Using Narratives to Infer Preferences: An Application to the Energy Efficiency Gap

Sébastien Houde[1] and Tobias Wekhof[2]

May 16, 2022

Abstract

In the transition toward a low-carbon economy, persistent market barriers may cause society to be too slow in adopting technologies; thus, identifying these barriers and their heterogeneity is key to policy design. In this paper, we use narratives, a novel approach based on unstructured text answers in surveys, to elicit the barriers to and determinants of energy-efficiency investments. Using recent advances in Natural Language Processing (NLP), we turn narratives into quantifiable metrics to rank households' barriers and determinants. We find financial motives are not the primary barriers to or determinants of energy-efficiency investments. Instead, such investments are highly opportunistic, and co-benefits, such as ecological concerns and comfort, play a predominant role. Substantial heterogeneity across the population in the type of barriers and determinants exists; however, demographics and building characteristics poorly predict heterogeneity patterns. This has important implications for targeting policies, and narratives could be a novel and effective way to implement policy targeting.

Keywords: technology adoption, energy-efficiency gap, natural language processing, policy targeting, open-ended questions

[1]Grenoble Ecole de Management, 38000, Grenoble, France, sebastien.houde@grenoble-em.com.
[2]ETH Zurich, Center of Economic Research, Zurich, Switzerland, twekhof@ethz.ch.

We would like to thank Massimo Filippini, Nina Boogen, Nilkanth Kumar, Adrian Obrist, Elliott Ash, Louis-Gaetan Giraudet, Anne-Kathrin Faust, Claudio Menn, and Andreas Meyer, in addition of numerous seminar participants. The Swiss Federal Office of Energy (SFOE) provided funding for this research under the grant SI/501886-01. SFOE was not responsible for the study design, the collection, analysis, and interpretation of data, or writing this paper. The content does not necessarily represent the official views of SFOE. All omissions and remaining errors are our responsibility.

1 Introduction

The transition toward a low-carbon economy does not only depend on new investments in technologies, but faces challenges when changing the behavior of the adopters—even if technologies are readily available, market participants are often slow in adopting them. The underlying reason is that barriers and determinants of technological adoption are complex, context specific, and change over time. In this paper, we propose a novel approach to uncover why households decide to adopt (or not) specific technologies: we ask households to speak their minds and elicit their personal narratives about barriers, determinants, and policy preferences they relate to low-carbon technologies.

We find that eliciting narratives, combined with Natural Language Processing (NLP) tools, is a powerful approach that should be added to the arsenal of researchers and policy makers alike. It allows to uncover decision-makers' rationales and complement existing non-choice- and choice-based approaches. We apply our approach to the conundrum brought by the adoption of energy-efficiency technologies. For more than 40 years, researchers and analysts have pointed out that society might be lagging behind in adopting energy-efficient technologies, a phenomenon known as the Energy Efficiency Gap (Jaffe and Stavins 1994). The core question about the ”Gap” is if there are systematic barriers and household preferences that impede the adoption of seemingly cost-effective energy-efficiency technologies. Eliciting personal narratives from households allows us to shed new light on this debate.

Using narratives, we are able to answer two related questions to help better design energy-efficiency policies in the residential sector: What are the key barriers to and determinants of investment in energy efficiency? What policies would households favor, and how are these policies linked to barriers and determinants of energy-efficiency investments? In this context, narratives not only serve to elicit barriers and determinants but also capture heterogeneity across different types of households. Narratives offer two clear advantages over typical closed-ended survey questions. First, at the respondent level, narratives elicit a narrower but more precise set of barriers and determinants. Specifically, respondents tend to focus on a few but more important topics explaining their decision making. Second, at the population-wide level, compared to closed-ended questions, narratives uncover a broader set of barriers and determinants.

Our paper makes three main contributions. First, we devise a method to extract households' preferences using narratives elicited in a large-scale survey. Our approach is easy to implement for researchers and policy-makers, scalable to large samples, and can be replicated across contexts. Second, we demonstrate how this method performs in a real-world and policy-relevant context and compare it to a benchmark of traditional closed-ended questions. Together, our first and second contributions offer a proof-of-concept that asking people to write narratives and applying NLP-tools to these texts yield rich information. Third, we contribute to the debate on the Energy Efficiency Gap. Our results highlight the complexity of the problem and the challenges policy makers face when addressing it.

The case of deep (whole-home) retrofitting illustrates why it is difficult to solve the Energy Efficiency Gap and the limitations of existing empirical approaches. Engineering estimates systematically suggest deep retrofitting is the most cost-effective way to invest in energy-efficiency. However, these calculations do not account for the possible substantial so-called hassle costs of performing such investment and the associated benefits that may occur (e.g., greater comfort). These consumer- and building-specific hassle costs and co-benefits vary over time and ultimately are determined by highly heterogeneous consumer preferences and building characteristics. Moreover, several factors that may slow down the adoption of energy-efficient technologies are not caused by a dysfunctional market (i.e., classic market failures). In contrast to market failures, these factors, *market barriers*, are normal components of markets (Sutherland 1991). Although market failures may be a rationale for policy interventions, it is less clear if that is the case for market barriers (Jaffe and Stavins 1994). Thus, understanding the barriers and determinants of energy-efficiency investments is key to designing and targeting policies.

There is a large and still-growing source of empirical literature on the barriers to and determinants of energy-efficiency investments (Cagno et al. 2013; Cattaneo 2019; Christensen et al. 2021; Gerarden et al. 2017; Gillingham et al. 2018; Schleich et al. 2016; Sorrell et al. 2004). Our approach complements the existing approaches used to study technology adoption. Under non-choice-based approach, analysts will typically construct a survey with well-defined options of barriers and determinants they think households might face (e.g., Hrovatin and Zorić 2018; Lee 2015; Trotta 2018). Under choice-based methods, barriers and determinants are inferred from choices, stated or revealed. Hypothetical choice situations can be constructed to have a perfectly controlled environment, which allows estimating choice models and inferring underlying preferences (e.g., Alberini et al. 2013; Banfi et al. 2008; Blasch et al. 2019; Fischbacher et al. 2021; Schleich et al. 2019). Naturally occurring observational (e.g., Kahn et al. 2014) or experimental data (e.g., Allcott and Greenstone 2017; Asensio and Delmas 2016; Gilbert and Zivin 2014) can also be collected. These data, together with a model that provides the micro-foundations for the mapping between preferences and observed choices, are used to infer preferences and, incidentally, particular barriers and determinants. A common problem arising with non-choice-based as well as choice-based approaches is that preferences can be highly heterogeneous. For non-choice-based elicitation procedures, the analysts must take a strong stance ex ante on which barriers and determinants to focus, which makes them prone to inducing an elicitation bias. For choice-based methods, highly heterogeneous preferences translate into an identification problem: it might be too difficult to find the right model that explains the data.

Using narratives to elicit preferences can overcome these challenges. It is also deceptively simple and can be exceptionally powerful for understanding a wide range of economic phenomena (Shiller 2020). Eliciting narratives involves asking people with an open-ended question what they think and letting them speak (or write) their minds. In practice, this approach should yield very noisy, hard-to-interpret, qualitative data. However, recent advances in NLP allowed us to turn narratives into quantifiable metrics to elicit proxies for household preferences and market barriers.

Open-ended questions have been used in social sciences research since the 1940s, but systematic applications on a large scale have not been seen (Krosnick 1999).[1] With advances in NLP methods, Roberts et al. (2014) suggested revisiting the concept of open-ended survey questions.[2] In line with newly emerging literature, open-ended questions combined with NLP have been used to elicit opinions on important societal issues such as immigration (Bursztyn et al. 2020), climate change (Tvinnereim and Fløttum 2015), and macroeconomic shocks (Andre et al. 2021, 2019), as well as to elicit policy preferences (Ferrario and Stantcheva 2022; Stantcheva 2020). We contribute to this nascent literature in economics by using narratives to explain the drivers of technology adoption and policy preferences in the environmental context. Our approach is hereby cross-cutting across fields in social sciences. We provide a method that allows to classify the text-answers into topics and explain both revealed and stated preferences. In addition, we validate the narratives from the open-ended questions by comparing them to a benchmark of mirroring closed-ended questions.

Our results suggest financially related barriers and determinants are important, but they may not be necessarily the dominating ones. The narratives we obtained from the open-ended questions tell us energy-efficiency investments are highly opportunistic: households that do not invest in energy-efficiency often believe their house is already energy efficient enough, and households that do invest do so when a particular building technology becomes obsolete. The heterogeneous vintage of buildings and technologies are thus important. However, this could be a normal market barrier policy makers may have little leverage to influence.

[1]With small samples, open-ended questions are used on a regular basis, e.g., (Kathlene and Martin 1991; Kolko and Neumark 2010; Langbein 2002; Schneider et al. 2006)

[2]The majority of the literature uses NLP with already existing text data, e.g., public comments (Dokshin 2021), newspaper articles (Belmonte and Rochlitz 2019; Benesch et al. 2019), congressional speech (Gentzkow et al. 2019), or Twitter-texts (Baylis 2020; Morales 2021).

The role of co-benefits, namely comfort and the ecological footprint, is important. It is also the most malleable with respect to the elicitation procedure: using closed-ended questions, these two co-benefits dominate. In contrast, with narratives, those two co-benefits were found, in fact, to be much less prevalent investment determinants. This inconsistency suggests respondents' top-of-mind awareness combined with the effort to express decision making in an open-ended question render this elicitation procedure not only narrower but also more precise. From a policy targeting standpoint, it has important implications.

With respect to other categories of barriers and determinants, we find some but not overwhelmingly strong support for behavioral barriers, in spite of receiving recent attention in the literature (Gillingham et al. 2018; Harding and Hsiaw 2014; Schleich et al. 2016; Yeomans and Herberich 2014). Our survey instrument was especially designed to capture some behavioral dimensions of decision making, such as energy-related financial literacy, that are correlated with some determinants.

Finally, we find narratives are also useful in eliciting preferences for policy interventions because there is a consistent mapping between policy preferences and determinants of energy-efficiency investments. Altogether, our results suggest that policy interventions should be targeted toward the opportunistic component of energy-efficiency decision and non-financial attributes should be prioritized. According to our elicited narratives, more information and generous subsidies might be more wishful thinking than strong determinants of decisions.

The remaining parts of this paper are organized as follows: in Section 2, we revisit the taxonomy used to classify the barriers and determinants of energy-efficiency investments, which is at the source of the Energy Efficiency Gap. Next, we present the data and our empirical context in Section 3, and then show in Section 4 the main results about the elicitation of barriers, determinants, and policy preferences. We build on these results in Section 5, where we focus on the heterogeneity of barriers/determinants and how to use this heterogeneity for policy targeting. This is followed by a concluding section.

2 A Taxonomy of Barriers and Determinants

Several frameworks have been proposed to identify and categorize the barriers and determinants of energy-efficiency investments. Sorrell et al. (2004) proposed one particularly influential taxonomy that distinguished between three different perspectives: economic, behavioral, and organizational.

