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Narrowing the energy efficiency gap: The impact of educational programs, online support tools and energy-related investment literacy*

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Abstract

There is evidence that many individuals make suboptimal investment decisions when the benefits and costs associated with that decision are distributed over time. One example is the decision to adopt new electrical appliances, with the benefits of choosing a more energy-efficient device materializing only in the future. This paper analyses the impact of the level of an individual's energy-related investment literacy on the adoption of energy-efficient appliances. Moreover, the empirical analysis explores the impact of decision support tools such as educational slides on the probability that individuals identify the appliance with the lowest lifetime cost, which is ideally also the most energy-efficient appliance. To test the influence of these decision support tools, we developed an online randomized controlled trial and implemented it on two independently chosen samples of the Swiss population. One treatment offers a short education program on how to calculate the lifetime cost of an appliance – via a set of information slides. The second intervention provides access to an online calculator that supports the investment decision-making of the individual. Results across the two samples are encouraging. We find that i) pre-treatment energy and investment literacy positively impact on the probability of identifying the appliance with the lowest lifetime cost; ii) the reinforcement of energy-related investment literacy increases the rate at which individuals identify the appliance with the lowest lifetime cost; and iii) while both interventions are effective in increasing the chances that an appliance with the lower lifetime cost is chosen, the online calculator turned out to be more effective than the educational program. Public policy implications are discussed.

Keywords: energy-efficient appliances; energy-related investment literacy; appliance choice; bounded rationality; educational programs; online tool

JEL Classification Codes: D12, D80, Q41, Q48

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1 Introduction

On a daily basis, individuals have to take decisions that have an economic and financial impact. Some of these decisions are simple, e.g., whether or not to buy an ice-cream, go to a movie theatre, or take a taxi. Other decisions, generally characterized by benefits and costs distributed over time, are more complex, e.g., to decide the retirement age, to buy state bonds, to renovate a house, to change the heating system or to replace an old refrigerator. In order to make these more complex decisions, individuals need to collect information, make assumptions regarding the future, and perform an investment analysis.

There is ample evidence that many individuals make suboptimal decisions when it comes to financial decision-making such as investment, credit card use and pension decisions, which can have strong implications for society as a whole (Agarwal and Mazumder, 2013; Altman, 2013). One possible reason for this is that individuals are boundedly rational (Simon, 1959), as information acquisition is costly and individuals' capacity to process complex information is limited. Furthermore, individuals face problems predicting uncertain future outcomes and their implications. Also the framing of a decision situation and influence of other individuals (herd behaviour) may affect individual decisions in a negative way (Altman, 2013).

As shown by Lusardi and Mitchell (2014), to make these complex decisions, the level of financial literacy of an individual, i.e. the ability to "process economic information and make informed decisions about financial planning, wealth accumulation, debt, and pensions" (Lusardi and Mitchell, 2014, p.2), is important. Financial literacy seems related to retirement planning and retirement wealth accumulation (Lusardi and Mitchell, 2011), day-to-day financial management skills (Hilgert et al., 2003), financial market participation (Christelis et al., 2010) and precautionary savings (de Bassa Scheresberg, 2013). In fact, information cost and optimization cost strongly influence optimal economic decision-making and create trade-offs between the time spent on decision-making and the quality of the decision (Pingle, 2015; Gabaix et al., 2006; Conlisk, 1988; Stigler, 1961). Every decision-maker faces a different level of information and deliberation cost, depending on his or her level of knowledge of the decision-problem at hand, and on individual-specific cognitive abilities. Empirically, it has been demonstrated that the quality of economic decisions in various domains changes with an individual's knowledge and cognitive abilities. Several studies show that individuals with strong cognitive abilities are less prone to behavioural anomalies such as risk aversion (Frederick, 2005; Dohmen et al., 2010; Benjamin et al., 2013). In the same vein, Agarwal and Mazumder (2013) find that individuals scoring high in a test for cognitive abilities are more likely to avoid a suboptimal use of their credit cards when transferring their credit card balance to a new card.

In other fields too, knowledge and cognitive abilities seem indispensable for making optimal economic decisions. One such area is the energy sector, where many decisions taken by the households show benefits and costs over a long period of time. For instance, the choice to perform or not to perform an energy-efficient renovation of a house can have an impact on the energy costs for more than 30 years. Another example is the choice of heating systems and of electrical appliances. For instance, more energy-efficient devices are frequently offered at relatively high purchase prices, yet they pay off by reducing energy costs throughout their lifetime. Identifying the electrical appliance with the lowest 'lifetime cost' can be challenging for the consumer. To make an economically rational choice, an individual should perform an investment analysis before every purchase, i.e. an inter-temporal optimization including both purchase price and future operating costs. To evaluate an investment in the energy domain, it is important that the consumers have some basic energy-related knowledge in the form of information on technical aspects such as the capacity of an appliance or a heating system, the energy consumption per unit of usage of an appliance as well as the efficiency rating of an appliance. Further, to calculate the lifetime cost of the appliance, the consumer has to take into account the electricity consumption of the appliance, the expected intensity and frequency of use, the expected lifetime of the appliance as well as current and future electricity prices. Performing this calculation requires not only that all this information is available in the purchase situation but also that the consumer is able to process the information. As shown by Attari et al. (2010) for the US, Brounen et al. (2013) for the Netherlands and Blasch et al. (2017a) for Switzerland, the level of energy-related knowledge and investment literacy, i.e. the ability to perform an investment analysis, in the population tends to be relatively low. Moreover, Blasch et al. (2017b) show that a great share of individuals do neither know the annual electricity consumption of their household or the typical consumption of appliances such as a washing machine in kWh, nor do they consider the lifetime cost of electrical appliances when choosing between two appliances. As energy-efficient electrical appliances are usually more costly than less efficient appliances, boundedly rational consumers will tend to opt for the less efficient appliances with lower upfront cost. This situation can be classified as a behavioural failure (Broberg and Kazukauskas, 2015).

Given the importance of knowledge and cognitive abilities for optimal decision-making in many domains, the design of the decision-making environment should receive greater attention by researchers and policy makers (Altman, 2012, 2013). It has been demonstrated that setting up education programs and providing high-quality decision aids in the decision situation can empower consumers to make better financial decisions (Bernheim et al., 2001; Goda et al., 2014; Savikhin, 2013). The increasing distribution of internet access among households presents an opportunity to propose educational materials and decision aids that can be accessed quickly and at low cost.

In this paper, we analyze the impact of a short online educational program and an online calculator tool on an individual's ability to identify the electrical appliance with the lower lifetime cost when confronted with a choice between two appliances. The first intervention, based on educational slides, is designed to improve the consumers' knowledge on how to compare the lifetime cost of appliances, i.e. to increase energy-related investment literacy. The second intervention, a simple online calculator to compare the lifetime costs of two appliances, potentially minimizes the cognitive effort that an individual needs to spend on the calculation. Impact of the two interventions is analysed by performing an online randomized controlled trial among two independent samples of Swiss households in which participants have to compute the lifetime cost of two appliances differing in purchase price and energy consumption. It is to be noted that in this experiment, the participants are not asked to choose an appliance, but to identify the electrical appliance that minimises the total lifetime cost. The first sample comprises 916 households residing in the city of Bern whereas the second sample comprises $5,015$ households randomly sampled from households residing in the German- and French-speaking parts of Switzerland.

By estimating several bivariate and recursive bivariate probit models, we find that the investment calculator is highly effective in increasing the probability that an individual identifies the electrical appliance with the lowest lifetime cost. This supports the insight that the cognitive effort to calculate and compare the lifetime cost is a major barrier for individuals in identifying the most efficient appliance. At the same time, a simple online calculator is a low cost tool that could effectively empower boundedly rational consumers to make optimal decisions. The educational slides presenting information on how to compute the lifetime cost of an electrical appliance also showed a positive effect on the choice of the appliance with the lower lifetime cost, yet the effect is less pronounced than the investment calculator. This suggests that the information slides reduce the cognitive cost of making the calculation, yet not as strongly as the online calculator. Our results are robust in that they manifest in two independently drawn samples of Swiss households. We conclude that online tools such as simple investment calculators that could be provided through mobile phone applications can be particularly effective in supporting consumers' decisions, be it in the domain of electrical appliances or other domains that require solving complex, inter-temporal optimization problems. From a policy point of view, they provide a cost-effective and easy to implement instrument to empower the boundedly rational consumer in making optimal choices.

The remainder of the paper is organized as follows. Section 2 discusses the role of decision aids and energy-related investment literacy and proposes a simple theoretical framework to study their impact on appliance choice. The dataset and the experimental design is presented in Section 3. The econometric specifications are presented in Section 4. Section 5 presents the results and Section 6 concludes.

2 The impact of energy-related investment literacy and decision-support tools on appliance choice

In the domain of household energy-efficiency, knowledge and cognitive abilities to perform economic calculations play a crucial role. For instance, calculating the expected lifetime cost of an electrical appliance creates both 'information cost' and 'optimization cost' (Conlisk, 1988) for the consumer. These are often also referred to as 'deliberation cost' (Pingle, 2015), a concept that is closely interrelated with the concept of 'bounded rationality' (Simon, 1959; Sanstad and Howarth, 1994) which reflects that information acquisition is costly and the processing of information is cognitively burdensome. Consequently, boundedly rational individuals tend to not optimize when making an investment decision but to follow simple rules of thumb or decision-making heuristics (Wilson and Dowlatabadi, 2007; Frederiks et al., 2015; Andor et al., 2017).

