
social		−.013*	−.034**	−.025*
		(.007)	(.014)	(.014)
politic		−.050***	−.084**	−.080**
		(.016)	(.037)	(.033)
Price		−.012	−.030*	−.028**
		(.011)	(.016)	(.014)
temp		.019*	.035**	.039**
		(.010)	(.017)	(.020)
constant	7.984*	.086***	7.034***	9.253***
	(4.721)	(.027)	(2.421)	(2.323)
Observations	94	94	94	94
R^2	.336	.124	.470	.480
Adjusted R^2	.218	.064	.324	.338
Residual Std. Error	.283 (df = 79)	.310 (df = 87)	.263 (df = 73)	.260 (df = 73)
F Statistic	2.853*** (df = 14; 79)	2.059* (df = 6; 87)	3.233*** (df = 20; 73)	3.376*** (df = 20; 73)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 9: Moderator analyses for effect 'HZ'

	Dependent variable: elaHZ			
	(1)	(2)	(3)	(4)
year	.0001		.002	.002
	(.001)		(.002)	(.002)
country = 1	−.054***		−.043	−.042
	(.007)		(.032)	(.035)
country = 2	−.0001		.079	.009
	(.019)		(.066)	(.045)
country = 5	−.016		.026	−.014
	(.013)		(.039)	(.027)
country = 6	−.022**		.053	.009
	(.010)		(.055)	(.046)
country = 7	−.020**		−.040	−.040
	(.010)		(.074)	(.065)
country = 8	−.032***		.024	−.017
	(.009)		(.058)	(.058)
experiment	.035***		−.041	−.037
	(.011)		(.063)	(.057)
investment = 1	−.083**		−.084***	−.095***
	(.039)		(.030)	(.035)
investment = 2	−.080**		−.068	−.079*
	(.038)		(.045)	(.045)
share	.018		−.068	−.060
	(.038)		(.072)	(.074)
share2	−.065		.024	−.012
	(.062)		(.077)	(.088)
log(df))		−.009*		−.022**
		(.005)		(.009)
df			−0.00000***	
			(0.00000)	
house		−.005	.014	.020
		(.017)	(.073)	(.064)
social		−.013	.019	.008
		(.013)	(.061)	(.058)
price		−.007	−.018	.010
		(.011)	(.043)	(.033)
temp		.003	−.060	−.018
		(.008)	(.067)	(.068)
constant	−.183	.103*	−4.119	−4.419
	(1.213)	(.056)	(3.668)	(3.509)
Observations	61	61	61	61
R^2	.213	.087	.301	.354
Adjusted R^2	.016	.004	.024	.099
Residual Std. Error	.373 (df = 48)	.376 (df = 55)	.372 (df = 43)	.357 (df = 43)
F Statistic	1.081 (df = 12; 48)	1.054 (df = 5; 55)	1.087 (df = 17; 43)	1.387 (df = 17; 43)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 10: Moderator analyses for effect 'Own'

	Dependent variable: effOwn			
	(1)	(2)	(3)	(4)
year	.002**		.004***	.004**
	(.001)		(.001)	(.002)
country = 1	.033**		.035	.032
	(.015)		(.049)	(.045)
country = 2	.020		.030	−.065
	(.033)		(.060)	(.082)
country = 3	.051**		.103***	.080*
	(.024)		(.038)	(.044)
country = 4	−.044		.042	.085*
	(.036)		(.034)	(.050)
country = 5	−.053		−.064	−.083
	(.036)		(.053)	(.052)
country = 6	.048		.054	.015
	(.054)		(.087)	(.088)
country = 7	.033		.002	−.042
	(.028)		(.051)	(.053)
country = 8	−.060*		−.123	−.156*
	(.033)		(.086)	(.085)
experiment	−.078***		−.065	−.063
	(.029)		(.050)	(.049)
investment = 1	.019		.012	.009
	(.015)		(.016)	(.015)
investment 2	.023		.025	.023
	(.016)		(.017)	(.014)
share	.181*		.136*	.183**
	(.097)		(.080)	(.092)
share2	−.189**		−.170**	−.217**
	(.091)		(.086)	(.092)
log(df)		.003		−.031***
		(.007)		(.010)
df			−0.00000***	
			(0.00000)	
house		−.034*	−.052*	−.081**
		(.020)	(.031)	(.036)
social		.023	−.038	−.070
		(.015)	(.044)	(.046)
politic		−.029	−.026	−.102*
		(.027)	(.055)	(.061)
Price		.024*	.019	.059
		(.014)	(.031)	(.036)
temp		.005	.053	.109**
		(.016)	(.043)	(.055)
constant	−3.711**	.004	−7.250***	−7.431**
	(1.704)	(.065)	(2.334)	(3.177)
Observations	70	70	70	70
R^2	.467	.157	.681	.623
Adjusted R^2	.331	.077	.551	.469
Residual Std. Error	.320 (df = 55)	.376 (df = 63)	.262 (df = 49)	.285 (df = 49)
F Statistic	3.442*** (df = 14; 55)	1.961* (df = 6; 63)	5.225*** (df = 20; 49)	4.052*** (df = 20; 49)

Note: *p<0.1; **p<0.05; ***p<0.01

section, the average study contains around 22 different covariates, which means that we cannot rule out correlations between pairs or multiple variables that might have an effect on the effect size of our variables of interest (either by inflating the effect size through a mediation or confounding effect or by supressing the effect size). If one assumes a critical degree of correlation between at least one of the five household characteristics and another covariate in the regression equation, effect measures from studies that include the covariate will differ from effect measures from studies that do not, as in the latter case, the omission of that covariate will create an omitted variable bias. The degree to which this becomes a problem will depend on the correlation between the household characteristic and this particular covariate and will most likely affect studies to different degrees, depending on their respective household sample. Attempts to overcome this shortcoming in meta-studies on regression coefficients have been conducted for linear regression models with continuous dependent variables and covariates (see e.g., Becker and Wu, 2007, for an overview). However, to the best of our knowledge no approach has been suggested to date to handle this problem for results from non-linear regression models, models with binary outcome variables, and for model specifications with categorical covariates. Therefore, we follow the suggestions by Eagly and Wood (1994); Stanley and Jarrell (1989); Stanley (2001) and Doucouliagos and Paldam (2006) and include further moderator variables that address differences in the model specifications of the respective studies. However, given the vast number of different variables that are included in the studies, we have no realistic way of fully controlling the impact of each of these variables on the coefficient estimates of our variables of interest. Therefore, we attempt to proxy this influence by including dummy variables that indicate whether covariates of a specific type were included in the regression model.