The economic perspective considers rational utility-maximizing agents as the benchmark to understand agents' choices regarding adopting energy-efficient technologies. The behavioral perspective departs from this purely neo-classical framework and considers different manifestations of bounded rationality, which have also been referred to as behavioral failures in the literature (Gillingham et al. 2009), or internalities (Allcott and Sunstein 2015). Finally, the organizational perspective considers the role of institutions with which agents interact. Those could be institutions governments have very little ability to transform, such as values and culture, or others they have considerable influence over, such as fiscal, competition, and regulatory policies.

Although this taxonomy has been proven useful when navigating the different explanations at the source of the Energy Efficiency Gap, a more precise categorization is needed for the purpose of policy design. Our taxonomy is motivated by a utility-based model of investment in which four types of barriers interact: market, non-market, financial, and behavioral barriers.[3]

Consider the case of a household that is deciding whether to invest in an energy-saving technology. To fix ideas, we can consider the case of a whole-home (deep) retrofit, where e_{jt} is the quantity of energy consumed at time t if there is an investment, denoted by $j = 1$, or no investment, denoted by $j = 0$. A deep retrofit influences energy usage, but it is also associated with other benefits and so-called hidden costs. We denote co-benefits (good) by

[3] In our framework, organizational barriers are not explicitly modeled, but their impact on households' decisions can be accounted for through non-market barriers and determinants that manifest as hassle costs.

g_j and hidden costs (bad) by b_j. Examples of co-benefits are improvements in indoor air quality, thermal comfort, or aesthetics, to name a few. Hidden costs could be increases in technology complexity (and hence maintenance) or other inconveniences caused by a deep retrofit. We consider that g_j and b_j have mostly non-market values, but they are nonetheless important for households. Households trade off the capital cost of the investment, denoted c_j where $c_0 = 0$ (no investment case), with the discounted sum of the energy savings: $\sum_t \rho^t \cdot p_t^e \cdot (e_{1t} - e_{0t})$, which is the function of the price of energy, p_t^e and the discount factor ρ. Other than energy, households consume a numeraire good, y. Income is a function of an hourly salary, which varies as a function of how much leisure time and non-work related activities are allocated by the consumer. We denote t as the total time endowment available to do hourly work and l as the time allocated to other activities. A deep retrofit takes time to plan and implement. Those are the hassle costs that can be modelled as an increase in l if $j = 1$.[4] Finally, households have other sources of income, denoted as I and preferences are quasi-linear with respect to the numeraire good y.

Household's utility for each investment option, $j = \{0, 1\}$ is thus given by

$$V_{jt} = U(e_{jt}, g_j, b_j|\theta) + y \tag{1}$$

where utility is maximized subject to the budget constraint:

$$c_j + \sum_t \rho^t \cdot p_t^e \cdot e_{jt} + y \leq w \cdot (t - l_j) + I \tag{2}$$

The function $U(\cdot)$ is a utility function that varies with the vector of parameters θ. Together, $U(\cdot)$ and θ characterize households' preferences. Finally, the discount factor, ρ can also be considered a household-specific preference.

[4] To simplify the notation, we include l only in the budget constraint, not in the utility function. An increase in l takes away wage-related income and thus always decreases utility.

The decision to invest is thus determined by the following inequality:

$$U(e_{1t}, g_1, b_1|\theta) - U(e_{0t}, g_0, b_0|\theta) \geq c_1 + \sum_t \rho^t \cdot p_t^e \cdot (e_{1t} - e_{0t}) + w \cdot (l_1 - l_0) \tag{3}$$

The expression on the left-hand side (LHS) corresponds to the net non-market benefits of investing in energy efficiency, which may include comfort, air quality, noise, and other amenities that a deep retrofit may affect. On the right-hand side (RHS), we have the different cost components. First, we have the capital cost, c_1, the discounted energy savings, $\sum_t \rho^t \cdot p_t^e \cdot (e_{1t} - e_{0t})$, and the hassle costs, $w \cdot (l_1 - l_0)$. A household will invest when the LHS is larger than the RHS.

This framework can be used to summarize the important strands of research on the Energy Efficiency Gap and the different economic and behavioral barriers that have been investigated.[5] Based on Sorrell et al.'s (2004) economic, behavioral, and organizational perspectives, our taxonomy distinguishes between behavioral, financial, non-market, and market barriers.

Behavioral barriers

The empirical research has mainly focused on determining whether households correctly perceive the energy savings component of the net costs of investment. Allcott and Greenstone (2012) used the term γ to scale $\sum_t \rho^t \cdot p_t^e \cdot (e_{1t} - e_{0t})$, where γ corresponds to any type of investment inefficiencies. Some of these inefficiencies may be behavioral and thus be considered as internalities (Allcott and Sunstein 2015), such as inattention and biased beliefs about energy prices, to name a few. These behavioral barriers can, however, be confounded with neo-classic market barriers such as different access to credit or time discounting preferences. The γ parameter thus encompasses behavioral and market barriers, which are internal to household decision making (Cagno et al. 2013; Myers 2020; Schleich et al. 2016).

[5] As discussed previously, organizational barriers and determinants can be partly accounted for via their impact on hassle costs.

Financial barriers

A second set of economic barriers focuses on the role of external financially related factors. The price of energy might be too low, the costs of investment too high, subsidies might not be generous enough, and/or there could exist various financial distortions. In our framework, the role of financially related barriers operates through the price variables and interacts with the marginal utility of money (i.e., sensitivity to price) that is embedded in the vector preference parameters: θ.

Non-market barriers

A third subcategory of economic barriers consists of the non-market components of the investment, the LHS in Equation 3, which includes the various co-benefits and hidden costs of such investments. The literature has pointed out specific co-benefits could be important, and contingent valuation methods have been primarily used to investigate those (Jakob 2006; Ürge-Vorsatz et al. 2014). External organizational constraint factors could affect the hassle costs on the RHS, which we also consider a form of a non-market barrier.

Market barriers

Finally, there are classic market barriers that are normal components of well-functioning markets. These barriers could arise because of heterogeneity in building stock, technologies, and/or preferences. For policy makers, understanding this heterogeneity could allow them to target and tag energy-efficiency policies to increase their cost effectiveness (Allcott et al. 2015). This point has been long recognized, and several studies have investigated different dimensions of heterogeneity in the decision to adopt energy-efficient technologies (e.g., Jakob 2007).

As we can see, there is a wide range of explanations for the Gap. Table 1 summarizes the four important categories of barriers we consider in this paper.

Table 1: Proposed Taxonomy of Barriers to Energy Efficiency Investments

Type of Barrier	Description	Examples
Market	Normal components of markets that impact decisions	Heterogeneity in building stock, heterogeneity in building/household expected lifetime
Non-market	Non-market goods or bads that impact decisions	Comfort, hassle costs (including costs due to bureaucracy)
Financial	Variables related to prices and costs	Price of energy, interest rate, investment cost
Behavioral	Elements of households' decision-making	Bounded rationality, energy- and investment-literacy, myopia

3 Data and Environment

To elicit narratives related to energy-efficiency investments, we conducted a large survey of owners of single-family houses living in the canton of Zurich, Switzerland. The survey was specifically designed to investigate the decision of whether to invest in energy-efficient technologies and services.

The survey had several modules. The first module collected information on past and future energy efficiency-related behaviors: whether households performed or intended to perform retrofits and the type of retrofits. We used these different behaviors to distinguish takers and non-takers of energy-efficiency investments. The goal of the remaining modules was then to determine the components of the households' decisions that influenced these behaviors. One of the most important modules focused on different types of barriers and determinants. To elicit these components, we used open-ended questions, which provided narratives about specific aspects of the decision-making process. We also used structured closed-ended questions that closely mirrored the open-ended questions. Our goal was to provide a benchmark to open-ended questions. Another module focused on preferences for different types of energy-efficiency policies. Finally, the remaining modules elicited household and building characteristics, including some related to the decision-making process, such as financial and energy-related literacy. We used these variables to investigate heterogeneity along several dimensions.

3.1 Implementation

To recruit participants, we collaborated with the Statistical Office of the Swiss Canton of Zurich. We sent personalized invitation letters by postal mail to a random sample of homeowners. The letter contained a short description of our research project and a link to an online survey. Household respondents had to type the link in a web browser to complete the survey.

We stratified the sample according to the following rules: only single-family homes, year of construction prior to 1990, and 50% with renovation permits during the last five years; there was a wide range for tenant-age and the number of tenants. We also stratified to target homeowners who adopted the main certification for energy-efficient buildings in Switzerland: the Minergie certification.

In the Canton of Zurich, there are 127,950 single-family homes; 10,737 of those have applied for renovation permits between 2014 and 2019. The Statistical Office of the Canton Zurich sampled this population and sent out 16,700 letters February 3, 2020, on our behalf. A household member could complete the online survey until March 13, 2020. Of the 16,700 letters sent, the response rate was high: 3,471 respondents started the survey, which is a response rate of 20.8%. Furthermore, there was a completion rate of 82% with an average response time of 30 minutes.

Although our sampling strategy targeted a population of homeowners of single-family houses, a small number of respondents did not fall into this category. There were 161 (renting) tenants and a small number of respondents living in an apartment (n = 23). Those observations are excluded from our analysis.

3.2 Sample Composition: Classifying Household Types

We used past and intended energy efficiency-related behaviors to classify households into two broad segments. First, we distinguished homeowners who adopted the Swiss energy-efficiency certification for buildings, Minergie. Our stratified sampling strategy ensured we observed a large number of those households (n = 524). We used these households for a separate study and therefore omitted these observations for the main analysis. Second, we distinguished households depending on if they performed an energy-efficiency retrofit in the past five years or planned to do so within the next five years. Based on this criterion, households fell into two mutually exclusive categories:

- **Non-Takers**: households which did not perform energy-efficiency investments in the past and who were not planning to do one in the future (483 observations, 22% of the sample).

- **Takers**: households that either did perform energy-efficiency investments in the past five years or were planning to do at least one in the next five years (1,748 observations, 78% of the sample).

Table 2 shows the different household types and how they differ with respect to key building characteristics, demographics, and psychographics. A detailed description of the variables can be found in the Appendix. With respect to building characteristics, both takers and non-takers of retrofits did not differ in building age and floor size. However, non-takers reported a higher estimated rental value for their home. Moreover, non-takers had a slightly higher proportion of oil and gas heating, which is, however, the most common form of heating for both groups. Takers, on the other hand, had a higher proportion of electric heat pumps.

Both groups had roughly the same income levels. However, non-takers tended to be older, were a higher proportion of pensioners, and were less likely to be living with children. Regarding the psychographics, most variables do not differ, except for the share of respondents who attended economics classes during their education, which is higher for takers.[6]

[6] In the subsequent analysis, to avoid limiting the sample size, we did not use all the variables. Specifically, the variables not used were for the number of rooms, gardens, heating modes, and solar photovoltaic (PV) devices. Moreover, we excluded information about respondents' spouses because this would not allow us to analyze single-person households. We also reduced the employment measure to the dummy: its value is 1 if the respondent is a pensioner and zero otherwise.