In this paper, we are particularly interested in studying the behavioural failure related to the fact that consumers lack energy-related investment literacy defined as the ability to perform investment analysis or calculate lifetime cost of an energy consuming durable. Further, we are interested to study how to empower consumers to overcome this irrationality. If a consumer has a low level of energy-related investment literacy, the probability increases that he or she may use heuristic decision-making rather then performing a lifetime cost calculation when choosing between two appliances (Andor et al., 2017). A higher level of energy-related investment literacy, instead, can make such a calculation substantially 'less costly' for the consumer, which raises the chances that the individual will optimize over the lifetime cost of an appliance. In fact, individuals with a higher level of energy and energy-related investment literacy, including knowledge regarding total energy consumption and energy use of appliances as well as the ability to calculate compound interest, seem to be more likely to choose more efficient appliances. Recent research has shown that energy and investment literacy can positively influence the level of energy efficiency of a household (Blasch et al., 2017a) by supporting consumers' choices of more efficient electrical appliances and heating systems (Blasch et al., 2017b; Brounen et al., 2013).

When it comes to energy-related decision making, the level of education also seems to play a role. While an individual's level of education does not necessarily need to correlate with energy literacy and energy-related investment literacy, some studies find a positive correlation of these two constructs with an individual's general level of education (Mills and Schleich, 2010; Nair et al., 2010; Mills and Schleich, 2012). In an analysis conducted by Ramos et al. (2016) on survey data from Spain, education has a positive impact on the probability to invest in energy efficiency. Brounen et al. (2013) find that more educated respondents are more likely to make a rational investment decision when comparing two different heating systems that differ in energy-efficiency and upfront cost.

There should therefore be a substantial potential to raise the level of energy and financial literacy among consumers and to support them in the purchase situation by providing effective decision aids. For instance, Allcott and Taubinsky (2015) show that disclosing lifetime cost of light bulbs in the purchase situation indeed increased consumers' willingness to pay for energy-saving compact fluorescent light bulbs. Allcott and Sweeney (2015) test whether energy efficiency information through sales agents in the purchase situation positively impacts on consumers' purchases of energy-efficient appliances but they do not find an effect. Attari and Rajagopal (2015) compare and discuss various decision aids to help consumers make effective decisions, such as the Energy Star label, the appliance calculators of the US Department of Energy, and the Home Energy Saver online tool of the Lawrence Berkeley National Laboratory. They conclude that simplified versions of these tools are needed to support the decision-making of consumers, yet they do not empirically test the effectiveness of these tools. When it comes to education programs, Dwyer (2011) and Zografakis et al. (2008) show that an introduction of energy literacy curricula at schools can positively impact on the energy-related behaviour of students: Zografakis et al. (2008) report results from a small-scale energy-related information and education project in Greece that impacts positively on stated energy-saving behaviours. Dwyer (2011) develops an energy literacy curriculum for US students and evaluates its impact on stated energy-related attitudes. Apart from these studies, we are not aware of a study that investigates the impact of decision aids on the choice of efficient electrical appliances in the setting of a randomized controlled trial with a large household sample.

Moreover, the literature on the impact of decision-support tools such as information sheets, calculators or educational slides on decisions related to retirement, saving and financial decisions is relatively small. This literature reports several attempts to enhance consumers' financial literacy and cognitive abilities with the aim of improving the quality of their financial decisions. The studies show that providing simple decision aids in the decision-making situation can help individuals make better choices. Goda et al. (2014), for example, run a field experiment to test whether providing retirement income projections in the form of a brochure impacts on individual contributions to employer-sponsored retirement accounts. They find that that such a treatment increases individual contributions by 3.6% of the average contribution level or 0.15% of the average salary. Savikhin (2013) test visual analytics (VA) as a tool to support individuals' financial decision-making and find that VA reduce information cost and therefore improve the quality of the decisions. Evidence of the success of financial education programs is provided by Bernheim et al. (2001) who demonstrate that high school financial curriculum mandates in several US states have positive long-term effects on the exposure of the students to financial education and, ultimately, on wealth accumulation in adult life. In this paper, we study whether similar interventions have a potential to improve a household's decision making when it comes to the adoption of efficient electrical appliances.

2.1 Decision aids for appliance choice in a theoretical framework

The impact of decision aids to support an individual's energy and investment literacy on the choice of efficient electrical appliances can be studied in a theoretical framework that accounts for the influence of decision-making cost as well as energy and investment literacy on the decision to optimize or to follow a decision-making heuristic. Such a framework within a simple 2-period-model of expectation formation has been developed and formalized by Blasch et al. (2017b).[1] In this paper, we build upon the framework in Blasch et al. (2017b) and extend it by including the presence and quality of decision support tools as additional parameters. We provide an intuition on their possible impact on task complexity and energy-related investment literacy, and hence on the overall deliberation cost.

Given our setting, we sketch a simple stylized model in order to formulate several hypotheses which are later tested as part of the econometric analysis. The model relies on previous work of Conlisk (1988) and assumes that an individual assesses the expected lifetime cost of an appliance before purchase. While doing so, the individual minimizes two potential sources of loss: *i)* a loss in intertemporal utility by either underestimating the lifetime cost of an appliance in period 1 and thus not allocating enough of the budget in period 2 on the consumption of the energy service, or, by overestimating the lifetime cost of an appliance in period 1 and thereby restricting consumption of other goods in period 1 itself due to the individual's budget constraint, and *ii)* spending too much

[1] A similar theoretical approach is followed by Houde (2014), who presents a model of information acquisition for energy-intensive durables in which consumers optimize over the effort to collect and process energy information.

time and resources on decision-making itself.

The model by Blasch et al. (2017b) assumes that the individual aims at minimizing the following loss function:

$$(E(L(T)) - L)^2 + CT \tag{1}$$

with $E(L(T))$ representing the estimated lifetime cost of the appliance after having spent T units of time and other resources on deliberation at a unit deliberation cost of C. L represents the true lifetime cost of the appliance. The second component represents the decision cost CT, which are composed of the unit cost of performing the calculation task C multiplied by the amount of time and other resources devoted to deliberation T.

The unit deliberation cost C can be assumed to be a function of several components:

$$C = C(\epsilon, \gamma, \kappa, z_1, z_2) \tag{2}$$

with ϵ expressing the individual's energy literacy and γ expressing the individual's investment literacy, i.e. the individual's ability to perform an inter-temporal optimization. Thus, ϵ and γ together represent the individual's energy-related investment literacy. The third component κ represents the complexity of the optimization task which is not individual-specific. The unit deliberation cost C are increasing in κ but decreasing in both ϵ and γ, as a higher energy-related investment literacy will lower the individual's effort needed to perform the optimization.

Parameters z_1 and z_2 represent features of the decision-making environment. In our framework, they can depict the presence of two different types of decision support tools – z_1 may be a support tool that can influence the individual-specific energy-related investment literacy in the decision situation, e.g., information slides teaching how to compare two energy consuming durables by calculating their lifetime costs; and z_2 may be another type of support tool that could reduce the task complexity in the decision situation, e.g., a calculator-like device that can compute the future energy costs of an appliance. Thus, z_1 and z_2 represent the presence and the quality of decision-support tools provided in the purchase situation.[2]

Following Conlisk (1988) and Blasch et al. (2017b), we can write the individual's expected lifetime cost of the appliance as:

$$E(L(T^\star)) = \alpha f + (1 - \alpha)\, r(T^\star) \tag{3}$$

where

$$\alpha = \frac{S}{(S + T^\star)} = S\sqrt{\frac{C}{\sigma^2}} = S\sqrt{\frac{C(\epsilon, \gamma, \kappa, z_1, z_2)}{\sigma^2}} \tag{4}$$

with f representing a free estimator that is based on a simple rule of thumb and $r(T)$ denoting a costly improvement of the free estimator that depends on the time T spent on deliberation. $r(T)$ is as accurate as a sample mean of T independent observations taken from a distribution with mean R, the rational expectation of L, and variance σ^2. Both T and S represent the number of thoughts drawn from a distribution with mean R and variance σ^2.

By definition, α has an upper bound of 1 when the corner solution $T^\star = 0$ applies, i.e. when individual's rule of thumb choice is good enough. Eq. (3) can be seen to cover both the extremes; when $T^\star$ goes to infinity (i.e. $\alpha \to 0$), the expected lifetime cost converges to the rational expectation R. On the other hand, when $T^\star = 0$ (i.e. $\alpha = 1$), the expected lifetime cost is the free estimator f.

[2] We assume here that these support tools are readily available for the consumers and that there are no search and acquisition costs associated. Support tools such as web-pages, mobile-apps or education slides can be considered a mixed-public good, and therefore one could imagine that these tools could be provided by the state for free.

Depending upon the different parameters, an individual could be lying anywhere between the range of complete rationality and a rule of thumb approximation (Conlisk, 1988).

The estimation of the lifetime cost of the appliance will thus be closer to the rational expectation R as α gets smaller. From Eq. (4), α is the lower

- the lower S, i.e. the lower the amount of (costless) best guesses spent on estimating R, i.e. the less reliable the rule of thumb.
- the lower C. Since C is decreasing in ϵ and γ, increasing in κ, and depends upon the decision-support tools z_1 and z_2; this implies that α is the lower
  - the higher ϵ and γ, i.e. the higher the level of the individual's energy-related investment literacy and hence the lower the individual's effort to calculate the lifetime cost of the appliance.
  - the lower κ, i.e. the less complex the optimization task.
  - the higher the parameter z_1, i.e. the higher the quality of a decision aid like education slides that aims at enhancing an individual's energy-related investment literacy.
  - the higher the parameter z_2, i.e. the more effective a decision aid like a calculator tool that aims at reducing task complexity.
- the lower C relative to σ^2, i.e. the more economical the analysis relative to the size of the problem.