We run the standard residual tests for normality and heteroscedasticity, identify and remove some outliers with high leverage, and use Ramsey's RESET test to test all 18 model specifications. However, despite no apparent misspecifications of the regression model and despite a considerable number of moderator variables in the full model specification, even the model specification with the best fit can only explain around 30% of the variance in our effect measures (only taking the adj. R^2 values into account). On the one hand, this low fit implies that other important factors may influence the variation of our effect measures. On the other hand, we have to acknowledge that our effect measures are themselves rather noisy, which increases the overall noise of the regression models and will further depress the (adjusted) R^2 values.

Finally, following Houtven et al. (2017), we take the panel structure of our data into account by calculating cluster robust standard errors using the sandwich package (Zeileis, 2004; Berger et al., 2017).

4. Discussion

Can household characteristics consistently explain the heterogeneity in households' energy efficiency investments? Our results indicate that systematic patterns across the five standard characteristics as determinants of households' energy efficiency investments exist, though to a varying degree across all five household characteristics:

- Our results show a positive correlation between income and a household's propensity to invest in energy efficiency for all three weighing strategies. The findings listed in Table A.12 (see appendix) confirm this result. The majority of studies find a positive correlation between income and propensity to invest. However, the magnitude of the income effect on a household's propensity to invest remains small. A household with twice the income shows an increase in the propensity to invest of between 0.7 and 2.1 percentage points.
- The effect of age is ambiguous and statistically insignificant for all three weighing strategies. Elder households seem to have a slightly higher propensity to invest than middle-aged households, but the difference is too small to be of economic significance. The correlations listed in Table A.12 also show an ambiguous trend, with a similar amount of studies finding a negative/positive correlation.

- Education has a weakly positive effect on households' propensity to invest in energy efficiency. Household heads with at least some college education are between 0.3 and 2.4 percentage points more likely to invest in energy efficiency than households who did not attend college. In addition, the majority of studies in Table A.12 find a positive correlation between higher education and the propensity to invest.

- Household size has an overall positive effect on the propensity to invest. A doubling of the members in a household increases the average household's propensity to invest by between 0.2 and 2.3 percentage points.

- Home ownership seems to have the strongest positive effect on a household's propensity to invest. A household who own their home are between 2.4 and 3.5 percentage points more likely to invest in energy efficiency than a household who rent their home. Studies included in Table A.12 largely confirm the positive effect of ownership on households' propensity to invest.

Interpreting the trends in effect sizes, we have to point out that the mean effects for the most part are statistically insignificant from zero considering a 5% significance level. Furthermore, only 6 studies included in the meta-analysis consider the effect of all five household characteristics. Thus, the estimated mean effects for the different household characteristics are based on different subsets of our sample. The magnitude of the effect sizes for all five household characteristics should, therefore, be compared with caution, having this limitation in mind.

Tables 5 to 10 report the results for our moderator analysis. Focusing on the sample specific moderator variables in specifications 3 and 4, we find statistically significant differences in effect sizes for income, age, education and ownership across countries, in comparison to studies based on observations from multiple OECD countries as baseline. These findings may reflect country-specific differences that affect households' energy efficiency investments. The positive effect on the effect size for old-age in the USA, Germany and Northern Europe may, e.g., reflect easier access to capital for investments for elder households compared to younger households in these countries/regions compared to the average OECD country. Ireland and UK show a positive and significant effect on the effect size for ownership. This finding may show that split incentives play a larger role in Ireland and UK, so that homeowners have a larger incentive to invest in energy efficiency than tenants. The opposite may be the case in Canada, which shows a significant and negative effect on the effect size for ownership. However, at this stage, we can only speculate on the cause of cross country differences.

The investment moderators controlling for investment intensity unexpectedly show no statistically significant effects on the effect sizes for all household characteristics. We take a closer look at the effect of investment intensity in Table 11 and in the following paragraph. Altogether, as discussed in the previous section, the low (adjusted) R^2 values of the moderator analyses (specification 3 and 4) for income, age, education, household size and home ownership, suggest that a major part of the variance in the study results exists due to other unknown and, most likely, situational factors.

Table 11: Predicted effect measures for the three investment levels

	Investment class		
	0	1	2
Income	0.0318	0.0302	0.0357
AgeMid	0.0056	-0.0046	0.0003
AgeOld	0.0083	-0.0311	0.0020
Edu	0.0513	0.0225	0.0264
HZ	0.0747	-0.0096	0.0062
Own	0.0321	0.0440	0.0571

Although the investment moderators for investment intensity show no statistically significant effect on the effect measures, we find insightful trends for the predicted values of our effect measures, given the three investment levels. We compare the predicted values with our hypotheses from section 2. Table 11 shows how the predicted effect measures for the five household characteristics change with the investment class from 0 = minor investment to 2 = major investment.

- A higher income shows a positive effect on a household's propensity to invest across all investment classes with the largest impact for major investment. Considering the difference in effect sizes between minor, medium, and major investments, this difference confirms our hypothesis that the income effect, to some degree, strengthens as the capital intensity of the investment increases. The positive and reinforcing effect of income confirms that financial resources and access to capital play a relevant role in households' investment decision.