Table 2: Summary Statistics by Household Type

Variable	All	Non-Takers	Takers
Building Characteristics			
Building Age (years)	56.35	57.33	56.08
Floor Size (m^2)	168.52	167.54	168.78
# Rooms	5.74	5.60	5.78
% Garden	98.00	97.80	98.10
Rental Value (CHF/month)	3831.23	4050.27	3772.20
% Oil/Gas heating	49.60	52.50	48.80
% Heat Pump	32.50	26.00	34.20
% other heating	18.00	21.50	17.00
% Solar PV	18.60	13.30	20.00
Demographics			
Income	12509.89	12479.80	12517.97
Age	58.81	61.37	58.13
% Male	77.90	79.50	77.50
% Children	48.00	42.40	49.50
% University Degree	60.20	61.90	59.70
% University Degree Spouse	39.20	37.00	39.70
% Employed (fulltime)	33.80	31.10	34.50
Pensioner	34.30	38.30	33.20
Other employment	32.00	30.60	32.30
Spouse: Employed (fulltime)	16.10	15.70	16.20
Spouse: Pensioner	27.70	32.30	26.60
Spouse: other employment	56.20	51.90	57.20
Allergies	19.90	21.10	19.60
Psychographics			
Energy Literacy	3.76	3.72	3.76
% Took Econ	46.70	43.50	47.60
% Math Proficient	45.60	47.30	45.20
Energy Saving Score (/3)	2.29	2.25	2.31
% Donated Enviroment	55.00	53.40	55.40
Happiness Score (/4)	2.11	2.17	2.10

Note: This table presents the summary statistics for the entire survey sample, with the exception of respondents who live in a Minergie-certified building. The sample contains a total of 2,231 observations, out of which 483 (22%) are non-takers and 1748 (78%) are takers. Takers are defined as respondents who performed an energy-efficiency retrofit either in the past five years or plan to do so within the next five years.

3.3 Eliciting Energy Efficiency Narratives

We used open-ended questions to infer respondents' reasoning concerning their decision-making process pertaining to an energy-efficiency retrofit. We separately elicited barriers from the non-takers and determinants from takers. The structure of the questions was similar for both barriers and determinants.

When asking open-ended questions, it is important to provide some context to the participants and indicate why such questions are asked. We thus structured our survey by first presenting the following short introduction explaining the rationale for asking open-ended questions:

The reasons for energy efficiency retrofits are complex and different for each household. We would like to learn more about why you decided (or not) to renovate. What was important to you? Were there alternatives? Your response will help us to better understand how we can support energy efficiency retrofits.[7]

After providing context, we then asked the following question:

Describe the reasons why you decided (or not) to carry out energy efficiency retrofits. Please write a short text of about 4 sentences.

A key element of our survey design to assess the validity of our elicitation procedure for narratives is we also asked closed-ended questions at an earlier point in the survey. These were multiple choice questions that mirror the topics we expected respondents would state in their answers to the open-ended questions. For barriers, we listed 17 potential barriers discussed in the literature of the Energy Efficiency Gap. Those options were presented to non-takers who selected the barriers important to them. For the determinants, we established a list of eight potential determinants, and takers selected which were important to them.

[7] The survey was conducted in German. In the paper, our own translations of the original German questions and answers are presented.

At the end of the survey, in addition to barriers and determinants, we also extracted narratives about policy preferences. We first presented a short introduction:

The building sector has one of the greatest potentials for energy savings in Switzerland. One of the goals of our project is to improve public programs for energy-efficient building and renovation.

This introduction was then followed by the open-ended question:

We would now like to ask for your opinion. What approaches do you think the public sector should promote to encourage energy-efficient construction and renovation for households living in Switzerland?

Overall, implementation of the open-ended questions worked very well. By inspecting a large number of responses, we found respondents provided meaningful answers. The length of the answers to the three open-ended questions varied on average between 19 and 24 words. The standard deviation is about the size of these averages, and some respondents wrote very long and detailed answers.[8]

The questions on barriers and determinants were mandatory to all non-Minergie participants. As previously mentioned, only non-takers were asked about the barriers, and only takers were asked about the determinants. An overview of the summary statistics for the open-ended questions is given in Table 3. For these two open-ended questions, we observed an attrition rate of only 1.5% (i.e., upon having to answer one of these particular questions, only 1.5% decided to stop the survey altogether). The question on policy recommendations was not mandatory and was placed at the end of the survey. Furthermore, this question was presented to all respondents. We observed a higher, but still relatively low, attrition rate: 8.5%. Self-selection of respondents is thus not a major concern.

[8]The median number of words was between 12 and 21, and depending on the questions, the 90% percentile is between 43 and 47.

For each question, we extracted the entire text corpus and counted the number of unique words. The question related to determinants of energy-efficiency investments has the largest number of unique words and also the most words suitable for topic extraction. The words we identified for topic extraction serve as the basis of our main analysis.

Table 3: Summary Statistics: Open-Text Answers

Open-Text Answers	Barriers	Determinants	Policy Recommendations
# answers	463	1758	2482
% attrition	1.5	1.5	8.5
mean # words	24	21	19
median # words	21	17	12
90 percentile # words	47	44	43
sd # words	17	18	24
total # unique words	2528	5677	3193
# words after pre-processing	1371	3086	1912
total # words used for topics	215	629	478

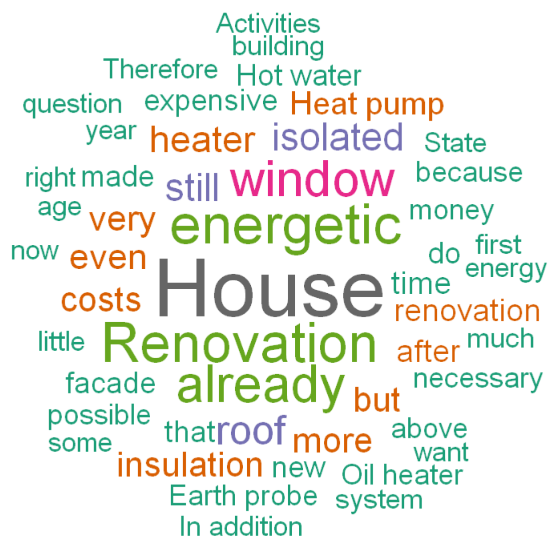
Note: The questions on barriers and determinants were mandatory to all non-Minergie participants. The question on policy recommendations was open to all respondents but not mandatory to complete the survey. We calculated the attrition for each open-ended question by comparing the number of respondents to this particular question versus the response rate to the last mandatory question that preceded it. For barriers and determinants, all nouns, verbs, adverbs, and adjectives with at least four characters were used. We only considered words with a length of at least 4 characters (with exception of the words ”CO2” and ”old”). For the policy questions, we only selected words that occurred at least twice in the corpus (except the word ”PV”, for photovoltaic).

Figure 1 shows a wordcloud that contains the 50 most used words for each of the 3 questions.[9] The wordclouds show that in the answers a small number of words tend to occur very frequently and dominate the wordclouds. For instance, the barriers are described using most frequently the words ”renovation”, ”energetic” and ”house”. The occurrence of these words is not surprising, given that the question was about energetic renovation for houses and respondents described why they did not perform such a retrofit. For this reason, the prominent words in the wordcloud are of little help to identity major topics in the text-answers. To do so, many of the less frequently occurring words are more interesting. For example the words ”expensive” and ”costs” for the barriers, which indicate that the particular respondents did not perform a retrofit for financial reasons, are only at the margins of the

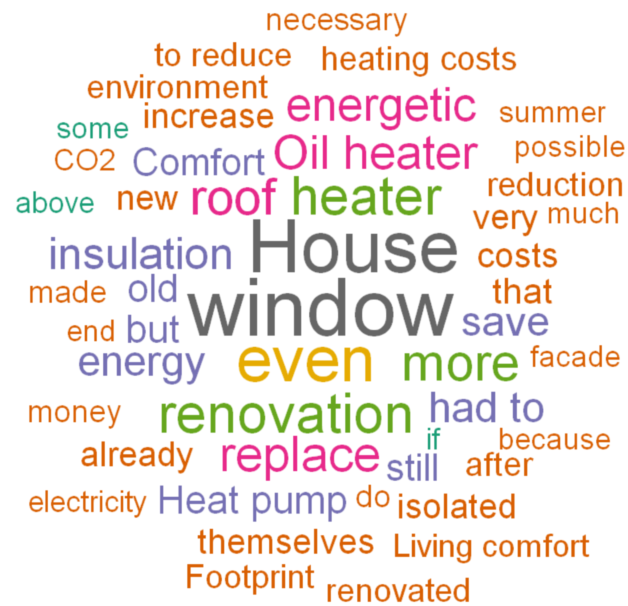
[9] The words selected for the wordcloud were from the original corpus of words in German. They were then translated in English for the rendering on Figure 1.

wordcloud. In order to obtain a more understandable description of the narratives, it is necessary to identify all the scattered words that can identify a certain topic.

Figure 1: Wordclouds for Barriers, Determinants and Policy Recommendations



"Barriers"



"Determinants"

"Policy Recommendations"

Note: Each wordcloud contains the 50 most used words per open-ended answer. Words with a larger font were used more frequently by respondents. All words were initially in German language and translated into English using Google-translator.

4 Uncovering Barriers, Determinants and Policy Preferences

The main idea of our analysis consists in classifying the text-answers using a dictionary based approach. This means that each topic is defined by a set of words; if an answer contains any of these words, it will be classified into the respective topic. Our approach allows to create dictionaries with a large number of words and with a high precision. Our analysis proceeded in three steps. First, we extracted topics from the open questions using NLP tools. Second, we ranked the topics based on their relative frequency. Third, we compared rankings obtained with open-ended versus closed-ended questions.[10]

To elicit topics from narratives in open-ended questions, we first extracted all the words from the respondents' answers and classified them as nouns, adjectives, verbs, or adverbs using the spaCy open-source software library for NLP (Honnibal et al. 2020). In this step, the algorithm only considers the lemmatized version of each word (e.g., ”good” is kept while ”better” will no longer be considered). The reason is to reduce the dimensionality of the text corpus to facilitate the subsequent classification step. After reducing the text to the lemmas, the spaCy algorithm applies part-of-speech tagging where all lemmatized words are marked as either noun, adjective, verb or adverb. In a next step, we used word embeddings to map each remaining word to a distance metric, whenever possible. Word embeddings are matrices that have a column of values for each word that indicate the relative semantic distance between words (e.g., the distance between the words heating and oil is smaller than the distance between heating and pencil). For a pair of words, it is thus possible to calculate their relative distance using the cosine similarity. To construct such a matrix for our corpus of unique words, we mapped all the words present in the answers to the pre-defined German fastText word embedding vectors (Grave et al. 2018). This pre-processing step reduces the

[10] The resulting topics differ significantly from the topics extracted with the standard algorithm for text classification used in the literature: the Latent Dirichlet Allocation (LDA). The reason is that with our method we are able to identify multiple topics per answer, while LDA tends to allocate only one major topic to each response and several other topics with a very low probability. Moreover, LDA tends to focus on the most frequently occurring words, e.g. ”renovation”, ”energetic” and ”house” for the barriers, which will distort the topics because these words are not relevant to identify barriers to retrofits.

number of unique words by about one third. However, most of the dropped words occur only once or twice in the entire text corpus and have little value for the subsequent clustering step.

In a third step, we clustered nouns, adjectives, verbs, and adverbs separately using k-means clustering and the measure of relative semantic distance. We performed a semantic clustering to ease the subsequent topic extraction (we chose the number of clusters so each cluster contained between 10 and 30 words).