2.2 Hypotheses

Any individual having to decide between several appliances on offer, will first assess the lifetime cost of all the appliances separately and then in a second step compare them to identify the one with the minimum lifetime cost. From the above described model, we derive two hypotheses with respect to whether the individual rather deliberates or follows a rule of thumb when comparing the appliances (choice of decision-making strategy). Depending on the choice of decision-making strategy, the individual will be either more likely, or less likely, to identify the appliance with the lower lifetime cost (identification of appliance).

Figure 1 depicts a scenario wherein a respondent is confronted with a situation in which he or she has to identify the appliance with the lowest lifetime cost between two alternatives. Given the task, the respondent would first opt for a decision strategy, either heuristic decision-making or optimization. Conditional on the chosen strategy, he or she then selects one of the appliances. With no intervention, a boundedly rational consumer might select one of the heuristic strategies instead of comparing the lifetime costs. A heuristic approach may or may not lead to correct identification of the appliance with the lower lifetime cost. If the decision-maker opted to compare the lifetime costs, he or she still has to perform the calculations correctly in order to successfully identify the appliance with the lower lifetime cost.

As shown in Figure 1, two interventions – education slides (blue arrows) and calculator (red arrows), could affect the decision-making environment. They lower the decision-making cost for an individual thereby increasing the likelihood that the individual chooses an optimization strategy, and in turn, is more likely to correctly identify the appliance with the lower lifetime cost.

In this paper, we propose that intervening in the decision-making of the individual by means of an educational program or a calculator tool impacts differently on the choice of the decision-making strategy, and consequently on the appliance choice. An educational program, represented by parameter z_1 in the theoretical framework, will impact on the choice of the decision-making strategy

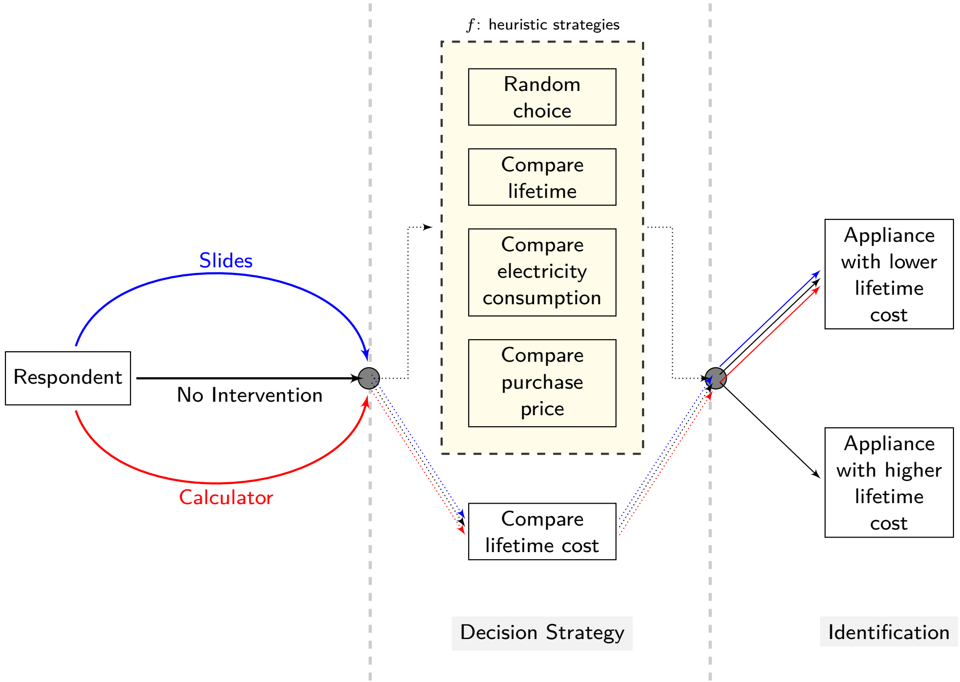

Figure 1: Decision making, interventions, and corresponding hypotheses.

primarily through an individual's level of energy-related investment literacy (ϵ, γ). As literacy will be enhanced by the program, the probability that the individual chooses an optimization strategy rather than heuristic decision-making will be increased due to a lowering of the unit costs of decision-making (C). However, a calculator tool, represented by parameter z_2 in the theoretical framework, may not directly influence an individual's level of energy or investment literacy but will substantially reduce the task complexity (κ). This too will lower the unit costs of decision-making (C) such that the probability to choose an optimization strategy increases.

We thus derive the following four hypotheses from our simple theoretical framework:

- *H1a:* A set of information slides (z_1) for educating individuals and enhancing their level of energy-related investment literacy has a positive impact on the individuals' ability to follow an optimization strategy rather than a heuristic decision-making strategy.
- *H1b:* A set of information slides (z_1) for educating individuals and enhancing their level of energy-related investment literacy has a positive impact on an individual's probability to identify the appliance with the lowest lifetime cost.
- *H2a:* A calculator tool (z_2) in the decision-situation that minimises task complexity (κ) has a positive impact on an individual's ability to follow an optimization strategy rather than a heuristic decision-making strategy.
- *H2b:* A calculator tool (z_2) in the decision-situation that minimises task complexity (κ) has a positive impact on an individual's probability to identify the appliance with the lowest lifetime cost.

In the empirical part, we also analyse the role of the pre-existing energy-related investment literacy of respondents on their decisions to follow an optimization strategy and to correctly identify the appliance with the lower lifetime cost.

3 Data and Experimental Design

We use data sources from two independent surveys, both of which implemented an online randomized controlled experiment asking the respondents to identify the appliance with the lowest lifetime cost between two refrigerators. One of the samples is part of a household survey on energy usage which relates to customers of an electric and gas utility serving the region of Bern in Switzerland (hereafter, referred to as HSEU-Bern). Another sample is part of the Swiss Household Energy Data Survey (SHEDS) covering a broader population belonging to the German and French speaking regions of Switzerland.

The online randomized controlled experiment, which is described later in Section 3.3, is the same in both samples and so are most of the survey questions that captured demographic and socio-economic information used in our empirical analysis. Each of these datasets are described below.

3.1 HSEU-Bern

The first dataset comes from a large web-based household survey on energy use conducted by the Centre for Energy Policy and Economics (CEPE) at the ETH Zürich in co-operation with participating electrical and gas utilities across several cities throughout Switzerland. The experiment considered here was run as an online randomized controlled experiment as part of the household survey for the customers of Energie Wasser Bern (EWB) in 2016.

EWB customers were invited with a letter accompanying one of their electricity (or gas) bills to access an online questionnaire.[3] The invitation letter was sent to a total of $29,000$ customers of which $1,145$ accessed the survey page (corresponding to a response rate of about 4%). After accounting for the correct target group and incomplete surveys, we have valid and complete data for 916 survey respondents that can be used for our analysis.[4]

To evaluate how well the HSEU-Bern sample reflects the basic demographic characteristics of the region of Bern, we compare the sample characteristics to population statistics for the city of Bern (Table 1) obtained from the Swiss Cities Association (SSV).

In terms of gender composition, the households in the HSEU-Bern sample seem to be representative of the population. The same largely holds for age groups, but we do notice a slight deviation (higher share of young and adult population between age 20 and 64 as compared to older household members). Regarding the mean household size, we observe that households in our sample comprise slightly more people than the average household in the region — 2.24 versus 2.10. Also the living space per person ($m^2/head$) is slightly above average. This, however, does not hold for the number of people per room, which is mostly at the average level. It is to be noted that the statistics at the city level in Bern may not completely reflect the statistics of the surveyed areas, i.e. the service areas of the respective utility, which usually also includes neighbouring municipalities.

[3] In general, the utilities in consideration had a rolling billing cycle over few months. After discussion with the utilities, the survey was open for about 19 to 21 weeks as a guideline so that customers have sufficient time to take part. For EWB, the survey was open for about 19 weeks during January to May in 2016. The survey was available to EWB customers in two languages —German and English. The questionnaire itself was first prepared in English, and then translated to German.

[4] A total of 987 respondents were filtered-in as the target group, of which 916 completed the survey. The target group consists of respondents (i) for whom the electricity/gas bill refers to their primary residence; (ii) who moved in their current residence before 01.01.2015; and (iii) who are one of the persons in their residence who decides about the purchase of goods and/or pays the bills.

Table 1: Comparison of statistics in HSEU-Bern sample versus population statistics for the city of Bern.

	HSEU-Bern	
	Sample (N=916)	*SSV (Bern)*
Share of females (%)	51.10	52.00
Share of population by age (%):-		
young (0-19 years)	18.47	15.87
adult (20-64 years)	70.19	66.53
elderly (65+ years)	11.34	17.60
Mean household size	2.24	2.10
Dwelling (mean values):-		
living space per head (m^2)	44.55	39.00
people per room	0.66	0.67

Data source: Statistik der Schweizer Städte 2017 (FSO, 2017b).
SSV data for Bern is at the city level from 2015.

3.2 SHEDS

The second dataset analyzed in this study corresponds to the first wave of the Swiss Household Energy Demand Survey (SHEDS). SHEDS has been developed to advance the research agenda of the Swiss Competence Center for Research in Energy, Society, and Transition (SCCER-CREST). SHEDS collects extensive information providing a comprehensive description of the energy-related behaviour of Swiss households. As such, SHEDS gathers data on psychological, sociological, marketing and economic factors expected to drive energy consumption (Burger et al., 2017).