- Age shows a mixed effect across investment classes for both age groups with small effect sizes especially for major investments. Thus, age appears to have a limited effect on households' propensity to invest across investment classes. Drawing on our investment model, we hypothesised an ambiguous effect of age, for major investments in particular, arguing with two opposing effects when age increases. Our empirical findings for both age categories may confirm our hypothesis; however, we cannot draw an unambiguous conclusion.

- The effect of having a higher education on a household's propensity to invest is largest for minor investments. Higher education increases the propensity to invest in minor energy efficiency improvements by 5.13 percentage points. The effect size is lower for medium and major investments. This result contradicts our hypothesis that the effect of education increases, the longer the amortisation period of an investment, i.e., the more capital-intensive an investment. Instead of being a pure effect of educational attainment, the larger effect for minor investments compared to medium and major investments may instead reflect the fact that households with a higher education tend to have a more environmentally-friendly attitude, which may correlate with a higher propensity for minor changes towards more energy efficiency.

- The effect of household size is positive and much larger for minor investments compared to medium and major investments. This finding confirms our hypothesis that larger households with higher demand for energy services compared to smaller households benefit over-proportionally from efficiency improvements through larger energy savings. The effect size is negative and/or smaller for medium and major investments, which suggests that a lower per capita income for larger households indeed decreases these households' financial ability to make medium or major efficiency investments. However, given the low predictive quality of the regression model, these results should be read with care.

- The predicted effect sizes for ownership show a clear and increasing trend across investment classes. This finding confirms our hypothesis that households that own their home are more likely to invest in energy efficiency than households that rent, and that this effect increases with the capital intensity of the investment. Home ownership appears to be the major determinant of households' energy efficiency investments. This result suggests that split incentives are a considerable barrier to energy efficiency improvements in the residential sector.

Our results confirm that households that own their home, have a high income, and fewer household members are most likely to invest in costly energy efficiency measures. Thus, these households appear to face fewer barriers to investing in large energy efficiency improvements than households that rent their home, have a low income, and a large household size.

The positive effect of income on a household's propensity to invest confirms that access to capital and financial resources plays an essential role in a household's efficiency investment decision. Targeting access to capital measures or incentive payments on households with low income that likely face liquidity constraints may increase the effectiveness of these policies. Moreover, we find the effect of home ownership on a household's propensity to invest most pronounced. This result confirms that split incentives present a considerable barrier to energy efficiency improvements. Households that rent their homes are less likely to invest. However, considering the fact that tenants are often not allowed to make investment decisions without the property owner's permission, targeting tenants with energy efficiency policies would probably not increase their investment propensity and would, thus, have a negative effect on the policy outcome. Policies to overcome split incentives could instead target property owners, e.g., through efficiency standards for rented properties.

5. Conclusion

Our empirical findings show–unsurprisingly–that income and ownership status reveal the clearest trends in explaining households' energy efficiency investments. This corresponds with our initial hypotheses, which we derived from the theoretical investment model. Policy makers and modellers could potentially use these readily observable household characteristics to account for heterogeneity in policy design. However, two things are worth noting. First, the magnitude of the trends we find is limited. Differences between groups of households account for, at most, single digit percentage points, which questions the economic significance of the results. Secondly, before designing targeted policies, the additional costs should be balanced with the expected benefits. Given the magnitude and insecurity, and especially the strong situational impact on the magnitude and direction of the average effects we found in our meta-analysis, it is uncertain whether any eventual benefits of more targeted policies would outweigh the additional costs of implementation. It is, therefore, questionable whether targeted policy measures really are a valid policy option beyond small and obvious areas of application. Indeed, simpler policy measures, such as carbon taxes, may in many instances generate the same effect at lower cost.

Acknowledgements

Catharina Wiese and Geraldine Henningsen are indebted to the 'SAVE-E' project, which was funded by the 'Innovation Fund Denmark' (grant number: 4106-00009B).

Declarations of interest

None.

References

Aaronson, S., Cajner, T., Fallick, B., Galbis-Reig, F., Smith, C. L., Wascher, W., 2014. Labor force participation: Recent developments and future prospects. Tech. Rep. 2014-64, Finance and Economics Discussion Series Divisions of Research & Statistics and Monetary Affairs Federal Reserve Board, Washington, D.C.

Abeliotis, K., Nikolaou, N., Sardianou, E., 2011. Attitudes of Cypriot consumers on the ownership of household appliances: the case of the city of Limassol. International Journal of Consumer Studies 35 (2), 132–137.

Achtnicht, M., Madlener, R., 2014. Factors influencing German house owners' preferences on energy retrofits. Energy Policy 68, 254–263.

Akhtar, N., 2017. Assessing determinants of consumers' energy conservation behavior in Pakistan. Master's thesis, Capital University of Science and Technology, Islamabad.

Alberini, A., Bigano, A., Boeri, M., 2014. Looking for free riding: Energy efficiency incentives and Italian homeowners. Energy Efficiency 7 (4), 571–590.

Allcott, H., Greenstone, M., 2012. Is there an energy efficiency gap? Journal of Economic Perspectives 26 (1), 3–28.

Allcott, H., Greenstone, M., May 2017. Measuring the welfare effects of residential energy efficiency programs. NBER Working Paper 23386.

Allcott, H., Mullainathan, S., Taubinsky, D., 2014. Energy policy with externalities and internalities. Journal of Public Economics 112, 72–88.

Allen, S., Dietz, T., McCright, A. M., 2015. Measuring household energy efficiency behaviors with attention to behavioral plasticity in the United States. Energy Research and Social Science 10, 133–140.

Ameli, N., Brandt, N., 2015. Determinants of households' investment in energy efficiency and renewables: evidence from the OECD survey on household environmental behaviour and attitudes. Environmental Research Letters 10 (4), 044015.