In the fourth and final step, we extracted topics. We assigned each word, when possible, to one of the existing topics from the corresponding closed-ended question (each word can only belong to a single topic). This step was not automated and was performed manually.[11] During the topic extraction process, we also discovered additional topics, which we then added to the list of predefined topics of the closed-ended question. Of all the unique words, we could assign between 15% to 20% of the words to a topic. Finally, after assigning words to topics, we labelled the text answers by automatically searching each text answer for the presence of the set of words that define a topic.

The same idea was applied to the question with barriers, but different keywords and topics were used. To give an example of an answer to the barrier question: "Other renovations were more important and urgent. Everything at the same time would not be financially affordable," two keywords — *affordable* and *financially* — both were selected to classify that answer in the topic *too expensive*. We proceeded in the same way for the policy question with the following answer: "good, neutral consulting, subsidies for energy-saving renovations." In

[11] There are various algorithms that can be used to automatically extract topics from text in an unsupervised way, such as the Latent Dirichlet Allocation (LDA) from MALLET (McCallum 2002), Structural Topic Model (Roberts et al. 2019), LDA2Vec (Moody 2016) or Top2Vec (Angelov 2020). We experimented with these various methods and found they tend to deliver topics difficult to interpret with the text answers we obtained for our open-ended questions. One of the shortfalls of those automated, unsupervised, clustering algorithms is they cluster the text answers without considering the question we asked the respondents. Moreover, the clusters obtained from those algorithms are sensitive to various model parameters. In comparison, supervised text classification relies on training the algorithm on a training set that usually was classified by humans. The algorithm then "learns" to replicate the human classification. Our approach is therefore more closely related to supervised NLP methods in which the initial classification criteria are defined by the researcher.

this example, the respondent used the keyword *consulting*, which is classified in the topic *more information*, and the keyword *subsidies*, which belongs to the *subsidy* topic. An overview of the most important words that were used to define topics can be found in the appendix in the form of wordclouds (Figure 2 for the two major barriers and Figure 3 for the four major determinants).

Using the approach outlined here, we ranked the barriers and determinants to energy-efficiency investments by tabulating topic frequency. We then contrasted the rankings with those obtained from the closed-ended questions. Compared to the closed-ended questions, the answers from the open-ended questions were not always consistent: a respondent could check the box for a certain topic, but not mention it in the text answer and vice versa. It could be however, that the text-classification was inaccurate. For this reason, we checked all inconsistent answers manually for the major topics and corrected the classification whenever necessary. In most of the cases, the initial classification was correct, which meant that the topic shares only changed marginally. We present a more detailed analysis of the consistency in the Appendix.[12]

4.1 Barriers

Table 4 presents the results for the barriers. From both the open-ended and closed-ended questions (Column 1 and Column 2, respectively), the most important barrier for non-takers is the statement that their home is already energy efficient. Whether this is a belief or a fact about the house the respondents live in, we cannot know for sure. Information about building characteristics in Table 2, however, provides us some indications that beliefs, particularly biased beliefs, might be partly at play. We found two important building characteristics that determine a house's energy-efficiency potential (i.e., vintage and type of heating system) are not drastically different between takers and non-takers. The fact households consider their

[12] Note that our survey was not designed to specifically study the underlying reasons for the inconsistencies between open- and closed-ended questions. Chang et al. (2021) observe a similar inconsistency between closed- and open-ended survey responses regarding opinions on US trade policies.

house is already energy efficient is a statement about personal preferences and thus can be considered a normal component of markets (i.e., a market barrier). However, one could argue there is also a behavioral component to this barrier. For instance, if it was the case that biased beliefs were important, information campaigns and subsidized audits could be justified to address those.

Regarding the consistency between the open-ended and closed-ended questions, we observed this barrier has a higher frequency when we focus on narratives: 47% of respondents wrote about this, but only 37% selected this option as a potential barrier in the closed-ended question. It remains, nonetheless, the most important barrier for both open-ended and closed-ended questions.

The cost of a retrofit and the fact it might be too expensive is the second most-important barrier. From the narratives, we observed a slightly higher percentage of people who mentioned this barrier. Although, financial barriers have been the centerpiece of energy-efficiency programs and result in offering generous subsidies, fewer than a quarter of non-takers mentioned this as an important barrier. In light of evidences that show a high rate of infra-marginal consumers taking advantage of energy-efficiency subsidies Boomhower and Davis (2014), our finding further supports the notion that policy makers could shift their primary focus away from this financial barrier.

In the narratives, the older age of the respondents is the third most important barrier. This is not a topic we a priori listed in the closed-ended question. In hindsight, we acknowledge this can be an important barrier. The fact homeowners anticipate the remaining period they will reside in their houses is too short when rationalizing a long-term investment is also a normal component of markets. That is, heterogeneous life expectancy is a market barrier.

We also observed several barriers were not mentioned in the answers to the open-ended question, but some were selected with a certain frequency with the closed-ended question. There are several potential explanations for this. When provided with a predefined list of options, it is almost costless for respondents to select an additional option. A greater diversity of barriers thus emerges from the closed-ended question, but cheap talk might be at play. To the contrary, for an open-ended question, writing about an additional barrier requires much more effort, but open-ended questions might then induce more truthfulness in eliciting the most important barrier(s) each non-taker has faced. For instance, aesthetics and the difficulties associated with renovating old buildings are two barriers that emerged from the closed-ended questions with a certain importance, but there was little mention of them in the narratives.

Table 4: Barriers to Energy-Efficient Retrofits

Barriers	Type of Barrier	Open	Closed
The building is already energy-efficient	Market	49.7	37.3
Too expensive	Financial	23	21.1
Old age	Market	7.2	0.0
Too complicated	Non-Market	6.4	9.7
Aesthetics	Market	2.5	7.9
Difficulties due to historic building	Market	2.5	6.0
Expert recommended against	Behavioral	1.7	1.7
Other priorities	Non-Market	1	0.0
Difficulties in applying for permits	Non-Market	0.8	3.1
Difficulties in obtaining financing	Financial	0.6	3.9
Craftsman recommended against	Behavioral	0.6	2.3
Hassle	Non-Market	0.4	0.0
Architect recommended against	Behavioral	0.2	1.7
I did not think of it	Behavioral	0	4.3
Planning to move	Market	0	6.2
Lack of information	Behavioral	0	8.3
The investment too risky	Behavioral	0	2.1
Leaving the house during the renovation	Non-Market	0	5.6
It is difficult to find experts or materials	Non-Market	0	4.3
Bad experiences with previous renovations	Non-Market	0	1.9

Note: Households that did not undertake a retrofit in the past five years and did not plan to do so in the next five years were asked to choose among several options for the reasons they decided against a retrofit. Later in the survey, we asked the same respondents in an open-ended question for the reasons they did not do a retrofit. We then classified the text answers into the same categories as the closed-ended answers and added several new topics, such as old age.

4.2 Determinants

Turning to the determinants of energy-efficiency renovations in Table 5, we first observe the elicitation procedure plays an even more important role. The ranking of the topics from the narratives is very different than the ones obtained using the closed-ended question.

From the narratives, we learn the main determinant of an energy-efficiency investment is a particular building technology was at its end of life. Unless firms strategically manipulate obsolescence, it is a normal component of the market. Therefore, this is not a rationale for a policy intervention. The importance of obsolesce as a determinant mirrors the fact the main barrier to investment is households consider fewer energy-efficiency improvements can be done. Taken together, this suggests investments in energy-efficient technologies are opportunistic in nature.

The answers to the closed-ended question suggests the most important determinants are comfort and reduction of the ecological footprint. Those determinants are also mentioned in the answers to the open-ended question, but they occur with a much lower frequency. Nonetheless, these non-market benefits associated with energy-efficiency investments are among the main determinants extracted from the narratives.

There is also a large discrepancy between the answers for open-ended and closed-ended questions regarding the role of financial-related determinants. One quarter of respondents mentioned this determinant in the narratives, but 36.7% selected this option in the closed-ended question. Moreover, the impact of energy efficiency on resale value received little attention in the open-ended question, but it was selected by as much as 25.2% of respondents in the closed-ended question.

Overall, the results send a clear message with respect to the reasons for making an energy-efficiency investment: non-market benefits, financial considerations, and obsolescence are all important. The respective importance of each of those determinants is, however, malleable and depends on the elicitation procedure. Again, this has important implications for targeting energy-efficiency policies. For instance, if we were to leverage the fact that co-benefits, such as comfort and ecological motives, are important in households' decisions, it would be difficult to systematically target those determinants using a single elicitation procedure.

Table 5: Determinants of Energy-Efficiency Retrofits

Determinants	Type of Determinant	Open	Closed
Replace broken elements	Market	42.6	57.7
To reduce my ecological footprint	Non-Market	29.6	68.9
Increase comfort	Non-Market	26.1	68.4
To save money	Financial	21.4	36.7
Increase resale value	Financial	4.8	25.2
Regulatory	Non-Market	2.9	0.0
Increase size of home	Market	2.6	0.0
Recommended by another expert	Behavioral	1.8	6.2
Aesthetics	Non-Market	1.6	0.0
Safety	Non-Market	1	0.0
Recommended by an architect	Behavioral	0.4	4.9
Recommended by a craftsman	Behavioral	0.3	4.1

Note: Households that performed a retrofit in the past five years or do not plan to do so in the next five years were asked to choose among several options for why they decided to perform a retrofit. Later in the survey, we asked the same respondents in an open way why they decided to do a retrofit. We then classified the text answers into the same categories as the closed answers and added several new topics, such as Regulatory.

4.3 Policy Preferences

In this section, we investigate the mapping between policy preferences and the most important barriers and determinants of households' energy-efficiency investment decisions. Uncovering policy preferences, especially the consistency between such preferences and the most important barriers and determinants, is key to understanding how policies should be designed and targeted. A first set of explanations we explored was the role past experience with policy measures and how general awareness of the policy landscape might shape preferences.

A first set of explanations that we explore is thus the role of past experience with policy measures and how general awareness of the policy landscape might shape preferences.

In our survey, we asked respondents about their awareness of different types of energy-efficiency policies. The four policies were: discounts on mortgage interest rates, tax exemptions or deductions, various subsidies from cantons and municipalities, and the so-called the Swiss Federal Building Program, a nationwide subsidy scheme. Respondents could choose one of the following four, mutually exclusive options for each of the policies: I was not aware of the option; I am aware of the option; I have used the option; or I intend to use the option. From these answers, we constructed indices of policy awareness and policy usage. For policy awareness, the index is constructed by creating a dummy variable for each policy, taking the value of 1 if the respondent did not answer the question, "I was not aware of the option." In a second step, the dummies for all policies were added, which means a respondent could have a maximum score of 4. Hence, the awareness measure gives an indication if a respondent is informed about a policy or made use of it. For policy usage, we proceeded similarly, except the dummy variable for each policy took the value of 1 if a respondent answered either "I have used the option" or "I intend to use the option." As for the awareness measure, the policy usage score was constructed by the sum of the dummy variables for all four policies. For awareness, non-takers had a slightly lower mean (2.69 compared to 2.87 for takers). That difference, however, is statistically significant with a t-test. Policy use significantly differed between the two groups (0.81 for the non-takers compared to 1.47 for the takers). That difference is also significant with a t-test.