The first wave of SHEDS was implemented in April 2016 via a web-based instrument.[5] SHEDS has collected information from 5,015 households located in the French and German parts of Switzerland[6] —which hosted around 94% of the population in Switzerland in 2015 (FSO, 2016).[7]

While SHEDS has been developed completely by researchers at SCCER-CREST, the fielding was delegated to Intervista —a company that contacts potential respondents and offers an incentive in the form of bonus points. Potential respondents were invited by Intevista until the sample size of 5,015 was reached based on quotas pre-selected by the SCCER-CREST researchers to replicate, when possible, population proportions as reported by the Federal Statistical Office (FSO, 2016, 2017a).

[5] SCCER-CREST plans to implement a total of four yearly waves to generate a rolling panel dataset. Further details are provided by Burger et al. (2017).

[6] The survey is available to the respondents in three languages —English, French, and German. The questionnaire was first prepared in English (the common working language among SCCER-CREST researchers), and then translated to German and French.

[7] This number includes Swiss nationals and foreigners. SHEDS gathers information from Swiss nationals and foreigners because foreigners represent 24.6 % of the 8.3 million people living in Switzerland in 2015 (FSO, 2016).

Table 2: Comparison of SHEDS statistics versus Swiss population statistics.

	SHEDS	
	Sample (N=5,015)	*Swiss population*
Share of females (%)	51.37	50.5
Share of population by age (%):-		
18-34 years	30.00	20.00
35-54 years	40.00	30.00
55 + years	30.00	29.00
Mean household size	2.25	2.30
Dwelling (mean values):-		
living space per head (m^2)	58.69	45.24
people per room	0.58*	0.60
Region (%):-		
French-speaking	25.00	21.00
German-speaking	75.00	74.00
Home-ownership (%):-		
tenants	62.50	62.40
owners	37.50	37.40

Data source: Switzerland's population in 2015 (FSO, 2016) and Statistik der Schweizer Städte 2017 (FSO, 2017b).
* Number of rooms including kitchen.

Table 2 compares the SHEDS sample statistics with the corresponding Swiss population statistics. The proportion of males and females reached by SHEDS closely replicate the population proportions —i.e. 51.37% versus 50.5% of female individuals in the Swiss population. Also, the proportion of people older than 55 years in SHEDS is similar to the population proportion —30% versus 29%. Notice, however, that SHEDS does not replicate the proportions of non-elderly Swiss people —i.e. there is a higher proportion of individuals between 18 and 54 years in SHEDS than in the Swiss population (70% versus 50%). This feature is a direct consequence of the fact that SHEDS was implemented only on respondents who report being involved (at least partially) in the household expenses. Thus, because individuals younger than 18 are not recruited to answer the survey, SHEDS has inflated the proportion of people between 18 and 54 years.[8]

The mean household size resembles the Swiss average — 2.25 versus 2.30. In terms of dwelling characteristics, SHEDS encompasses information of households living in relatively larger dwellings than the national average —as reflected by the 58.69 $m^2/head$ observed in SHEDS versus the national average of 45.24 $m^2/head$. Despite this feature, SHEDS appears to closely replicate the national average figures for people per room.

As one of the variables used to fill the quotas in SHEDS, the proportion of French-speaking households is inflated by 4% in comparison to the proportion observed in the Swiss population. This inflation results from focusing the attention only on the French and German parts of Switzerland, excluding the Italian region. Despite these inflated proportions, SHEDS provides a sample that is representative of the Swiss households based on home ownership (tenants versus owners)—a variable that has been documented to be a key determinant in the adoption of energy-efficient technologies (Meier and

[8]Notice that the quotas pre-selected by the SCCER-CREST researchers are filled with sample proportions applicable to respondents which do not necessarily represent the proportions of females and age categories of the people living in the sampled households.

Rehdanz, 2010; Rehdanz, 2007).

In conclusion, the characteristics of the surveyed households in both HSEU-Bern and SHEDS samples are generally in line with the average population characteristics of the corresponding region.[9] Importantly, despite the differences in sampling strategy and population of interest, both samples under study are similar across some of the relevant socio-economic variables like gender, age and household income.[10] Also, as we document in Section 5, the results are consistent across both samples regardless the differences in sampling strategy and sampled population.

3.3 Experimental design

The online randomized controlled experiment was embedded within the two household surveys.[11] All respondents were randomly assigned to one of the three groups – control group (CONTROL), a treatment group with education-slides (TRSLIDE), and another treatment group with access to an online calculator (TRCALC). Within HSEU-Bern, each respondents had an equal probability of being assigned to any of the three groups. Within SHEDS, about 20% of the total $5,015$ respondents were randomly selected to be part of one of the two treatment groups with equal probability —resulting in around 500 respondents assigned to TRSLIDE, and another 500 assigned to TRCALC, with around 4,000 belonging to the control group.[12]

The respondents were asked to imagine a situation in which they need to replace their refrigerator. They were given a choice between two refrigerators that differed only in terms of their purchase price and their energy consumption (in kWh/year). Respondents were asked which of the two refrigerators would minimize their expenditure on the cooling of food and beverages during 10 years of planned usage (Figure 2). The two refrigerator alternatives, and the two answer options within the decision making question, were presented to the respondents in a random order to control for any order bias.

It is worth pointing out that the question was not about the respondent's subjective preference for either of the refrigerators, but about which of the two entails lower lifetime costs from an objective point of view. In principle, the result of the comparison of lifetime cost will also be driven by the individual's subjective discount rate. Assuming that the average participant of our study is not familiar with the concept of discounting and would need a calculator to incorporate variable discounting in the analysis, they were asked to assume that 1 kWh of electricity will cost about 20 Rappen on average during the next 10 years and that the value of 1 CHF in 10 years is the same as the value of 1 CHF today.[13]

After the decision question, we ask each respondent about their respective decision-making strategy, i.e. how they reached their conclusions (Figure 3). Again here, the answer options to the debriefing question (except the 'Other reason' option) were presented in a random order to avoid any order bias.[14]

[9] There are some smaller exceptions with respect to age-groups, household size and living space. However, we do not think that these necessarily have any direct implication on the results of this research.

[10] The comparison between the two samples is discussed later in Section 3.4 when we present the descriptive statistics of the two samples.

[11] Note that the online experiment is a RCT (and not simply a stated choice exercise) because (i) the framework encompasses impact of an actual decision, which in this case is identification of the lowest lifetime cost appliance between two given refrigerators; and (ii) the assignment of respondents to control or treatment groups is completely random.

[12] SHEDS is a relatively long survey. Thus, to restraint the length of the survey, a smaller percentage of respondents (in comparison to the HSEU-Bern survey) has been chosen to be part of the interventions described here.

[13] Other studies in this domain also abstract from the concept of discounting (Allcott and Taubinsky, 2015).

[14] Each of the two treatment groups had an additional debriefing question, inquiring the usefulness of the education slide or the online calculator in supporting their decision (Figure 7 in the Appendix).

Assume that you need to replace your fridge. You expect that you live in your current residence for another 10 years. In a shop you find the following two fridges which are identical in terms of size and cooling service.

	Fridge - A	**Fridge - B**
Purchase Price:	3300 CHF	2800 CHF
Electricity Consumption:	100 kWh/year	200 kWh/year

Assuming that one kilowatt hour (kWh) of electricity will cost about 20 Rappen on average during the next 10 years and that the value of 1 CHF in 10 years is the same as the value of 1 CHF today:

Which of the two fridges minimizes your expenditure for cooling food and beverages during the lifetime of 10 years?

- The fridge for 3300 CHF
- The fridge for 2800 CHF

Figure 2: The refrigerator question in the identification task.

How did you reach your conclusion?

- I compared the lifetime energy cost of the two fridges.
- I compared the total lifetime cost of the two fridges (i.e. purchase price + lifetime energy cost).
- I had problems making a choice, so I chose randomly.
- I compared the electricity consumption of the two fridges.
- I compared the prices of the two fridges.
- Other reason

Figure 3: Debriefing question about the decision-making strategy.

For the CONTROL group, no additional support tool was provided to assist in identifying which of the two refrigerators would minimize their expenditure over 10 years.

The TRSLIDE treatment group underwent the first intervention: a set of education-slides designed to improve the consumers' knowledge on how to do an investment analysis and to compare lifetime cost of appliances (Figure 4 in the Appendix). After this, the respondents were asked the same question as the control group to identify the refrigerator with the lowest lifetime cost.

The TRCALC treatment group was part of the second intervention: access to a simple web-based tool in the form of an online calculator to compute the lifetime cost of an appliance. After the page with a link to the online calculator, the respondents were asked the same question as the control group to identify the appliance with the lowest lifetime cost.[15]

[15] The online calculator required a user to input the purchase price and yearly energy consumption in kWh/year of two refrigerators (Figure 5 in the Appendix). Following this, it calculates and presents a side-by-side comparison of the yearly energy cost, the total energy cost over appliance lifetime, and the total costs (i.e. purchase price + total energy costs).

Table 3 gives a summary on how the respondents were distributed as control and treatment groups in the two data samples. It also shows the share of responses for the two outcomes of focus in this study – i) the choice to compare the total lifetime costs as the decision strategy (compTLC=1); and ii) the correct identification of the refrigerator with the lower lifetime cost (idLowTLC=1). From the table, we see that the share of respondents in both outcomes is higher with either of the two interventions, TRSLIDE and TRCALC, when compared to the CONTROL group.

Table 3: Overview of the responses from the randomized controlled experiment.