Andor, M., Gerster, A., Sommer, S., 2016. Consumer inattention and decision heuristics: The causal effects of energy label elements. No. F05-V2 in Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Experiments. ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg.

Aravena, C., Riquelme, A., Denny, E., 2016. Money, comfort or environment? Priorities and determinants of energy efficiency investments in Irish households. Journal of Consumer Policy 39 (2), 159–186.

Baldini, M., Trivella, A., Wente, J. W., 2018. The impact of socioeconomic and behavioural factors for purchasing energy efficient household appliances: A case study for Denmark. Energy Policy 120, 503–513.

Barr, S., Gilg, A. W., Ford, N., 2005. The household energy gap: Examining the divide between habitual- and purchase-related conservation behaviours. Energy Policy 33, 1425–1444.

Becker, B., Wu, M.-J., 2007. The synthesis of regression slopes in meta-analyses. Statistical Science 22, 414–429.

Berger, S., Graham, N., Zeileis, A., 2017. Various versatile variances: An object-oriented implementation of clustered covariances in R. Tech. Rep. 2017-12, Working Papers in Economics and Statistics, Research Platform Empirical and Experimental Economics, Universität Innsbruck.

Blasch, J., Filippini, M., Kumar, N., 2017a. Boundedly rational consumers, energy and investment literacy, and the display of information on household appliances. Resource and Energy Economics In press.

Blasch, J., Filippini, M., Kumar, N., Cruz, A. L. M., 2017b. Investment literacy and choice of electric appliances: The impact of educational programs and online support tools.

Bollinger, B., Gillingham, K., 2012. Peer effects in the diffusion of solar photovoltaic panels. Marketing Science 31 (6), 900–912.

Borenstein, M., Hedges, L. V., Higgins, J. P. T., Rothstein, H. R., 2010. A basic introduction to fixed-effect and random-effects models for meta-analysis. Research Synthesis Methods 1, 97–111.

Braun, F. G., 2011. Technological change and energy - an empirical assessment of innovation and adoption. Ph.D. thesis, Technical University Berlin.

Brechling, V., Smith, S., 1994. Household energy efficiency in the UK. Fiscal Studies 15 (2), 44–56.

Brounen, D., Kok, N., Quigley, J. M., 2013. Energy literacy, awareness, and conservation behavior of residential households. Energy Economics 38, 42–50.

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.

Burlinson, A. C., 2017. The energy efficiency paradox, split-incentives and affordability: the elephant in England's residential sector. Ph.D. thesis, Warwick Business School.

Busic-Sontic, A., Czap, N. V., Fuerst, F., 2017. The role of personality traits in green decision-making. Journal of Economic Psychology 62, 313–328.

Busic-Sontic, A., Fuerst, F., 2017. The personality profiles of early adopters of energy-efficient technology. SOEP Papers on Multidisciplinary Panel Data Research 924, Berlin.

Charlier, D., 2015. Energy efficiency investments in the context of split incentives among French households. Energy Policy 87, 465–479.

Cirman, A., Mandič, S., Zorić, J., 2013. Decisions to renovate: Identifying key determinants in Central and Eastern European post-socialist countries. Urban Studies 50 (16), 3378–3393.

Collins, M., Curtis, J. A., 2017. Identification of the information gap in residential energy efficiency: How information asymmetry can be mitigated to induce energy efficiency renovations. ESRI Working

Paper 558, Dublin.

Das, R., Richman, R., Brown, C., 2018. Demographic determinants of Canada's households' adoption of energy efficiency measures: observations from the households and environment survey, 2013. Energy Efficiency 11 (2), 465–482.

Dato, P., 2018. Investment in energy efficiency, adoption of renewable energy and household behavior: Evidence from OECD countries. Energy Journal 39 (3), 213–244.

Datta, S., Filippini, M., 2016. Analysing the impact of energy star rebate policies in the US. Energy Efficiency 9 (3), 677–698.

De Groote, O., Pepermans, G., Verboven, F., 2016. Heterogeneity in the adoption of photovoltaic systems in Flanders. Energy Economics 59, 45–57.

Di Maria, C., Ferreira, S., Lazarova, E., 2010. Shedding light on the light bulb puzzle: The role of attitudes and perception in the adoption of energy efficient light bulbs. Scottish Journal of Political Economy 57 (1), 48–67.

Dieu-Hang, T., Grafton, R. Q., Martinez-Espineira, R., Garcia-Valinas, M., 2017. Household adoption of energy and water-efficient appliances: An analysis of attitudes, labelling and complementary green behaviours in selected oecd countries. Journal of Environmental Management 197, 140–150.

Doucouliagos, C., Paldam, M., 2006. Aid effectiveness on accumulation: A meta study. Kyklos 59, 227–254.

Dubin, J. A., Henson, S. E., 1988. The distributional effects of the federal energy tax act. Resources and Energy 10, 191–212.

Durham, C. A., Colby, B. G., Longstreth, M., 1988. The impact of state tax credits and energy prices on adoption of solar energy systems. Land Economics 64 (4), 347–355.

Eagly, A. H., Wood, W., 1994. The handbook of reserach synthesis. Russell Sage Foundation, New York, Ch. Using research synthesis to plan future research, pp. 485–500.

Ferguson, M. R., 1993. Energy-saving housing improvements in Canada (1979–82): A nested logit analysis. Environment and Planning A 25 (5), 609–625.

Friedman, C., Becker, N., Erell, E., 2018. Retrofitting residential building envelopes for energy efficiency: motivations of individual homeowners in Israel. Journal of Environmental Planning and Management 61 (10), 1805–1827.

Frondel, M., Vance, C., 2013. Heterogeneity in the effect of home energy audits: Theory and evidence. Environmental and Resource Economics 55 (3), 407–418.

Fujii, E. T., Mak, J., 1984. A model of household electricity conservation behavior. Land Economics 60 (4), 340–351.