In a second step, we relied on narratives to elicit policy preferences.[13] As for the other open-ended questions, we performed the topic extraction by clustering nouns, adjectives, verbs, and adverbs using word embeddings and k-means clustering. However, unlike the open-ended questions on renovation, we only selected words that occurred at least twice in the text corpus. This slight change in procedure was because we did not have a predefined list of topics from a closed-ended question. Moreover, this step considerably facilitated topic extraction.[14] An overview of the most used words for the four major topics in the form of wordclouds can be found in the appendix in Figure 4.

Table 6 presents the results for the open-ended question on policy preferences. A wide range of topics emerged from the narratives. When asked how policies could encourage energy-efficiency investments, for all types of households, the top suggestion was more generous subsidies. A greater focus on solar photovoltaic (PV) technology was the second most popular suggestion. It is interesting to note in Switzerland, energy-efficiency programs and incentives for solar PV technology are usually not combined. Households, however, would like to have more integration between those measures.

The remaining suggestions referred to providing more information, reducing bureaucracy, and favoring standards. Other topics, with smaller shares, also emerged from the narratives. Tax-related measures were discussed, but they were not a popular topic, espe-

[13] A closed-ended question for the narratives pertaining to policy preferences was not used. Our focus here was to simply extract important topics from the narratives and heterogeneity across the different types of households.

[14] Selecting words with a frequency equal to or higher than two significantly reduced the number of words and thus facilitated the topic clustering. Rarely occurring words are mainly important for very precise and small topics. Furthermore, because we did not compare the open policy question to a closed question, this level of precision was not necessary. Working with a corpus with a lower dimensionality also facilitated the initial discovery and definition of topics.

cially compared to subsidies. Although subsidy was the most popular topic, almost 65% of respondents favored other policy measures.

As with barriers and determinants, we classified all policy options proposed by the respondents in three broad categories. The first category consists of market-based instruments, which are policy options related to subsidies and taxes. The second category consists of behavioral instruments, including instruments motivated by behavioral biases, such as most notably, information provision and standards Finally, the third category consists of non-market-based policy instruments, which encompass other types of interventions such as reducing bureaucracy.

Table 6: Policy Preferences from Open-Ended Answers

Policy Preference	All	Non-Takers	Takers
More subsidy (market)	32.5	31.2	36.9
Focus PV	16.3	15.8	17.8
More information (behavioral)	16.1	15.7	17.8
Less bureaucracy (non-market)	15	14.3	17.4
Focus Heating	12.9	12.8	13.5
Standards (behavioral)	9.3	9.2	9.5
Tax deduction (market)	8.7	8.4	9.7
Pollution tax (market)	6.5	6.3	7.2
Focus on new buildings	4.8	4.9	4.1
Focus Insulation	3.6	3.8	2.9
Technology	3	3.1	2.9
Property tax (market)	1.5	1.3	2.1
Subsidy threshold	1.1	1.1	1.0
Credit (market)	0.5	0.6	0.2

Note: This table presents policy preferences obtained by classifying an open-ended answer. Keywords unique to each topic and responses that can be part of multiple topics were used in this classification.

5 Heterogeneity and Targeting

Several analysts have pointed out one way to increase the cost effectiveness of energy-efficiency policies is by implementing policy targeting and tagging (Allcott et al. 2015). In practice, this requires finding dimensions of heterogeneity that are correlated with important barriers and determinants of energy-efficiency investments. In this section, we take advantage of our rich survey data to uncover heterogeneity patterns.

To analyze how policies can be targeted, we first distinguish between takers and non-takers. In a second step, we analyze the correlation between the main barriers/determinants and the various observables, such as demographics, building characteristics, psychographics, and policy-related variables.

5.1 Heterogeneity: Takers and non-Takers

In Table 7,we present the heterogeneity between takers and non-takers using a linear probability model. The dependent variable is binary and takes the value of 1 if the respondent undertook a retrofit in the past five years or plans to do so in within the next five years. Results indicated no statistically significant difference between households in income, gender, and living with children. Takers of retrofits are younger than non-takers and tend to hold a university degree less frequently. Housing characteristics such as floor size, house age, and rental value were not statistically different between the two groups. For the psychographics, takers tended more frequently to have included economics classes in their educations. Apart from that variable, there are no statistically significant differences in psychographics between the two groups. Ceteris paribus, takers have a slightly lower policy awareness compared to non-takers, but they have a higher policy usage. There are no statistically significant differences for policy preferences between takers and non-takers. These results are in line with the intuition demonstrated in Table 2: the differences in observables between takers and non-takers are mainly due to classical market barriers.

Table 7: Linear Probability Model: Takers vs. Non-Takers

	Dependent variable: *Takers* = 1 / *Non- Takers* = 0	
	Coefficient	s.e.
Building Characteristics		
Building Age	−0.0005	(0.001)
Floor Size	−0.0001	(0.0002)
Log Rental Value	−0.052**	(0.025)
Demographics		
Log Income	0.045	(0.039)
Age	−0.006***	(0.001)
Male	−0.004	(0.027)
Children	−0.010	(0.028)
University Degree	−0.054**	(0.025)
Pensioner	0.086**	(0.037)
Psychographics		
Energy Literacy	0.011	(0.020)
Took Econ	0.058***	(0.022)
Math Proficient	−0.022	(0.022)
Energy Saving Score	0.004	(0.015)
Donated Environment	0.002	(0.021)
Happiness Score	−0.006	(0.008)
Policy Variables		
Policy awareness	−0.022**	(0.010)
Policy use	0.081***	(0.009)
Policy preference: Market	−0.002	(0.021)
Policy preference: Behavioral	−0.023	(0.023)
Policy preference: non-Market	0.021	(0.027)
Constant	1.078***	(0.367)
Observations	1,452	
R^2	0.082	

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

The dependent variable is binary and takes the value of 1 if respondents did an energy-efficiency retrofit during the past five years or plan to do so within the next five years.

5.2 Heterogeneity: Barriers

We now investigate the barriers to energy-efficiency retrofits. Table 8 presents three linear probability models, one for each major barrier elicited with the narratives. In these regression models, the dependent variable is a zero-one dummy variable that takes a value of 1 if the respondent mentioned a particular barrier in the open-ended question. The regressors are the different variable categories for demographics, building characteristics, and behaviors and policy-related variables, which we further explain.

In order to obtain more detailed information to help target policies, we included five policy variables as covariates in each regression: the index for policy awareness, the index for policy usage, and three dummy variables from the open-ended question that capture policy preferences. The first two indices are based on questions that assess how many existing policies the respondents are aware of and how many of these policies respondents have made use of or intend to use. For the policy-preference variables, we used the same classification for policy preferences as described earlier: market-based instruments (subsidies and tax deductions), behavioral instruments (such as information provision and standards), and non-market-based policy instruments (reducing bureaucracy). Then, we created a dummy variable for each of those categories taking a value of 1 if a respondent mentioned a policy option in this category and zero otherwise.

Column 1 presents the heterogeneity for the barrier the building is *already energy-efficient*. Most of the coefficients for traditional observable covariates are not statistically significant, except for the variable that measures energy literacy, which has a strong positive correlation with that barrier. However, respondents with this barrier tend to have a high degree of both policy knowledge and policy usage. In Column 2, for the financial barrier *(Expensive)*, income has a strong negative correlation. This result is intuitive: it simply implies higher-income households are less likely to express financially related issues as a barrier. In addition, these respondents have used existing policies less for retrofits. Column

3 investigates the *old age* barrier, where tenant age is significant and positive, which is again very consistent with the nature of the barrier expressed in the narratives. Here, none of the policy variables showed any statistical significance. Although there are a few variables strongly correlated with each of the main barriers, observables explain little of the overall variance. This shows the difficulty of policy targeting and tagging for policy makers. Results indicate there is heterogeneity in both policy awareness and policy usage for the three main barriers. There is, however, no particular policy preference associated with any barrier, which suggests the policy preferences are uniformly distributed over the different barriers.

Table 8: Linear Probability Model on Major Barriers of Retrofits

	Barriers		
	Already Efficient (1)	Expensive (2)	Old Age (3)
Building Age	−0.003**	0.002	0.0003
	(0.001)	(0.001)	(0.001)
Floor Size	0.001	−0.00004	−0.0004
	(0.001)	(0.001)	(0.0003)
Log Rental Value	0.045	0.160**	−0.036
	(0.068)	(0.063)	(0.036)
Log Income	0.031	−0.245**	−0.019
	(0.106)	(0.098)	(0.056)
Age	−0.001	−0.003	0.003
	(0.004)	(0.004)	(0.002)
Male	−0.053	0.121*	−0.065
	(0.077)	(0.072)	(0.041)
Children	−0.064	0.014	0.018
	(0.079)	(0.073)	(0.041)
University Degree	0.139**	−0.129**	0.043
	(0.069)	(0.063)	(0.036)
Pensioner	−0.022	−0.053	0.033
	(0.102)	(0.094)	(0.054)
Energy Literacy	0.129***	−0.001	0.023
	(0.049)	(0.046)	(0.026)
Took Econ	−0.035	0.054	0.013
	(0.061)	(0.056)	(0.032)
Math Proficient	−0.090	0.053	−0.032
	(0.060)	(0.056)	(0.032)
Energy Saving Score	−0.021	0.019	−0.026
	(0.040)	(0.037)	(0.021)
Donated	0.052	−0.045	0.048
	(0.057)	(0.052)	(0.030)
Happiness Score	0.007	0.005	−0.005
	(0.022)	(0.020)	(0.012)
Policy Variables			
Policy Awareness	0.057**	−0.022	−0.016
	(0.024)	(0.022)	(0.013)
Policy Usage	0.086***	−0.067***	−0.006
	(0.027)	(0.025)	(0.014)
Policy Market	0.036	0.005	−0.033
	(0.056)	(0.052)	(0.030)
Policy Behavioral	0.034	−0.034	−0.012
	(0.063)	(0.058)	(0.033)
Policy Non-Market	0.044	0.022	0.005
	(0.077)	(0.071)	(0.040)
Constant	−0.681	1.397	0.448
	(0.999)	(0.923)	(0.526)
Observations	298	298	298
R^2	0.167	0.115	0.091

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

Each column presents a separate linear probability model where the outcome is the respective barrier. The barrier is a binary variable that takes the value of 1 if the respondent mentioned it in the open text answer and zero otherwise.

5.3 Heterogeneity: Determinants

Turning to determinants, Table 9 presents four linear probability models, one for each major determinant of retrofits. Column 1 shows the result for the determinant *replacement of existing parts* (i.e., obsolescence). Tenant age is significant and negatively correlated with that determinant, which can be explained by the shorter period older tenants expect to live in their homes. Building age is positively correlated with that determinant, which is expected because older buildings need more frequent repairs compared to newer buildings. Moreover, these respondents tend to have a higher policy awareness but no difference in the actual use of various subsidies. The replacement determinant is also associated with a policy preference for both market-oriented and non-market-oriented policies; however, there is no difference for behavioral policies. In Column 2, we present the heterogeneity for the financial determinant *to save money*. Interestingly, both a university degree and previous donations to environmental organizations are negatively associated with that determinant. In addition, respondents with a financial determinant do not have a higher policy awareness, but they do have a higher usage of policies. This group does not have any specific policy preferences. Column 3 displays the *comfort*-related determinant. There are only a few weakly significant variables associated with that determinant, namely a negative correlation for both pensioners and floor size and a positive correlation for math proficiency. Moreover, this determinant does not seem to show any statistically significant heterogeneity with respect to their awareness, usage of policies, or policy preferences. Finally, in Column 4, the results indicate several dimensions of heterogeneity are correlated with *environmental* concerns. Both income and previous donations to environmental organizations have a strong and statistically significant association with that determinant. Similar to respondents who renovate to save money, environmental concerns are associated with a higher degree of policy usage but not with more awareness. Furthermore, environmental motivations to renovate are strongly associated with behavioral policy preferences.