	HSEU-Bern ($N = 916$)			**SHEDS** ($N = 5,015$)		
	N	*compTLC=1*	*idLowTLC=1*	*N*	*compTLC=1*	*idLowTLC=1*
CONTROL	311	57.6%	30.6%	4,031	39.8%	26.7%
TRSLIDE	291	67.0%	40.2%	494	57.9%	32.8%
TRCALC	314	55.7%	44.3%	490	44.3%	36.3%
Total =	**916**	**59.9%**	**38.3%**	**5,015**	**42.1%**	**28.2%**

compTLC=1: Decision strategy = comparison of total lifetime costs.
idLowTLC=1: Correct identification of the refrigerator with the lower lifetime cost.

Two interesting points can be noticed in both samples – i) the share of respondents declaring the use of a lifetime cost comparison based decision strategy is the highest under the TRSLIDE intervention (67% in HSEU-Bern and 57.9% in SHEDS); and ii) between the two interventions, respondents with access to calculator correctly identify the refrigerator with the lower lifetime cost more often than those undergoing the education program (44.3% versus 40.2% in HSEU-Bern and 36.3% versus 32.8% in SHEDS). Both these observations appear to be reasonable given our discussion in Section 2 on the inter-relationship of the interventions and consumer decisions.

It must be highlighted that the experiment was designed in a way that the refrigerator with the lower energy consumption, i.e. the more energy-efficient appliance (Fridge - A in Figure 2), was *not* the appliance that minimized the total lifetime cost. This seems counter-intuitive, as in such a case an 'energy-efficiency gap' does not exist. It is perfectly rational for the consumer to choose the less energy-efficient appliance, at least from a private perspective. This specific setting was chosen to identify those individuals who performed a lifetime cost calculation in order to identify the refrigerator with the lowest lifetime cost and to distinguish them from the respondents who simply followed a heuristic decision-making strategy.[16]

3.4 Descriptive Statistics

The econometric part of the paper makes use of empirical models based on the bivariate probit and recursive bivariate probit specifications in order to explain decision of the participants in the experiment. This sub-section describes the variables of interest and presents some descriptive statistics.

[16] Given our experimental setting, two different decision strategies could have helped respondents to identify the refrigerator with the lowest lifetime cost – i) a comparison based on lifetime cost calculation, or ii) a comparison based on the purchase price (i.e. opting for the appliance with the lower purchase price). Table 7 in the Appendix presents an overview of the experimental outcome given these two decision-making strategies across the control and intervention groups. As can be noticed in both the samples, most people reach the correct outcome to the identification task by following the lifetime cost calculation strategy and not by comparing the purchase prices.

In addition to the RCT, the questionnaire in both datasets included several other questions related to the household's energy consumption, socio-demographics of the respondents, their attitudes towards energy conservation as well as their energy and investment literacy. Specifically, we control for respondents' socio-economics — i.e. gender, age, ownership of the house, income, and education. Gender is represented by a binary variable (FEMALE) that takes the value one if the respondent is female, and zero otherwise. Respondents' age is captured through three binary variables that define age groups —less than 40 years (AGE40M as reference category), between 40 and 60 (AGE40_59), and older than 60 (AGE60P). Ownership of the house is captured through a binary variable (OWNER) that takes the value one if a member of the household owns the house, and zero otherwise. Monthly gross household income is included through three binary variables that define income groups —less than CHF 6,000 (HHI6K as reference category), between 6,000 and 12,000 (HHI6_12K), and more than CHF 12,000 (HHI12K).[17] UNIV is a binary variable that takes the value one if the respondent has attended the university, and zero otherwise. For the SHEDS sample, we also include the variable LANG_FR which takes the value one if the respondent speaks French as preferred language, and zero otherwise. Additionally, the binary variable ALPS is one if the respondent lives in the alpine region. We also control for pro-environmental attitude towards energy conservation by asking for agreement or disagreement to a statement, "I feel morally obliged to reduce my energy consumption", on a 5-point Likert scale. The binary variable ATTMORAL is one if the respondent chose 'agree' or 'strongly agree'.

All econometric specifications also control for the pre-treatment energy-related investment literacy of the respondents. The energy-related investment literacy is captured with the help of two variables —an energy literacy index (ENLIT_IN) and an investment literacy indicator (INVLIT). ENLIT_IN refers to an index summarizing the literacy of the respondent over several dimensions of energy-related knowledge. The index is built based on correct responses to several questions that examine (i) knowledge of the average price of a kilowatt hour of electricity in Switzerland; (ii) knowledge of the usage cost of different household appliances; and (iii) knowledge of the electricity consumption of various household appliances. This index ranges from 0 to 11 in the HSEU-Bern data, and from 0 to 9 in the SHEDS data.[18] The specifications on the HSEU-Bern data also control for pre-treatment investment literacy. INVLIT is a binary variable that takes the value one if the respondent correctly solved a compound interest rate calculation, and zero otherwise.[19] Compound interest rate calculations are usually used to assess an individual's financial literacy (Lusardi and Mitchell, 2014; Brown and Graf, 2013).

Finally, all specifications include two variables reflecting the two treatments described earlier. TRSLIDE takes the value one if the respondent received a short education program via a set of information slides, and zero otherwise. TRCALC takes the value one if the respondent had access to an online calculator, and zero otherwise. The reference category is CONTROL which takes the value one if the respondent was neither treated with slides nor with a calculator.

[17] Missing values on monthly household income (HHI_MISS) were imputed using a standard multiple imputation approach that makes use of socio-economic information like employment status of respondent, number of people within the house, type of dwelling, size of dwelling and postcode.

[18] The SHEDS dataset did not have a question on whether or not the respondent knows the average price of 1 kWh of electricity in Switzerland which is worth 2 points when constructing the index.

[19] Unfortunately, the investment literacy question was not present in the SHEDS survey. However, we do have a dummy variable UNIV which captures whether the respondent has completed an university level education.

Table 4: Summary Statistics for HSEU-Bern and SHEDS datasets.

	HSEU-Bern ($N = 916$)		**SHEDS** ($N = 5,015$)			
	Mean	*Std.Dev.*	*Mean*	*Std.Dev.*	*Min.*	*Max.*
FEMALE	0.467	0.499	0.509	0.500	0	1
AGE40M	0.406	0.491	0.391	0.488	0	1
AGE40_59	0.367	0.482	0.393	0.489	0	1
AGE60P	0.227	0.419	0.216	0.411	0	1
OWNER	0.248	0.432	0.365	0.482	0	1
HHI6K	0.265	0.442	0.270	0.444	0	1
HHI6_12K	0.468	0.499	0.446	0.497	0	1
HHI12K	0.159	0.366	0.136	0.343	0	1
HHI_MISS	0.107	0.309	0.148	0.355	0	1
UNIV	0.524	0.500	0.404	0.491	0	1
ATTMORAL	0.778	0.416	0.609	0.488	0	1
LANG_FR	—	—	0.261	0.439	0	1
ALPS	—	—	0.214	0.410	0	1
ENLIT_IN#	4.669	2.796	3.191	2.452	0	11
INVLIT	0.717	0.451	—	—	0	1
CONTROL	0.340	0.474	0.804	0.397	0	1
TRSLIDE	0.318	0.466	0.099	0.298	0	1
TRCALC	0.343	0.475	0.098	0.297	0	1
compTLC	0.599	0.490	0.421	0.494	0	1
idLowTLC	0.383	0.486	0.282	0.450	0	1

ENLIT_IN varies from 0 to 9 in SHEDS dataset.

An overview of the summary statistics for the variables used in our econometric models for both datasets are presented in Table 4. The two samples are found to be quite similar in terms of the socio-economic variables like age, sex and income. However, we do observe some notable deviations, e.g., HSEU-Bern has a lower share of people living in owned residences and has a higher share of respondents with a university level degree. This could be explained by the difference in geographical reach of the two surveys — unlike SHEDS, HSEU-Bern concerns only to an urban region. We also notice that about 60% of respondents in the HSEU-Bern sample used lifetime cost calculation as their decision strategy compared to 42% in the SHEDS dataset. Furthermore, a higher share of respondents in HSEU-Bern were able to correctly identify the refrigerator with the lower lifetime cost.

4 Econometric Specification

Empirically, our interest is in identifying the determinants of two decisions —whether a respondent identifies the refrigerator with the lower lifetime cost, and whether he or she decides to carry out a comparison based on lifetime cost calculation. Among the determinants of such decisions, we pay particular attention to the treatments described in Section 3.3.

Similarly to the analysis in Blasch et al. (2017b), our identification strategy relies on the estimation of a recursive bivariate probit. This econometric strategy is equipped to handle i) the binary nature of both decisions; ii) their correlation; and iii) the sequential nature of the decision process.

The correlation in the decisions under analysis arises from their simultaneity, and can be modelled through a bivariate probit (BP) model. The BP models the two binary decisions as a seemingly unrelated system of two probit equations, and captures the correlation in the decisions via the correlation between the error terms.

Formally, let y_1 be a binary variable that takes the value one if the respondent performs a lifetime cost calculation, and zero otherwise. Also, let y_2 be a binary variable that takes the value one if the respondent selects the refrigerator with the lower lifetime cost, and zero otherwise. These binary variables are indicators of whether their latent continuous counterparts are larger than zero —i.e. $y_1 = 1$ if $y_1^* > 0$, and $y_2 = 1$ if $y_2^* > 0$. These latent continuous variables can be considered as measuring, each in the form of a continuous normalized index, the disposition to perform a calculation of lifetime cost (y_1^*) and the ability to correctly identify the refrigerator with the lowest lifetime cost (y_2^*). Thus, the seemingly unrelated system of two probit equations assumed by a BP looks as follows

$$y_1^* = \boldsymbol{\beta}_1'\boldsymbol{x}_1 + \epsilon_1 \quad , \quad y_1 = 1 \quad \text{if} \quad y_1^* > 0 \quad , \quad y_1 = 0 \quad \text{otherwise,} \tag{5}$$

$$y_2^* = \boldsymbol{\beta}_2'\boldsymbol{x}_2 + \epsilon_2 \quad , \quad y_2 = 1 \quad \text{if} \quad y_2^* > 0 \quad , \quad y_2 = 0 \quad \text{otherwise,} \tag{6}$$

$$\begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \quad ,$$

where the vectors $\boldsymbol{x}_1$ and $\boldsymbol{x}_2$ include the variables that are of particular interest in this paper — i.e. the level of energy and investment literacy; and the treatments described in Section 3.3— plus additional control variables that capture the socio-economic characteristics of the respondent and his or her household.