Gamtessa, S. F., 2013. An explanation of residential energy-efficiency retrofit behavior in Canada. Energy and Buildings 57, 155–164.

Gans, W. L., 2012. The role of prices and information in residential energy consumption and investment behaviour. Ph.D. thesis, University of Maryland.

Gillingham, K., Harding, M., Rapson, D., 2012. Split incentives in residential energy consumption. Energy Journal 33 (2), 37–62.

Gillingham, K., Newell, R., Palmer, K., 2009. Energy efficiency economics and policy. Tech. rep., Resources for the Future.

Gillingham, K., Palmer, K., 2013. Bridging the energy efficiency gap: insights for policy from economic theory and empirical analysis. Tech. rep., Resources for the Future.

Gillingham, K., Tsvetanov, T., 2018. Nudging energy efficiency audits: Evidence from a field experiment. Journal of Environmental Economics and Management 90, 303–316.

Goto, H., Goto, M., Sueyoshi, T., 2011. Consumer choice on ecologically efficient water heaters: Marketing strategy and policy implications in Japan. Energy Economics 33 (2), 195–208.

Grösche, P., Schmidt, C. M., Vance, C., 2013. Identifying free-riding in home renovation programs using revealed preference data. Jahrbücher für Nationalökonomie und Statistik 233 (5–6), 600–618.

Hamilton, I. G., Summerfield, A. J., Shipworth, D., Steadman, J. P., Oreszczyn, T., Lowe, R. J., 2016. Energy efficiency uptake and energy savings in English houses: A cohort study. Energy and Buildings 118, 259–276.

Harrison, G. W., Lau, M. I., Williams, M. B., 2002. Estimating individual discount rates in Denmark: A field experiment. American Economic Review 92 (5), 1606 – 1617.

Hartman, R. S., 1988. Self-selection bias in the evolution of voluntary energy conservation programs. The Review of Economics and Statistics 70 (3), 448–458.

Hartman, R. S., Doane, M. J., 1986. Household discount rates revisited. Energy Journal 7 (1), 139–148.

Hasset, K. A., Metcalf, G. E., 1995. Energy tax credits and residential conservation investment: Evidence from panel data. Journal of Public Economics 57, 201–217.

Henningsen, A., Henningsen, G., 2018a. urbin: Unifying Estimation Results with Binary Dependent Variables. R package version 0.1-6.
URL `https://CRAN.R-project.org/package=urbin`

Henningsen, G., Henningsen, A., 2018b. Extracting and unifying semi-elasticities and effect sizes from studies with binary dependent variables.

Houde, S., 2014. How consumers respond to environmental certification and the value of energy information. Tech. rep., National Bureau of Economic Research.

Houtven, G. L. V., Pattanayak, S. K., Usmani, F., Yang, J.-C., 2017. What are households willing to pay for improved water access? Results from a meta-analysis. Ecological Economics 136, 126–135.

Islam, T., 2014. Household level innovation diffusion model of photo-voltaic (pv) solar cells from stated preference data. Energy Policy 65, 340–350.

Jaffe, A. B., Stavins, R. N., 1994. The energy paradox and the diffusion of conservation technology. Resource and Energy Economics 16 (2), 91–122.

Jakob, M., 2007. The drivers of and barriers to energy efficiency in renovation decisions of single-family home-owners. CEPE Working Paper 56, Center for Energy Policy and Economics.

Jappelli, T., 1990. Who is credit constrained in the US economy? The Quarterly Journal of Economics 105 (1), 219–234.

Johnson-Carroll, K. J. A., Brandt, J. A., Olson, G. I., 1987. Factors that influence energy-conservation alterations in Oregon households. Housing and Society 14 (2), 111–129.

Karlin, B., Davis, N., Sanguinetti, A., Gamble, K., Kirkby, D., Stokols, D., 2014. Dimensions of conservation exploring differences among energy behaviors. Environment and Behavior 46 (4), 423–452.

Kesternich, M., 2010. What drives WTP for energy efficiency when moving? Evidence from a Germany-wide household survey. Zew discussion papers 11-004, Zentrum für Europäische Wirtschaftsforschung (ZEW).

Ledesma-Rodriguez, R., 2014. The role of ethnicity and education in energy efficient technology adoption. Ph.D. thesis, Georgetown University.

Leelakulthanit, O., 2014. The factors affecting the adoption of LED lamps. International Business and Economics Research Journal (iber) 13 (4), 757–768.

Leicester, A., Stoye, G., 2013. People or places? Factors associated with the presence of domestic energy efficiency measures in England. Working Paper W13/14, Institute for Fiscal Studies (IFS).

Long, J. E., 1993. An econometric analysis of residential expenditures on energy conservation and renewable energy sources. Energy Economics 15 (4), 232–238.

Lyons, A. C., 2003. How credit access has changed over time for US households. The Journal of Consumer Affairs 37 (2), 231–255.

Martínez-Espiñeira, R., García-Valiñas, M. A., Nauges, C., 2014. Households' pro-environmental habits and investments in water and energy consumption: Determinants and relationships. Journal of Environmental Management 133, 174–183.

McCoy, D., Lyons, S., 2017. Unintended outcomes of electricity smart-metering: trading-off consumption and investment behaviour. Energy Efficiency 10 (2), 299–318.

Meier, H., Tode, C., 2015. How technological potentials are undermined by economic and behavioural responses: The treatment effect of endogenous energy efficiency measures. EWI Working Paper 15/04, Köln.

Mendelsohn, R., 1977. Empirical evidence on home improvements. Journal of Urban Economics 4 (4), 459–468.

Michelsen, C. C., Madlener, R., 2012. Homeowners' preferences for adopting innovative residential heating systems: A discrete choice analysis for Germany. Energy Economics 34 (5), 1271–1283.