Table 9: Linear Probability Model on Major Determinants of Retrofits

	Determinants			
	Replacement	Save Money	Comfort	Environmental
	(1)	(2)	(3)	(4)
Building Age	0.002***	0.0004	0.001*	−0.0001
	(0.001)	(0.001)	(0.001)	(0.001)
Floor Size	0.0004	0.00001	−0.001**	−0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log Rental Value	−0.002	−0.004	−0.016	−0.040
	(0.034)	(0.029)	(0.032)	(0.032)
Log Income	−0.054	0.075	0.033	0.114**
	(0.055)	(0.047)	(0.051)	(0.051)
Age	−0.007***	−0.002	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Male	−0.042	0.033	0.026	−0.013
	(0.038)	(0.033)	(0.035)	(0.036)
Children	−0.047	0.015	−0.022	0.005
	(0.039)	(0.033)	(0.036)	(0.037)
University Degree	0.021	−0.093***	−0.031	0.015
	(0.035)	(0.030)	(0.032)	(0.033)
Pensioner	0.016	0.024	−0.070	0.038
	(0.051)	(0.044)	(0.048)	(0.048)
Energy Literacy	0.063**	−0.007	0.008	−0.021
	(0.029)	(0.025)	(0.027)	(0.027)
Took Econ	−0.003	0.026	0.037	−0.004
	(0.032)	(0.027)	(0.029)	(0.030)
Math Proficient	−0.013	0.019	0.044	0.044
	(0.031)	(0.027)	(0.029)	(0.029)
Energy Saving Score	−0.019	−0.033*	0.028	0.029
	(0.022)	(0.018)	(0.020)	(0.020)
Donated	−0.035	−0.062**	−0.005	0.072**
	(0.030)	(0.025)	(0.028)	(0.028)
Happiness Score	−0.014	0.010	0.006	0.003
	(0.011)	(0.009)	(0.010)	(0.010)
Policy Variables				
Policy Awareness	−0.041***	0.007	0.004	0.017
	(0.015)	(0.013)	(0.014)	(0.015)
Policy Usage	−0.006	0.033***	0.014	0.035***
	(0.013)	(0.011)	(0.012)	(0.013)
Policy Market	0.087***	0.012	0.004	0.010
	(0.029)	(0.025)	(0.027)	(0.028)
Policy Behavioral	0.002	0.004	−0.008	0.079**
	(0.033)	(0.028)	(0.031)	(0.031)
Policy Non-Market	0.106***	−0.037	−0.004	−0.041
	(0.038)	(0.032)	(0.035)	(0.035)
Constant	1.125**	−0.345	−0.060	−0.660
	(0.516)	(0.441)	(0.480)	(0.486)
Observations	1,154	1,154	1,154	1,154
R^2	0.060	0.038	0.019	0.041

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

Each column presents a separate linear probability model where the outcome is the respective determinant. The determinant is a binary variable that takes the value of 1 if the respondent mentioned it in the open text answer and zero otherwise.

5.4 Targeting

Based on the insights from the heterogeneity analysis, we can draw conclusions for targeting on a broad scale between takers and non-takers of retrofits and, on a more granular scale within those groups, specific conclusions to each barrier and determinant.
Between takers and non-takers, the main difference related to targeting is a lower age for takers. Apart from age, we find no other observables policy makers could robustly use to target policies because policy awareness is actually lower for takers, and there are no significant differences in policy preferences. For this reason, we propose focusing on the specific barriers and determinants respondents mentioned in their open-ended questions' answers. By analyzing how to target specific barriers and determinants, policy makers can address the core reasons why homeowners decide for or against a retrofit. Within the two groups, we can use the results from this section to cluster respondents into groups and see if different household types emerge.

For the barriers, two types of homeowners emerge: those who do not renovate because they perceive their house already as being energy efficient and those who face financial constraints. Respondents who do not renovate because their building is already efficient do not differ in income or age from other non-takers. The main difference can be found in a higher educational level. Those respondents also have a high awareness of and experience in using policies; they do not have any particular policy preferences. For this reason, there are few options to target these homeowners with specific policies. In contrast, homeowners who did not renovate due to financial constraints have a lower income, but they also do not differ in terms of policy awareness or policy preferences, although they have less experience in using policies. It seems policy preferences do not play a role in explaining why certain consumers perform retrofits and others do not. Possibly, existing policies are not of sufficient magnitude to help overcome these barriers to retrofits.

The determinants have three major groups of interest for policy targeting: households that invest to replace parts of the building (replacers), households that see retrofits as profitable investments (money savers), and households that renovate out of ecological concerns (environmentalists). The replacers category is primarily motivated by a greater building age, a lower respondent age, and a high energy literacy. Moreover, this group has a lower awareness of existing policies and would prefer policies that reduce bureaucracy and higher subsidies. Most of the characteristics for this group are very rational given the primary motivation is to replace broken parts of the home (which is often a necessity). Even though policy awareness is low for this group, respondents do not favor more information on policies but would prefer less bureaucracy and higher subsidies. It seems respondents with this motivation renovate out of necessity and would like to facilitate this process. The second group renovates to save money and is characterized by less education and fewer donations to environmental organizations. This group also has a weakly higher income compared to others. For their retrofits, these respondents use existing policies more compared to other groups, but they do not have any particular policy preferences. Compared to the replacers group who renovate out of necessity, it seems respondents who renovate to save money act out of financial opportunity. For this reason, these homeowners use existing policies, but they do not have any particular preference about what policy makers could improve. For targeting, this group does not show any particular angle policy makers can address. The last group consists of respondents who renovated out of environmental concerns. Those respondents have a higher income and previously donated to environmental organizations. They use policies more compared to other groups and would strongly favor behavioral policies such as information campaigns and ecological standards. For policy targeting, this group is particularly interesting because those respondents do not renovate out of necessity or financial opportunity. Policy makers could target this group by providing easier access to information regarding policies.

6 Conclusions

In this paper, we propose a novel approach to elicit the barriers and determinants of energy-efficiency investments. Narratives offer a powerful way to elicit and rank important barriers and determinants of households' retrofit decisions. Our results first suggest energy-efficiency investments are highly opportunistic. Non-takers believe, rightfully or not, few opportunities for energy efficiency exist in their home. Takers primarily invest in energy efficiency out of necessity to replace old parts of the building or out of financial opportunity when they perceive the investment as profitable. The monetary aspect is also important as a major barrier because many respondents stated they face financial constraints with respect to renovation plans. However, several co-benefits of energy efficiency, mainly increased comfort, also emerged as important determinants. Finally, environmental concerns showed to be a major determinant for energy-efficiency retrofits.

A more granular analysis of barriers and determinants provided further insights into how to target energy-efficiency policies. The majority of characteristics that influence a respondent's decision to perform a retrofit are difficult to target for policy makers. For instance, the main difference between takers and non-takers is a higher tenant age for non-takers. We asked respondents about their awareness and usage of existing policies and about preferences for additional policy measures. These policy measures were particularly useful in explaining heterogeneity within the group of takers between different determinants. Based on these results, the most promising group for future policy targeting are homeowners who renovate out of environmental concerns. This group tends to have higher incomes and would favor behavioral policies consisting of information campaigns and building standards.

From a methodological standpoint, eliciting barriers and determinants with closed-ended vs. open-ended questions uncovered the difficulties of precise policy targeting. Both methods yielded broadly consistent results, but there are some important differences. If we were to target energy-efficiency policies based on closed-ended vs. open-ended questions, we might achieve a very different allocation.

References

Alberini, A., Banfi, S. and Ramseier, C.: 2013, Energy efficiency investments in the home: Swiss homeowners and expectations about future energy prices, *The Energy Journal* **34**(1).

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

Allcott, H. and Greenstone, M.: 2017, Measuring the welfare effects of residential energy efficiency programs, *NBER Working Paper* (w23386).

Allcott, H., Knittel, C. and Taubinsky, D.: 2015, Tagging and targeting of energy efficiency subsidies, *American Economic Review* **105**(5), 187–91.

Allcott, H. and Sunstein, C. R.: 2015, Regulating internalities, *Journal of Policy Analysis and Management* **34**(3), 698–705.

Andre, P., Haaland, I., Roth, C., Wohlfart, J. et al.: 2021, Inflation narratives.

Andre, P., Pizzinelli, C., Roth, C. and Wohlfart, J.: 2019, Subjective models of the macroeconomy: Evidence from experts and a representative sample, *Available at SSRN 3355356* .

Angelov, D.: 2020, Top2vec: Distributed representations of topics, *arXiv preprint arXiv:2008.09470* .

Asensio, O. I. and Delmas, M. A.: 2016, The dynamics of behavior change: Evidence from energy conservation, *Journal of Economic Behavior & Organization* **126**, 196–212.

Banfi, S., Farsi, M., Filippini, M. and Jakob, M.: 2008, Willingness to pay for energy-saving measures in residential buildings, *Energy Economics* **30**(2), 503–516.

Baylis, P.: 2020, Temperature and temperament: Evidence from twitter, *Journal of Public Economics* **184**, 104161.

Belmonte, A. and Rochlitz, M.: 2019, The political economy of collective memories: Evidence from russian politics, *Journal of Economic Behavior & Organization* **168**, 229–250.

Benesch, C., Loretz, S., Stadelmann, D. and Thomas, T.: 2019, Media coverage and immigration worries: Econometric evidence, *Journal of Economic Behavior & Organization* **160**, 52–67.

Blasch, J., Boogen, N., Daminato, C. and Filippini, M.: 2021, Empower the consumer! energy-related financial literacy and its implications for economic decision making, *Economics of Energy & Environmental Policy* **10**(2).

Blasch, J., Filippini, M. and Kumar, N.: 2019, Boundedly rational consumers, energy and investment literacy, and the display of information on household appliances, *Resource and Energy Economics* **56**, 39–58.

Boomhower, J. and Davis, L. W.: 2014, A credible approach for measuring inframarginal participation in energy efficiency programs, *Journal of Public Economics* **113**, 67–79.

Bursztyn, L., Haaland, I. K., Rao, A. and Roth, C. P.: 2020, Disguising prejudice: Popular rationales as excuses for intolerant expression.

Cagno, E., Worrell, E., Trianni, A. and Pugliese, G.: 2013, A novel approach for barriers to industrial energy efficiency, *Renewable and Sustainable Energy Reviews* **19**, 290–308.

Cattaneo, C.: 2019, Internal and external barriers to energy efficiency: which role for policy interventions?, *Energy efficiency* **12**(5), 1293–1311.

Chang, A., Ferguson, T., Rothschild, J. and Page, B.: 2021, Ambivalence about international trade in open-and closed-ended survey responses, *Institute for New Economic Thinking Working Paper Series* (162).