The correlation ρ of the standard bivariate normal distribution describing the two error terms in equations (5) and (6) represents the tetrachoric correlation between the observed binary variables y_1 and y_2. Consequently, ρ is expected to be positive. That is, a respondent that aims to choose the refrigerator with the lowest lifetime cost more likely decides to carry out a lifetime cost calculation. And the reasoning works the other way round —a respondent that does not care about choosing the refrigerator with the lowest lifetime cost very likely decides to skip the lifetime cost calculation.

However, a BP does not capture all relevant features of the decision process we are interested on. In particular, the BP misses the sequential nature of the decisions. Schematically, once a respondent has taken the seemingly unrelated decisions described by equations (5) and (6), he or she carries out two sequential steps to choose the refrigerator with the lower lifetime cost. In the first step, a lifetime cost calculation is carried out —or not. In the second step, conditional on the result of the lifetime cost calculation, the respondent chooses the refrigerator that he or she believes entails the lowest lifetime cost.

This sequential nature is modelled by the recursive bivariate probit (RBP) model. Building upon the BP, a RBP assumes that the error ϵ_2 in equation (6) has two components —one that is deterministic (δy_1^*), and other that remains random (ν_2). Thus, a RBP looks as follows

$$y_1^* = \boldsymbol{\beta}_1'\boldsymbol{x}_1 + \epsilon_1 \quad , \quad y_1 = 1 \quad \text{if} \quad y_1^* > 0 \quad , \quad y_1 = 0 \quad \text{otherwise,} \tag{7}$$

$$y_2^* = \boldsymbol{\beta}_2'\boldsymbol{x}_2 + \delta y_1 + \nu_2 \quad , \quad y_2 = 1 \quad \text{if} \quad y_2^* > 0 \quad , \quad y_2 = 0 \quad \text{otherwise,} \tag{8}$$

$$\begin{pmatrix} \epsilon_1 \\ \nu_2 \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \zeta \\ \zeta & 1 \end{pmatrix}\right] \quad ,$$

where ζ is the correlation of the standard bivariate normal distribution describing the error terms ϵ_1 and ν_2 in equations (7) and (8).

Importantly, in contrast to the BP specification for which ρ is expected to be positive to reflect the positive correlation between y_1 and y_2, the ζ in a RBP model does not necessarily reflect such correlation. This is because once the expected positive impact from y_1 on y_2 has been taken into consideration (i.e. $\hat{\delta} > 0$), the error terms in equations (7) and (8) can be either negatively correlated (i.e. $\hat{\zeta} < 0$) or positively correlated (i.e. $\hat{\zeta} > 0$).[20]

5 Empirical results

In this section, we report results from the estimation of two types of models: a bivariate probit (BP) and a recursive bivariate probit (RBP). Both models are estimated on the two datasets described in Section 3 —HSEU-Bern and SHEDS. Both models analyse the choices of interest as simultaneous decisions.

Table 5 reports results from four econometric specifications. The first two specifications are estimated on the HSEU-Bern data, and the last two on the SHEDS data. The first and third sets of results are obtained through a BP estimated on, respectively, the HSEU-Bern and the SHEDS data. The second and fourth sets of results are obtained through a RBP estimated on, respectively, the HSEU-Bern and the SHEDS data.

Table 5 reports parameter estimates that are not interpretable as marginal effects, thus we present the discussion about the magnitude of the impacts afterwards.

Here, we first briefly comment on the direction of the effects from the control variables. When analysing the HSEU-Bern sample, both BP and RBP yield insignificant effects from most socio-economic and attitudinal controls. With respect to the decision to calculate lifetime cost, owners carry out a calculation of lifetime cost with a higher probability than tenants; and college-educated respondents also choose the lifetime cost calculation with a higher probability than respondents with less years of education. With respect to the selection of the refrigerator, females identify the refrigerator with the lowest lifetime cost with a lower probability than men; and also respondents older than 60 are less likely to identify the refrigerator with the lowest lifetime cost in comparison to respondents younger than 40.

When analysing the SHEDS sample, both BP and RB yield the same directions in the effects from most socio-economic and attitudinal variables. With respect to the decision to calculate lifetime cost, female respondents are less likely to carry out a calculation; the same for respondents older than 40. College-educated respondents or households with a yearly income higher than CHF $12,000$ are more likely to carry out an lifetime cost calculation. With respect to the selection of the refrigerator, the RBP yields only one significant effect from the socio-economic controls: respondents with household income between CHF $6,000$ and CHF $12,000$ are less likely to identify the refrigerator that entails the lowest lifetime cost.

We discuss now the estimates of the correlation parameter (CORR) from the BP specifications — reported at the bottom of Table 5. As explained in Section 4, when a BP is estimated, CORR refers to ρ which captures the correlation between the two simultaneous decisions. According to the results in Table 5, CORR is statistically significant and positive for both datasets — 0.721 for HSEU-Bern, and 0.579 for SHEDS. Thus, as expected, the decision of carrying out a lifetime cost calculation is positively correlated with the selection of the refrigerator with the lower lifetime cost. This positive correlation is itself a policy-relevant result because it confirms that an education

[20]The interpretation of the error term in a recursive bivariate setting has been somewhat unclear in the literature. See Filippini et al. (2017) for details on this issue.

Table 5: Estimation results

	HSEU-Bern		SHEDS	
	BP	*RBP*	*BP*	*RBP*
...Stage 1: Choice of lifetime cost calculation approach...				
Constant	−0.6273***	−0.7379***	−0.2782***	−0.3309***
	(0.1827)	*(0.1839)*	*(0.0591)*	*(0.0590)*
FEMALE	−0.1059	−0.0931	−0.3419***	−0.3308***
	(0.0975)	*(0.0973)*	*(0.0379)*	*(0.0378)*
AGE40_59	−0.0471	−0.0064	−0.1886***	−0.1824***
	(0.1081)	*(0.1079)*	*(0.0433)*	*(0.0429)*
AGE60P	−0.1147	−0.0705	−0.3261***	−0.3293***
	(0.1326)	*(0.1335)*	*(0.0539)*	*(0.0536)*
OWNER	0.2058*	0.2096*	0.0361	0.0488
	(0.1180)	*(0.1183)*	*(0.0417)*	*(0.0414)*
HHI6_12K	0.1293	0.0508	0.0555	0.0604
	(0.1033)	*(0.1043)*	*(0.0407)*	*(0.0406)*
HHI12K	0.3252**	0.2226	0.2507***	0.2466***
	(0.1485)	*(0.1498)*	*(0.0595)*	*(0.0590)*
UNIV	0.2876***	0.4482***	0.2112***	0.2824***
	(0.0847)	*(0.0905)*	*(0.0361)*	*(0.0361)*
ATTMORAL	0.1223	0.0769	0.0235	0.0264
	(0.1096)	*(0.1118)*	*(0.0379)*	*(0.0376)*
LANG_FR	—	—	−0.0124	−0.0219
			(0.0427)	*(0.0424)*
ENLIT_IN	0.0652***	0.0618***	0.0533***	0.0544***
	(0.0165)	*(0.0165)*	*(0.0077)*	*(0.0077)*
INVLIT	0.4499***	0.4433***	—	—
	(0.1005)	*(0.0997)*		
TRSLIDE	0.0465	0.2664**	0.4066***	0.3878***
	(0.1027)	*(0.1034)*	*(0.0565)*	*(0.0585)*
TRCALC	−0.1827*	−0.1013	0.1122*	0.1173*
	(0.1067)	*(0.1062)*	*(0.0623)*	*(0.0618)*
...Stage 2: Choice of refrigerator with the lower lifetime cost...				
Constant	−0.8891***	−1.7026***	−0.4357***	−1.3154***
	(0.1875)	*(0.2023)*	*(0.0606)*	*(0.0657)*
FEMALE	−0.2800***	−0.2115**	−0.3397***	−0.0488
	(0.0993)	*(0.1045)*	*(0.0396)*	*(0.0471)*
AGE40_59	−0.1489	−0.0567	−0.1067**	0.0554
	(0.1066)	*(0.1167)*	*(0.0448)*	*(0.0456)*
AGE60P	−0.3534***	−0.2416*	−0.2296***	0.0511
	(0.1363)	*(0.1394)*	*(0.0566)*	*(0.0592)*
OWNER	0.0092	−0.1369	0.0219	−0.0125
	(0.1175)	*(0.1172)*	*(0.0438)*	*(0.0430)*
HHI6_12K	0.2147**	0.0284	−0.031	−0.0956**
	(0.1078)	*(0.1183)*	*(0.0424)*	*(0.0414)*
HHI12K	0.3778***	0.0085	0.1419**	−0.1008
	(0.1418)	*(0.1577)*	*(0.0604)*	*(0.0639)*
ATTMORAL	−0.0284	−0.1137	−0.0936**	−0.1069***
	(0.1082)	*(0.1000)*	*(0.0393)*	*(0.0386)*
ORDEFF	0.0415	0.0387	—	—
	(0.0810)	*(0.0825)*		
LANG_FR	—	—	0.0563	0.0574
			(0.0456)	*(0.0438)*
ALPS	—	—	−0.0052	0.0075
			(0.0462)	*(0.0445)*
ENLIT_IN	0.0512***	−0.003	0.0351***	−0.0085
	(0.0162)	*(0.0183)*	*(0.0080)*	*(0.0087)*
INVLIT	0.4687***	0.0351	—	—
	(0.1056)	*(0.1338)*		
TRCALC	0.2255**	0.4248***	0.2560***	0.1971***
	(0.0936)	*(0.0996)*	*(0.0621)*	*(0.0653)*
compTLC	—	2.4078***	—	2.0235***
		(0.1736)		*(0.1028)*
CORR	0.7212***	−0.7617***	0.5797***	−0.7175***
	(0.0374)	*(0.2027)*	*(0.0187)*	*(0.0930)*

***, **, * $\Rightarrow$ Significance at 1%, 5%, 10% level. Robust standard error in parenthesis.

program that increases the chances that potential consumers perform a lifetime cost calculation will also positively impact the probability that appliances with the lower lifetime costs will be purchased. However, up to here, no causality can be inferred —as CORR measures only association.