Miller, K. H., Colantuoni, F., Cargo, C., 2014. An empirical analysis of residential energy efficiency adoption by housing types and occupancy. In: AAEE Annual Meeting, Minneapolis.

Mills, B., Schleich, J., 2010a. What's driving energy efficient appliance label awareness and purchase propensity? Energy Policy 38 (2), 814–825.

Mills, B., Schleich, J., 2012. Residential energy-efficient technology adoption, energy conservation, knowledge, and attitudes: An analysis of European countries. Energy Policy 49, 616–628.

Mills, B. F., Schleich, J., 2009. Profits or preferences? Assessing the adoption of residential solar thermal technologies. Energy Policy 37 (10), 4145–4154.

Mills, B. F., Schleich, J., 2010b. Why don't households see the light? Explaining the diffusion of compact fluorescent lamps. Resource and Energy Economics 32 (3), 363–378.

Min, S.-H., Lim, S.-Y., Yoo, S.-H., 2017. Consumers' willingness to pay a premium for eco-labeled LED TVs in Korea: A contingent valuation study. Sustainability 9 (5), 814.

Murray, A. G., Mills, B. F., 2011. Read the label! Energy Star appliance label awareness and uptake among US consumers. Energy Economics 33 (6), 1103–1110.

Nair, G., Gustavsson, L., Mahapatra, K., 2010. Factors influencing energy efficiency investments in existing Swedish residential buildings. Energy Policy 38 (6), 2956–2963.

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.

Neveu, A. R., Sherlock, M. F., 2016. An evaluation of tax credits for residential energy efficiency. Eastern Economic Journal 42 (1), 63–79.

Newell, R., Siikamäki, J., 2013. Nudging energy efficiency behavior: The role of information labels. Journal of the Association of Environmental and Resource Economists 1(4), 555 – 598.

Newell, R., Siikamäki, J., 2015. Individual time preferences and energy efficiency. American Economic Review: Papers & Proceedings 105(5), 196–200.

Noonan, D. S., Hsieh, L.-H. C., Matisoff, D., 2015. Economic, sociological, and neighbor dimensions of energy efficiency adoption behaviors: Evidence from the US residential heating and air conditioning market. Energy Research and Social Science 10, 102–113.

O'Doherty, J., Lyons, S., Tol, R. S. J., 2008. Energy-using appliances and energy-saving features: Determinants of ownership in Ireland. Applied Energy 85 (7), 650–662.

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.

Palmer, K., Walls, M., O'Keeffe, L., 2015. Putting information into action: What explains follow-up on home energy audits? Tech. Rep. DP 15-34, RFF.

Pon, S., Alberini, A., 2012. What are the effects of energy efficiency incentives? evidence from the us consumer expenditure survey. In: Energy Challenge and Environmental Sustainability, 12th IAEE

European Conference, September 9-12, 2012. International Association for Energy Economics.

Powers, T. L., Swan, J. E., Lee, S.-D., 1992. Identifying and understanding the energy conservation consumer: A macromarketing systems approach. Journal of Macromarketing 12.2, 5–15.

Qiu, Y., Colson, G., Grebitus, C., 2014. Risk preferences and purchase of energy-efficient technologies in the residential sector. Ecological Economics 107, 216–229.

R Core Team, 2018. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
URL `https://www.R-project.org/`

Ramos, A., Labandeira, X., Löschel, A., 2016. Pro-environmental households and energy efficiency in Spain. Environmental and Resource Economics 63 (2), 367–393.

Reynolds, T., Kolodinsky, J., Murray, B., 2012. Consumer preferences and willingness to pay for compact fluorescent lighting: Policy implications for energy efficiency promotion in Saint Lucia. Energy Policy 41, 712–722.

Rowlands, I. H., Scott, D., Parker, P., 2003. Consumers and green electricity: Profiling potential purchasers. Business Strategy and the Environment 12 (1), 36–48.

Sahari, A., 2017. Electricity prices and consumers' long-term technology choices: Evidence from heating investments. Working Paper 95, VATT Institute for Economic Research.

Sardianou, E., 2007. Estimating energy conservation patterns of Greek households. Energy Policy 35, 3778 – 3791.

Sardianou, E., Genoudi, P., 2013. Which factors affect the willingness of consumers to adopt renewable energies? Renewable Energy 57, 1–4.

Scasny, M., Urban, J., 2009. Household behaviour and environmental policy: Residential energy efficiency. OECD.

Schleich, J., Gassmann, X., Faure, C., Meissner, T., 2017. Determinants of household adoption of energy efficient technologies in europe: Focussing on preferences for risk, time and losses. Briskee project report D 3.3, Grenoble Ecole de Management.

Schwarz, P., Herron, M., Depken, C., 2014. How would carbon pricing affect purchases of energy-efficient appliances? The case of refrigerators. SSRN Electronic Journal.

Scott, S., 1997. Household energy efficiency in Ireland: A replication study of ownership of energy saving items. Energy Economics 19 (2), 187–208.

Shen, J., 2012. Understanding the determinants of consumers' willingness to pay for eco-labeled products: An empirical analysis of the China environmental label. Journal of Service Science and Management 5 (1), 87–94.

Smiley, R., 1979. The levels and determinants of household insulation activity. Energy 4 (6), 1087–1098.

Song, G. B., 2008. Spatial analysis of participation in the Waterloo residential energy efficiency project.

Master's thesis, University of Waterloo.

Sopha, B. M., Klockner, C. A., Hertwich, E. G., 2011. Adopters and non-adopters of wood pellet heating in Norwegian households. Biomass and Bioenergy 35 (1), 652–662.

Stanley, T., 2001. Wheat from chaff: Meta-analysis as quantitative literature review. The Journal of Economic Perspectives 15 (3), 131–150.

Stanley, T., Jarrell, S., 1989. Meta-regression analysis: A quantitative method of literature surveys. Journal of Economic Surveys 3, 161–170.