Christensen, P., Francisco, P., Myers, E. and Souza, M.: 2021, Decomposing the wedge between projected and realized returns in energy efficiency programs, *The Review of Economics and Statistics* pp. 1–46.

Dokshin, F. A.: 2021, Variation of public discourse about the impacts of fracking with geographic scale and proximity to proposed development, *Nature Energy* **6**(10), 961–969.

Ferrario, B. and Stantcheva, S.: 2022, Eliciting people's first-order concerns: Text analysis of open-ended survey questions, *AEA Papers and Proceedings*.

Fischbacher, U., Schudy, S. and Teyssier, S.: 2021, Heterogeneous preferences and investments in energy saving measures, *Resource and Energy Economics* **63**, 101202.

Gentzkow, M., Shapiro, J. M. and Taddy, M.: 2019, Measuring group differences in high-dimensional choices: Method and application to congressional speech, *Econometrica* **87**(4), 1307–1340.

Gerarden, T. D., Newell, R. G. and Stavins, R. N.: 2017, Assessing the energy-efficiency gap, *Journal of Economic Literature* **55**(4), 1486–1525.

Gilbert, B. and Zivin, J. G.: 2014, Dynamic salience with intermittent billing: Evidence from smart electricity meters, *Journal of Economic Behavior & Organization* **107**, 176–190.

Gillingham, K., Keyes, A. and Palmer, K.: 2018, Advances in evaluating energy efficiency policies and programs, *Annual Review of Resource Economics* **10**, 511–532.

Gillingham, K., Newell, R. G. and Palmer, K.: 2009, Energy efficiency economics and policy, *Annual Review of Resources Economics* **1**(1), 597–620.

Grave, E., Bojanowski, P., Gupta, P., Joulin, A. and Mikolov, T.: 2018, Learning word vectors for 157 languages, *Proceedings of the International Conference on Language Resources and Evaluation (LREC 2018)*.

Harding, M. and Hsiaw, A.: 2014, Goal setting and energy conservation, *Journal of Economic Behavior & Organization* **107**, 209–227.

Honnibal, M., Montani, I., Van Landeghem, S. and Boyd, A.: 2020, spaCy: Industrial-strength Natural Language Processing in Python.

Hrovatin, N. and Zorić, J.: 2018, Determinants of energy-efficient home retrofits in slovenia: The role of information sources, *Energy and Buildings* **180**, 42–50.

Jaffe, A. B. and Stavins, R. N.: 1994, The energy-efficiency gap what does it mean?, *Energy policy* **22**(10), 804–810.

Jakob, M.: 2006, Marginal costs and co-benefits of energy efficiency investments: The case of the swiss residential sector, *Energy Policy* **34**(2), 172–187.

Jakob, M.: 2007, The drivers of and barriers to energy efficiency in renovation decisions of single-family home-owners, *CEPE Working Paper* (56).

Kahn, M. E., Kok, N. and Quigley, J. M.: 2014, Carbon emissions from the commercial building sector: The role of climate, quality, and incentives, *Journal of Public Economics* **113**, 1–12.

Kathlene, L. and Martin, J. A.: 1991, Enhancing citizen participation: Panel designs, perspectives, and policy formation, *Journal of Policy Analysis and Management* **10**(1), 46–63.

Kolko, J. and Neumark, D.: 2010, Do some enterprise zones create jobs?, *Journal of Policy Analysis and Management* **29**(1), 5–38.

Krosnick, J. A.: 1999, Survey research, *Annual Review of Psychology* **50**(1), 537–567.

Langbein, L. I.: 2002, Responsive bureaus, equity, and regulatory negotiation: An empirical view, *Journal of Policy Analysis and Management* **21**(3), 449–465.

Lee, K.-H.: 2015, Drivers and barriers to energy efficiency management for sustainable development, *Sustainable Development* **23**(1), 16–25.

Lusardi, A. and Mitchell, O. S.: 2008, Planning and financial literacy: How do women fare?, *American Economic Review* **98**(2), 413–17.

Lyubomirsky, S. and Lepper, H. S.: 1999, A measure of subjective happiness: Preliminary reliability and construct validation, *Social Indicators Research* **46**(2), 137–155.

McCallum, A. K.: 2002, Mallet: A machine learning for language toolkit. http://mallet.cs.umass.edu.

Moody, C. E.: 2016, Mixing dirichlet topic models and word embeddings to make lda2vec, *arXiv preprint arXiv:1605.02019* .

Morales, J. S.: 2021, Legislating during war: Conflict and politics in colombia, *Journal of Public Economics* **193**, 104325.

Myers, E.: 2020, Asymmetric information in residential rental markets: Implications for the energy efficiency gap, *Journal of Public Economics* **190**, 104251.

Roberts, M. E., Stewart, B. M. and Tingley, D.: 2019, stm: An R package for structural topic models, *Journal of Statistical Software* **91**(2), 1–40.

Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B. and Rand, D. G.: 2014, Structural topic models for open-ended survey responses, *American Journal of Political Science* **58**(4), 1064–1082.

Schleich, J., Gassmann, X., Faure, C. and Meissner, T.: 2016, Making the implicit explicit: A look inside the implicit discount rate, *Energy Policy* **97**, 321–331.

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

Schneider, M., Elacqua, G. and Buckley, J.: 2006, School choice in Chile: Is it class or the classroom?, *Journal of Policy Analysis and Management* **25**(3), 577–601.

Shiller, R. J.: 2020, *Narrative economics*, Princeton University Press.

Sorrell, S., O'Malley, E., Schleich, J. and Scott, S.: 2004, *The Economics of Energy Efficiency: Barriers to Cost-Effective Investment*, Edward Elgar Publisher.

Stantcheva, S.: 2020, Understanding economic policies: What do people know and how can they learn, *Harvard University Working Paper* .

Sutherland, R. J.: 1991, Market barriers to energy-efficiency investments, *The Energy Journal* **12**(3).

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

Tvinnereim, E. and Fløttum, K.: 2015, Explaining topic prevalence in answers to open-ended survey questions about climate change, *Nature Climate Change* **5**(8), 744–747.

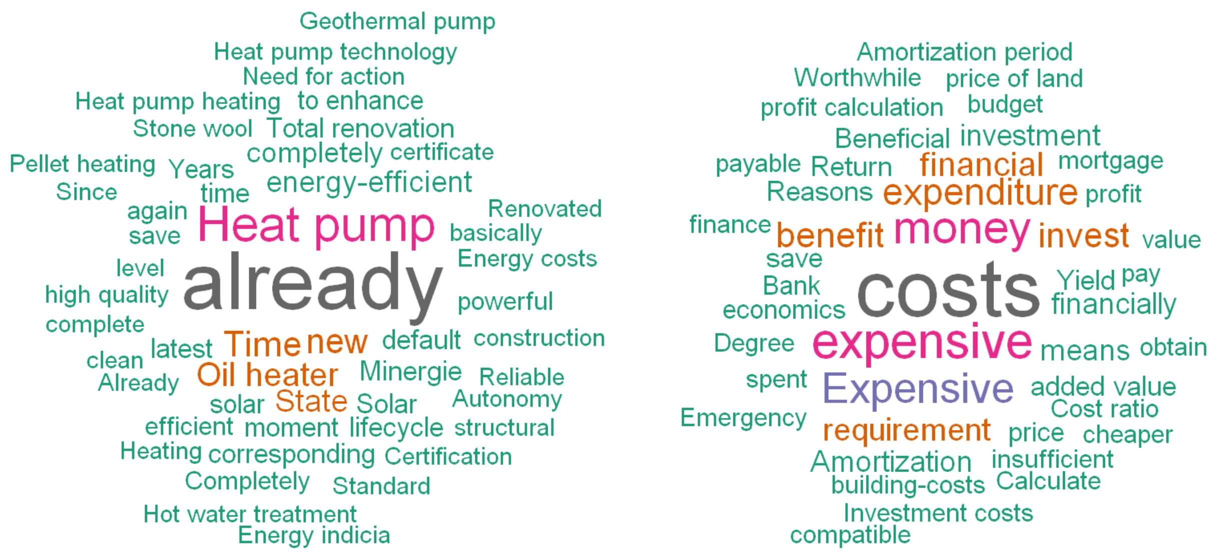
Ürge-Vorsatz, D., Herrero, S. T., Dubash, N. K. and Lecocq, F.: 2014, Measuring the co-benefits of climate change mitigation, *Annual Review of Environment and Resources* **39**, 549–582.

Yeomans, M. and Herberich, D.: 2014, An experimental test of the effect of negative social norms on energy-efficient investments, *Journal of Economic Behavior & Organization* **108**, 187–197.

7 Appendix

7.1 Most used words to define topics

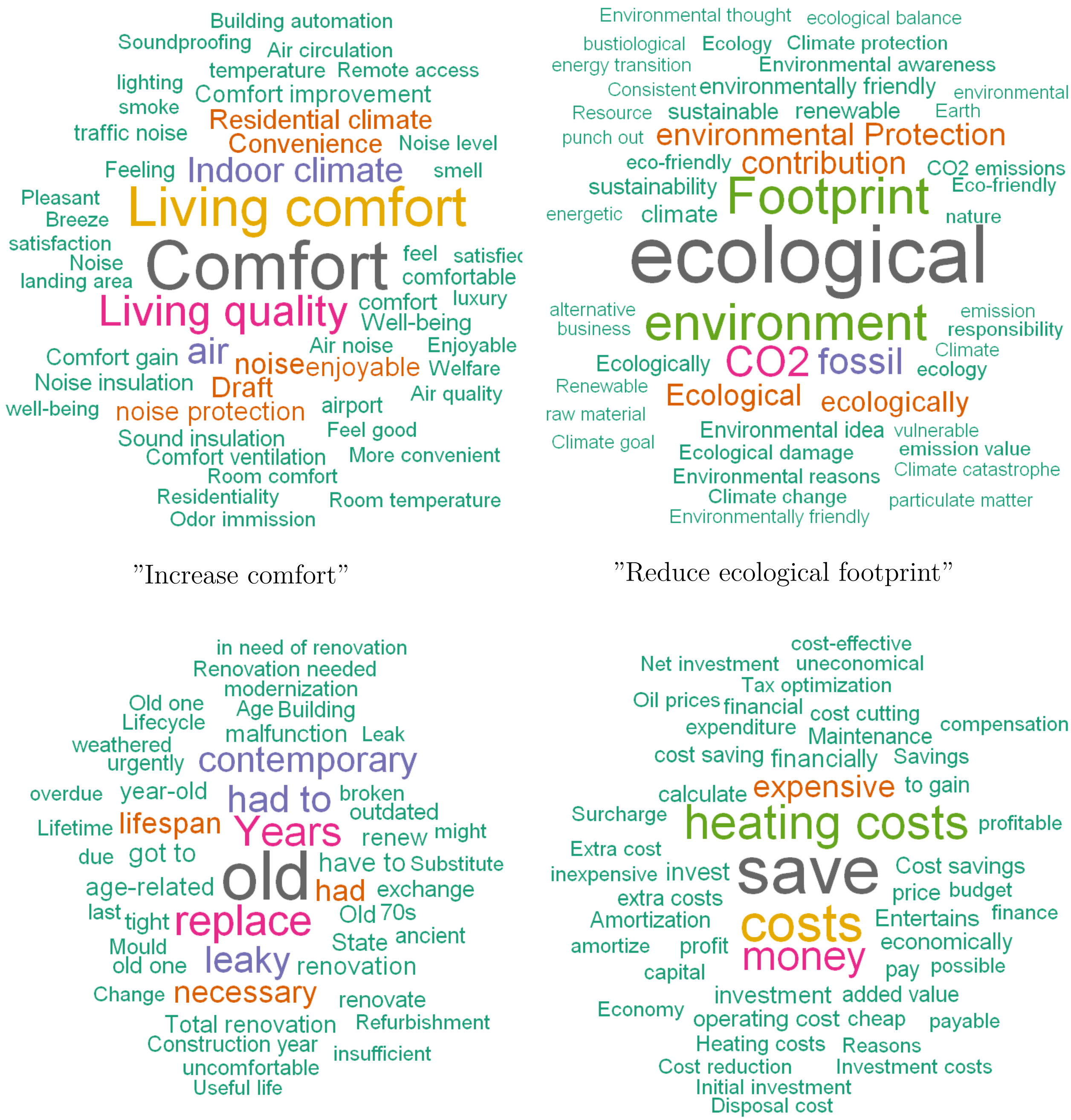
Figure 2: Two major topics for barriers from open-ended text answer



"The building is already efficient" "Too expensive"

Note: Each wordcloud contains the 50 most used words that were used to classify a topic. Words with a larger font were used more frequently by respondents. All words were initially in German language and translated into English using Google-translator.