In order to make causal statements, we turn our discussion to the estimates of the parameter associated with the investment decision (compLTC), together with the estimates of the correlation parameter (CORR) from the RBP specifications. The estimates of the parameter associated to compLTC are reported in the second to last row of Table 5. This parameter is statistically significant and positive for both datasets — 2.408 for HSEU-Bern, and 2.024 for SHEDS. We can conclude that choosing to perform a lifetime cost calculation increases the probability of recognizing the refrigerator with the lowest lifetime cost.

Notice that the RBP yields correlation parameters that are significant and negative for both samples under analysis. This negative sign might appear to be counter-intuitive —as the decisions are expected to be positively correlated. However, as pointed out in Section 4, the correlation parameter loses interpretability in the RBP. In this case, the positive impact of the lifetime cost calculation decision is already taken care of through the coefficient associated with compTLC, leaving the sign of the correlation parameter to be mechanically determined (Filippini et al., 2017).

Marginal effects

Statements about the magnitude of effects can only be drawn from marginal effects estimates. In a RBP, it is possible to compute a direct and an indirect effect of a given variable. These effects can be added to obtain the total marginal effect (TME) of the variable on the second outcome, i.e. identification of the refrigerator with the lower lifetime cost. The direct effect of a variable occurs 'directly' in the second equation on the selection of the refrigerator. The indirect effects occurs via the effects on the decision to calculate and compare lifetime costs (the first equation) as this decision variable is also an explanatory variable in the second equation.[21]

Table 6 reports total marginal effects (TME) on the identification of the refrigerator with the lowest lifetime cost. We report TME yielded from the RBP —as it is the model that appropriately accommodates the simultaneous and sequential nature of the decisions under analysis.

Table 6: Total Marginal effects (TME) on the selection of the refrigerator with the lower lifetime cost.

	HSEU-Bern	**SHEDS**
TRSLIDE#	0.0488	0.0871
	(0.0237)	*(0.0190)*
TRCALC#	0.1698	0.1222
	(0.0404)	*(0.0275)*
compTLC	0.6784	0.6459
	(0.0021)	*(0.0003)*
ENLIT_IN	0.0104	0.0089
	(0.0068)	*(0.0036)*
INVLIT#	0.1081	—
	(0.0446)	—

Robust standard error in parenthesis.
Effects are at means and for the recursive bivariate probit setting.
Marginal effects of exogenous dummy variables on compTLC=1.

[21] Details on these calculations are described by Blasch et al. (2017b).

Thus, from Tables 5 and 6, we learn that both treatments increase the probability of identifying the refrigerator with the lowest lifetime cost. Moreover, from Table 6, we learn that the impact of the online calculator is higher. For the case of HSEU-Bern, the effect of the online calculator is almost four times larger than the impact of the four-slide treatment —17 versus 4.9 percentage points. For the case of SHEDS, the effect of the online calculator is around 1.5 times larger than the impact of the four-slide treatment —12.2 versus 8.7 percentage points. These relative magnitudes imply that the online calculator is more effective in terms of increasing the probabilities that a respondent identifies the refrigerator with the lowest lifetime cost.

With respect to the impact of the decision of performing a lifetime cost calculation, results from both datasets are remarkably similar: an increase of 67.8 percentage points in the HSEU-Bern dataset versus an increase of 64.6 percentage points in the SHEDS dataset. This consistency across datasets can be interpreted as evidence of robustness of our results.

Finally, we discuss the marginal effects from pre-treatment energy and investment literacy. Respondents with higher pre-treatment energy literacy do have a higher probability of recognizing the most refrigerator with the lowest lifetime cost, a result that holds across datasets —1 percentage point for HSEU-Bern, and 0.9 percentage point for SHEDS. For the case of HSEU-Bern, pre-treatment investment literacy has a positive impact on the selection of the refrigerator with the lower lifetime cost —with a TME of 10.8 percentage points.

6 Conclusions

A higher adoption rate of energy-efficient appliances is expected to contribute towards energy efficiency improvements in the residential sector. However, consumers' investment decisions have not completely aligned yet — even though the most energy-efficient appliances in the ideal case also reduce the lifetime cost of consuming a specific energy service.

We point out that the identification of the most energy-efficient appliance with the lowest lifetime cost may be a challenging task, as individuals need to compare the purchase prices and future operating cost of the electrical appliances to make economically rational decisions. This requires a certain level of energy-related investment literacy. Previous studies have shown that the level of energy-related investment literacy among people is relatively low and that many individuals refrain from making elaborate calculations in decision situations. Therefore, it is highly relevant whether decision support tools can improve the level of energy-related investment literacy of individuals. Building upon previous research (Blasch et al., 2017b,a), we explored the impact of simple decision-support tools in the form of a set of information slides and an online calculator on an individual's ability to identify the appliance with the lowest lifetime cost when confronted with two appliances with differing energy consumption, offered at different purchase prices. We designed an online randomized controlled trial and implemented it on two independently chosen samples of the Swiss population. The short education program —via information slides— aimed at enhancing an individual's energy-related investment literacy, whereas the the second intervention, an online calculator, aimed at reducing task complexity. Both interventions were expected to reduce deliberation cost for the individual and hence to increase the probability that the individual chooses optimization rather than a heuristic decision making strategy, and hence the probability to identify the appliance with the lowest lifetime cost.

The similarities in the results obtained from the two independent samples of Swiss consumers are encouraging. Results from both samples support our hypothesis that decision-aids that either reinforce an individual's energy-related investment literacy or reduce task complexity, increases the rate at which individuals optimize rather than follow a heuristic decision-making strategy, and in turn, also improves the rate at which they identify the appliance with the lowest lifetime cost. A relevant nuance has become clear in both samples: while both interventions are effective at increasing the chances that an appliance with the lower lifetime cost is chosen, the online calculator is more effective than the set of information slides in reducing deliberation cost. The probability to identify the appliance with the lower lifetime cost increased by 12 to 17 percentage points for individuals who had used the online calculator as compared to individuals who had not used the calculator. Apart from these results, evidence also suggest that pre-treatment energy and investment literacy positively impacts on the probability of identifying the appliance with the lowest lifetime cost.

These results have important policy implications. Making a complex, inter-temporal optimization appears to be an important barrier for consumers who are boundedly rational when it comes to the choice of investments, pension plans and appliances or other devices with hidden future operating costs. New solutions are needed to overcome this barrier. The development and promotion of web-based educational programs to improve the level of financial or investment literacy as well as the provision of online or mobile phone calculator tools could be effective instruments to promote various important policy goals in the areas of public health, public finance and environmental sustainability. From a policy point of view, these measures are easy to implement in order to encourage the boundedly rational consumer to make optimal choices. Moreover, because of the mixed-public good characteristics of such instruments, they should be supplied by the state to avoid under-provision. These instruments are a particularly interesting policy measure as they can be offered at relatively low cost, while a large part of the population would benefit from them.

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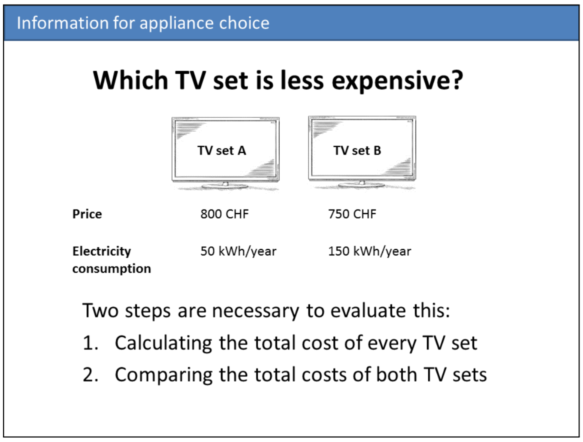
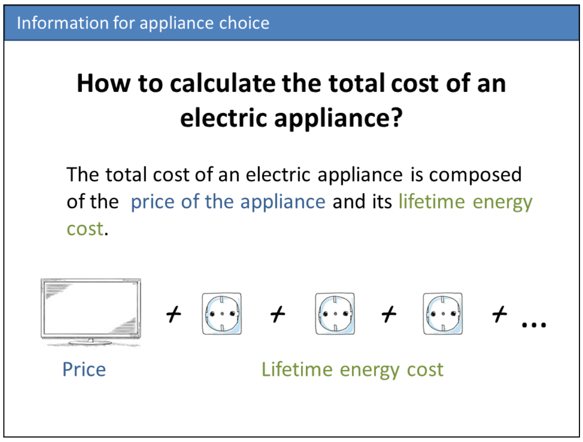
Appendix