Stern, P. C., October 1992. What psychology knows about energy conservation. American Psychologist 47 (10), 1224–1232.

Stolyarova, E., 2016. Rénovation énergétique de l'habitat en France: analyse microéconométrique du choix des ménages. Ph.D. thesis, L'Université de recherche Paris Sciences et Lettres.

Testa, F., Cosic, A., Iraldo, F., 2016. Determining factors of curtailment and purchasing energy related behaviours. Journal of Cleaner Production 112, 3810–3819.

Trotta, G., 2018a. The determinants of energy efficient retrofit investments in the English residential sector. Energy Policy 120, 175–182.

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

Tsvetanov, T., Segerson, K., 2014. The welfare effects of energy efficiency standards when choice sets matter. Journal of the Association of Environmental and Resource Economists 1 (1/2), 233–271.

Viechtbauer, W., 2010. Conducting meta-analyses in R with the metafor package. Journal of Statistical Software 36 (3).

Walsh, M. J., 1989. Energy tax credits and housing improvement. Energy Economics 11 (4), 275–284.

Ward, D. O., Clark, C. D., Jensen, K. L., Yen, S. T., Russell, C. S., 2011. Factors influencing willingness-to-pay for the energy star® label. Energy Policy 39 (3), 1450–1458.

Welsch, H., Kühling, J., 2009. Determinants of pro-environmental consumption: The role of reference groups and routine behavior. Ecological Economics 69 (1), 166–176.

Wilson, C., 2008. Understanding and influencing energy efficient renovation decisions. Ph.D. thesis, University of British Colombia.

Yang, S., Zhao, D., 2015. Do subsidies work better in low-income than in high-income families? Survey on domestic energy-efficient and renewable energy equipment purchase in China. Journal of Cleaner Production 108, 841–851.

Yue, T., Long, R., Chen, H., 2013. Factors influencing energy-saving behavior of urban households in Jiangsu province. Energy Policy 62, 665–675.

Zeileis, A., 2004. Econometric computing with HC and HAC covariance matrix estimators. Journal of Statistical Software 10 (11), 1–17.

Zhou, H., Bukenya, J. O., 2016. Information inefficiency and willingness-to-pay for energy-efficient technology: A stated preference approach for China energy label. Energy Policy 91, 12–21.

AppendixA. Tables and figures

AppendixA.1. Further empirical evidence for heterogeneity in household energy efficiency investment behaviour

Table A.12 summarises further empirical evidence of heterogeneity in households' energy efficiency investments, which we could not include in our meta-analysis due to methodological constraints or limitations on data availability.

Column (1) and (2) define the study under consideration and the country of origin of the studied data. Column (3) describes the type of investment decision that each study investigates. Activity level "0" represents minor investments, mainly considering investment behaviour with respect to energy-efficient light bulbs. Activity level "1" refers to investments of a medium size, e.g., appliances. Activity level "2" corresponds to large retrofit investments, which include envelope renovations, solar panels, and heating systems. Column (4) indicates the sample size of the analysis. Columns (5)-(9) show the estimated coefficient of regression of a household's decision to invest in energy efficiency on the characteristics income, age, education, household size and home ownership, which are identified by the studies under consideration. A positive (negative) coefficient, indicating higher (lower) propensity to invest in energy efficiency, is represented by "+" ("−"). "∅" marks the case where a study does not address one or more of the respective determinants. The values in parenthesis show the t-statistics for the estimates, where bold font indicates statistical significance. Given the coefficients and standard errors, we computed the t-values when a study did not directly report them. "NA" indicates that t-values were unobtainable or unsuitable for the applied methodology. These cases also include studies with categorical estimates (frequently used for the determinants income, age and education), which implies two issues: First, non-linear effects, which we indicate by "+/−" and second, different t-values for each category, which we report as "NA" because finding a weighted average was not possible due to missing summary statistics. A bold font "NA" again indicates statistical significance, as reported in the studies.

Studies that apply multiple models, i.e., consider different subgroups or dependent variables, appear in multiple rows. We provide further information on these and all other studies in the Online Appendix.

Table A.12: Further Evidence for Heterogeneity in Household Energy Efficiency Investment Behaviour

Study	**Country**	**Activity level**	**N**	**Income**	**Age**	**Education**	**Household size**	**Home ownership**
Achtnicht and Madlener (2014)	Germany	2	379	+ **(-61.69)**	− **(-6.15)**	− (0.11)	∅	∅
		2	379	+ **(-4.75)**	− **(-2.05)**	+ **(1.86)**	∅	∅
Akhtar (2017)	Pakistan	1	404	− NA	− NA	− NA	∅	∅
Barr et al. (2005)	UK	0/1/2	1265	+ **NA**	+ **NA**	+ **NA**	− **NA**	+ **NA**
Busic-Sontic et al. (2017)	UK	2	1581	− NA	− **NA**	+ NA	∅	∅
Busic-Sontic and Fuerst (2017)	Germany	2	2948	− NA	− **NA**	+ NA	∅	∅
		2	2939	+ **NA**	− **NA**	+ **NA**	∅	∅
Charlier (2015)	France	2	16 111	+ NA	+ **(4.98)**	∅	∅	+ **(10.20)**
Charlier (2013)	France	0/2	16 780	+/− NA	+/− NA	+/− **NA**	∅	+ **(2.23)**
		0/2	16 780	+/− NA	+/− NA	+ **NA**	∅	+ (1.56)
De Groote et al. (2016)	Belgium	2	8471	+ **(10.75)**	+ **NA**	− **NA**	+ **NA**	+ **(3.85)**
Dubin and Henson (1988)	USA	2	688	+ **(9.47)**	∅	∅	∅	∅
Ferguson (1993)	Canada	2	450	+ **(2.81)**	+ **(3.08)**	∅	∅	∅
Friedman et al. (2018)	Israel	2	451	+ (0.50)	− **(−1.68)**	− (−0.35)	+ (1.51)	− (−1.30)
Goto et al. (2011)	Japan	1	841	+ NA	+ **NA**	∅	− NA	∅
Grösche et al. (2013)	Germany	2	2128	+ (0.3)	∅	∅	∅	∅
		2	2128	− (-1.44)	∅	∅	∅	∅
		2	2128	+ (0.89)	∅	∅	∅	∅