Figure 3: Four major topics for determinants from open-ended text answer

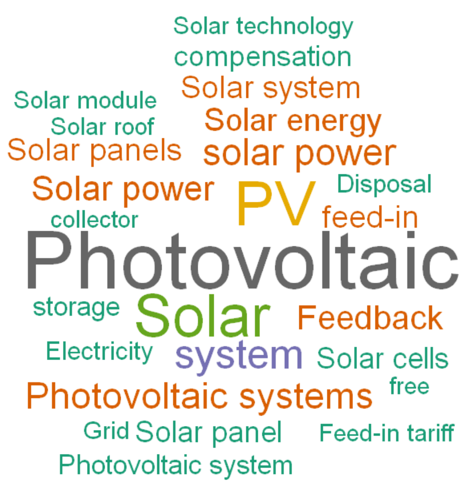


Note: Each wordcloud contains the 50 most used words that were used to classify a topic. Words with a larger font were used more frequently by respondents. All words were initially in German language and translated into English using Google-translator.

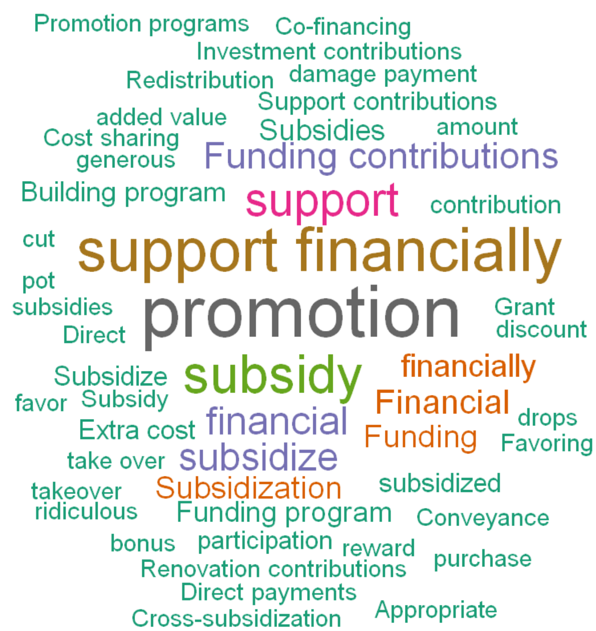
Figure 4: Four major topics for policy recommendations from open-ended text answer

"Bureaucracy"

"More Information"



"More solar PV"



"More subsidies"

Note: Each wordcloud contains the 50 most used words that were used to classify a topic. Words with a larger font were used more frequently by respondents. All words were initially in German language and translated into English using Google-translator.

7.2 Consistency of the open-ended text answers

Tables 4 and 5 show that narratives compared to their closed-ended counterpart give different topic shares for both barriers and determinants. Because each respondent answered the open *and* the mirroring closed-ended question, we can compare the answers and check if the respondent was consistent and mentioned the same topics in both answers.

To illustrate how we assess consistency, consider the following example. Suppose that respondent i discusses in an open-ended question, denoted o, the topics: A_i^o, B_i^o, and C_i^o. When presented with the closed-ended question c, which has a predefined list of topics, the same respondent i selects the topics A_i^c, C_i^c, and D_i^c. We can then assess topic-level consistency. Put simply, topic-level consistency measures whether respondents systematically identify the same topics, say topic A, in a pair of open- and closed-ended questions. For instance, if every time a respondent selects topic A in the closed-ended question and also mentions this topic in the associated open-ended question, we have consistency at the respondent level for this topic. If this is the case for all respondents that select A, the topic-level consistency score will take a value of 100%, the maximum score possible. Note that a consistency score of 100% does not mean that the topic is mentioned by all respondents. It needs only to be systematically selected in both types of questions. The lowest value for the consistency score is thus 0 which can arise under two scenarios. It is possible that topic B is only mentioned in the open question by a subset of respondents. This means that we did not propose topic B in the predefined list of topics in the closed-ended question and the consistency score hence will be 0. On the other hand, a topic such as D could be exclusively selected by some respondents in the closed-ended question but it is never mentioned in the answer to the open-ended question, which would result in a consistency score of 0.

To evaluate if the lack of consistency was not due to a wrong classification of the open-ended answers, we checked all inconsistent answers manually and reclassified them if necessary. Table 10 presents the results of this manual analysis for the major barriers and determinants. For the barriers, more answers needed to be corrected compared to the determinants, which may be due to the smaller sample size for the barriers. As for the determinants, the consistency only changes marginally after manually checking all answers. The shares for all topics from the open-ended questions only change little, because overall, the majority of open-ended answers was classified correctly.

Table 10: Consistency of open-ended answers compared to closed-ended answers

Topic	Old consistency	Corrected consistency	Original share	Corrected share
Barriers				
The building is already energy-efficient	0.61	0.77	0.47	0.50
Too expensive	0.76	0.82	0.25	0.23
Determinants				
Save money	0.64	0.71	0.26	0.21
To reduce my ecological footprint	0.52	0.55	0.28	0.30
Increase comfort	0.48	0.52	0.23	0.26
Replace broken elements	0.56	0.60	0.44	0.43
Increase resale value	0.75	0.76	0.05	0.05

This table presents the consistency between the open- and closed-ended answers for the major barriers and determinants. Each barrier and determinant was presented as a topic in the closed-ended question. Later in the survey, respondents answered to the same question in an open way by writing a text. If one of the topics appeared in the text-answer, the respondent's answer was classified in the respective topic.

7.3 Variable Descriptions

Building Characteristics

Building Age

The respondent's building's age in years.

Floor size

The floor size in square meters.

Number of rooms

Number of rooms, excluding kitchen, bathroom, and WC.

Garden

A dummy variable that takes the value of 1 if the respondent's house has a garden and zero

Rental Value

The self-estimated monthly rental value respondents would obtain for renting their houses on the market. Respondents usually have a proxy for that rental value because it is important in Switzerland for tax purposes.

Heating

Respondents were asked what primary source of heating they use for their houses. They could choose between four options: oil, gas, heat pump, and other. Oil and gas were taken together as one variable.

Solar PV

A dummy variable that takes the value of 1 if the respondent's house has solar panels.

Demographics

Income

The respondents gross household income. Respondents could choose between the following brackets: below 8 000 CHF, 8 000 to 12 000 CHF, 12 000 to 16 000 CHF, 16 000 to 20 000 CHF, above 20 000 CHF, and no answer. Respondents with no answers were omitted from the dataset. We converted below 8 000 CHF to 8 000 CHF and above 20 000 CHF to 22 000 CHF. For all other brackets, we chose the average number between the two bounds (10 000, 14 000, and 18 000 CHF, respectively).

Age

The respondent's age in years.

Male

A dummy variable that takes the value of 1 if the respondent's gender is male and zero otherwise.

Children

A dummy variable that takes the value of 1 if the respondent's household includes children.

University Degree

A dummy variable that takes the value of 1 if the respondent holds a university degree. We also inquired if a respondent's spouse holds a university degree, when applicable.

Employment

Three categories for respondent's current employment situation: full-time employment, pensioner, and other employment (including part-time employment). We also inquired the same information for a respondent's spouse if applicable.

Allergies

A dummy variable that takes the value of 1 if a respondent or a member of their household suffers from any of the following allergies: dust mites, pollen, animal hair, or feathers.

Psychographics

Energy Literacy

n order to obtain a proxy on financial literacy in the context of energy-efficient investments, we used a reduced version of a score based on Blasch et al. (2021). Specifically, we first used the three classical financial literacy questions by Lusardi and Mitchell (2008): the first question inquired of the knowledge about interest rates; the second about the effect of inflation on investment; and the third addressed the importance of portfolio diversification. Each question can be answered correctly or incorrectly, which gives each respondent a total score from zero to three. Following Blasch et al. (2021) we added two questions to this score: the first questions asked for an estimate of the electricity price in the Canton of Zurich. The actual price is around 0.20 CHF/kWh, but we considered all responses in the range between 0.06 CHF/kWh and 0.30 CHF/kWh as being in the correct order of magnitude. The second question gave a hypothetical investment decision in two heating systems with different initial costs and different energy savings per year. The respondent had to calculate which of the two heating systems is less expensive after 20 years (without considering inflation or alternative investments). In total, respondents answered five questions and could obtain a score between 0 and 5.

Took Econ

A dummy variable that takes the value of 1 if the respondent took economics classes during their education.

Math Proficient

We asked respondents how they self-assess their math proficiency while they were in school. The possible answers were: "I do not remember anymore," "below average," "average," and "above average." From these answers, we constructed a dummy variable that takes the value of 1 if the respondent answered "above average" and zero otherwise.

Energy Saving Score

We presented respondents with three everyday activities that consume energy but also allow one to save energy: use washing machine and dishwasher only if it is fully loaded, turn off the light when leaving the room, even for a short amount of time, and fully turn-off electrical appliances such as TV or computer (no standby). For each situation, respondents could choose between "never," "rarely," "sometimes," "often," and "always." We constructed for each of the three situations a dummy variable that takes the value of 1 if the respondent chose “often” or “always” and zero otherwise. To obtain a score between zero and 3, we added the three dummy variables.

Donated

A dummy variable that takes the value of 1 if the respondent donated to an environmental organization during the past 12 month and zero otherwise.

Happiness Score

We asked two questions formulated by Lyubomirsky and Lepper (1999) with which respondents could rate their own happiness and their perceived happiness relative to their peers on a scale of 1 to 7. Similarly, we asked respondents to rate their happiness with their home on a scale of 1 to 7 and their happiness with their home relative to their peers. For each question, we created a dummy variable that takes the value of 1 if the individual’s score is above the mean score for the entire sample and zero otherwise. We then took the sum of the four dummy variables to obtain a score between zero and four for each respondent.