Table A.12: Further Evidence for Heterogeneity in Household Energy Efficiency Investment Behaviour

Study	**Country**	**Activity level**	**N**	**Income**	**Age**	**Education**	**Household size**	**Home ownership**
		2	2128	+ (0.17)	∅	∅	∅	∅
Hartman and Doane (1986)	USA	2	507	+ **(5.35)**	− **(-4.26)**	∅	∅	+ **(4.00)**
Hartman (1988)	USA	2	658	∅	∅	∅	∅	+ **(-3.10)**
Houde (2014)	USA	1	49279	+ **NA**	+ **NA**	+/− **NA**	− **NA**	∅
		1	76115	+ **NA**	+ **NA**	+/− **NA**	− **NA**	∅
		1	76115	+/− NA	+/− NA	+/− NA	+ **NA**	∅
Islam (2014)	Canada	2	298	∅	− (−0.64)	+/− NA	∅	∅
Karlin et al. (2014)	USA	0/1/2	540	+ **NA**	+ **NA**	+ **NA**	∅	+ **NA**
Leelakulthanit (2014)	Thailand	0	555	+ (1.76)	0 (0)	− (−0.51)	∅	∅
Long (1993)	USA	2	5871	+ **(8.02)**	+ **(2.49)**	∅	− (−1.42)	∅
Mendelsohn (1977)	USA	2	5539	+ **(4.32)**	+/− NA	∅	∅	∅
		2	5539	+ **(2.28)**	+/− NA	∅	∅	∅
Miller et al. (2014)	USA	0/1/2	11115	+/− NA	∅	+ NA	+ (0.75)	+ **(19.81)**
Mills and Schleich (2012)	EU and Norway	1	4915	∅	∅	+ **NA**	∅	∅
		1	4915	∅	∅	+ **NA**	∅	∅
Min et al. (2017)	Korea	1	1000	+ **(4.00)**	+ **(3.76)**	+ **(3.08)**	∅	∅
Nair et al. (2010)	Sweden	0/1/2	1045	+ **NA**	− **NA**	+ **NA**	∅	∅
O'Doherty et al. (2008)	Ireland	1	23526	+ **(10)**	+/− **NA**	∅	∅	+ **NA**

Table A.12: Further Evidence for Heterogeneity in Household Energy Efficiency Investment Behaviour

Study	**Country**	**Activity level**	**N**	**Income**	**Age**	**Education**	**Household size**	**Home ownership**
Olsthoorn et al. (2017)	EU	2	6265	+ **(2.50)**	+ (0.77)	− (−0.13)	− **(−4.62)**	∅
Powers et al. (1992)	USA	2	690	+ **(2.68)**	− (−0.67)	+ **(2.48)**	− (−0.63)	∅
Reynolds et al. (2012)	Saint Lucia	0	264	+/− **NA**	+/− **NA**	∅	∅	∅
		0	264	+/− **NA**	+/− NA	∅	∅	∅
Rowlands et al. (2003)	Canada	0	466	+ **NA**	− **NA**	+ **NA**	∅	∅
Sardianou and Genoudi (2013)	Greece	2	150	+ **(3.93)**	+ **(3.46)**	+ **(3.04)**	∅	+ (0.84)
Scott (1997)	Ireland	2	1200	∅	∅	+/− **NA**	∅	∅
		2	1200	∅	∅	+ **NA**	∅	∅
Shen (2012)	China	1	3000	+ **(1.79)**	− **(−3.65)**	+ **(1.68)**	∅	∅
Smiley (1979)	USA	2	1049	+ **NA**	− **NA**	∅	∅	∅
Song (2008)	Canada	2	5717	+ **NA**	+ **(2.00)**	− **(−3.00)**	∅	∅
Sopha et al. (2011)	USA	2	960	− **NA**	− **NA**	− **NA**	∅	∅
Stolyarova (2016)	France	2	17618	+ **NA**	+ **NA**	∅	+ **NA**	+ **NA**
		2	17618	− **NA**	− **NA**	∅	+ **NA**	+ **NA**
		2	14861	+/− NA	+ NA	∅	+ NA	+/− **NA**
		2	1350	− NA	0 NA	∅	+ **NA**	− NA
		2	1350	− **NA**	− NA	∅	+ **NA**	− NA
Testa et al. (2016)	Italy	0/1	198	+ (0.42)	− (−0.90)	− (−0.49)	∅	∅

Table A.12: Further Evidence for Heterogeneity in Household Energy Efficiency Investment Behaviour

Study	**Country**	**Activity level**	**N**	**Income**	**Age**	**Education**	**Household size**	**Home ownership**
Ward et al. (2011)	USA	1	355	− (-0.18)	+ **(-5.51)**	− (-0.37)	∅	∅
Wilson (2008)	Canada	2	295	+ **NA**	− **NA**	∅	∅	∅
Yang and Zhao (2015)	China	0/1	526	− NA	+ **NA**	+ NA	∅	∅
Yue et al. (2013)	China	0/1	581	+ **NA**	− **NA**	+ **NA**	∅	∅
Zhou and Bukenya (2016)	China	1	1569	+/− **NA**	+ NA	+ NA	− **NA**	∅

Legend: Activity level 0 = Minor investment, 1 = Medium investment/Appliances, 2 = Major investment/Retrofit.
"+" positive correlation, "−" negative correlation, "∅" not part of the study.
"NA" t-values unobtainable or unsuitable.