(a) Slide-1



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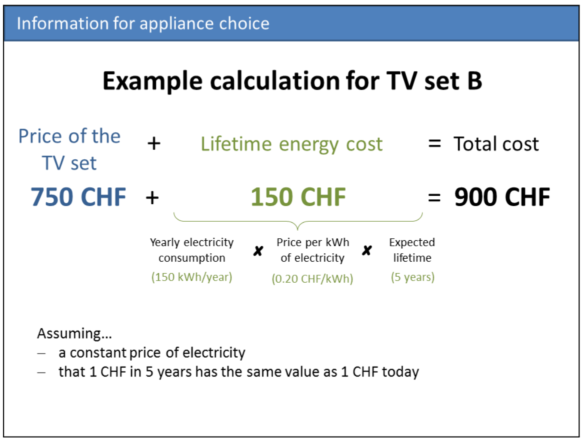

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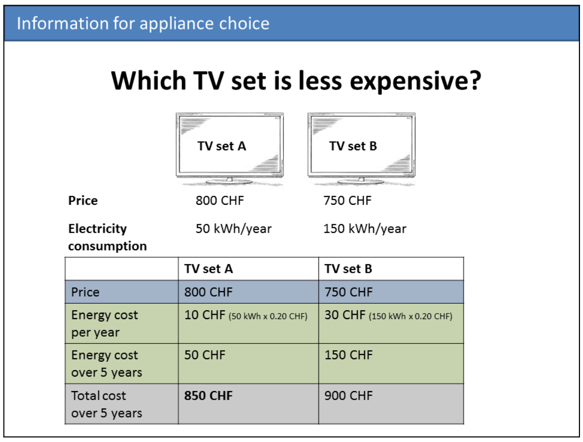


(d) Slide-4

Figure 4: Education-slides as intervention for the TRSLIDE treatment group.

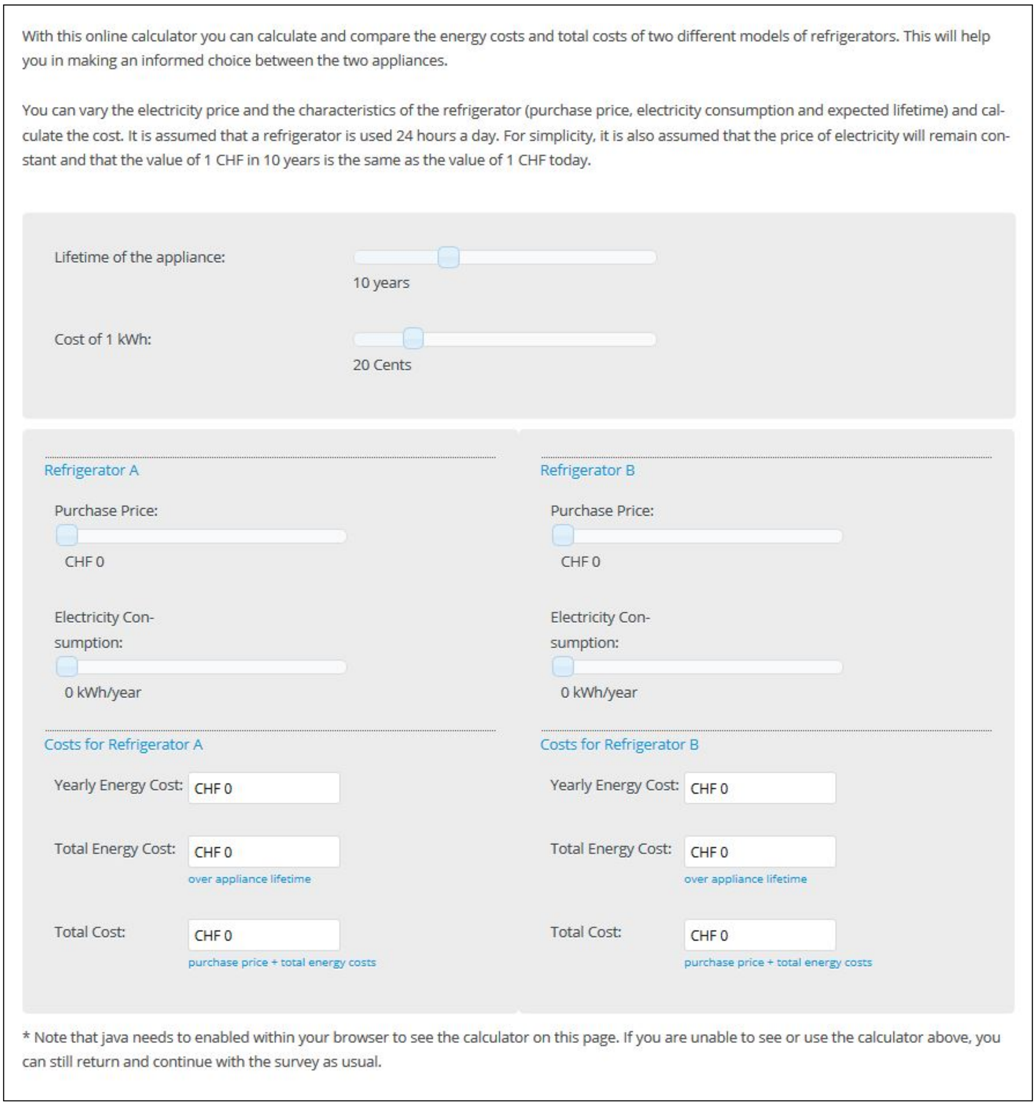
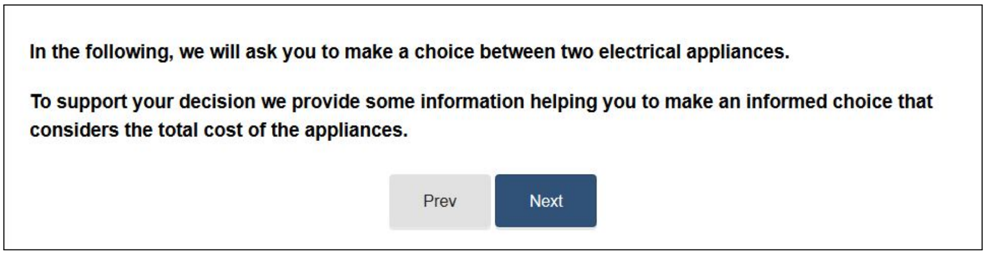
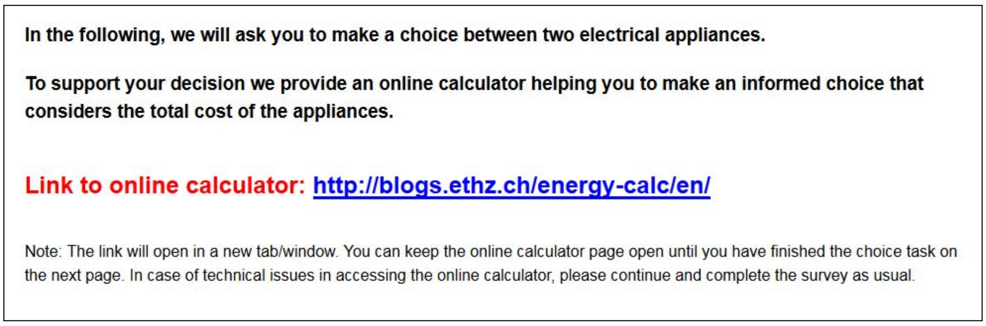


Figure 5: Online calculator as intervention to the TRCALC treatment group.

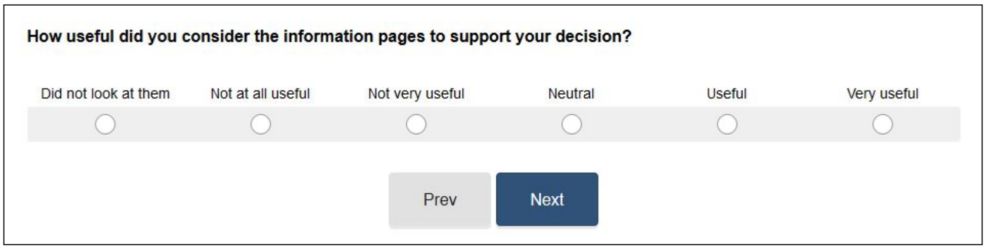


(a) TRSLIDE group

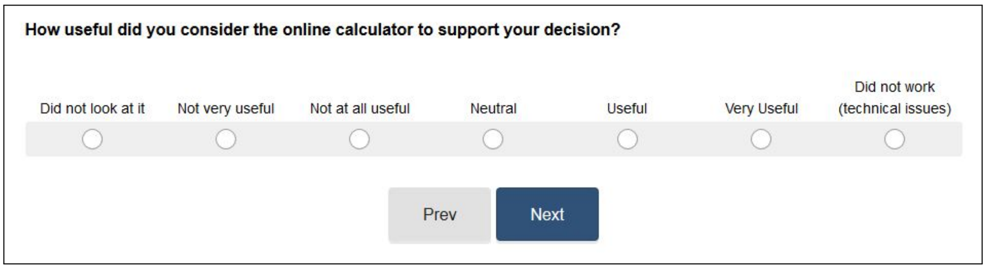


(b) TRCALC group

Figure 6: Pages shown to the two treatment groups prior to the experiment.



(a) TRSLIDE group



(b) TRCALC group

Figure 7: Debriefing questions specific to the two treatment groups.

Table 7: Overview of the experiment outcome given the decision strategy.

HSEU-Bern (N=916)						
Decision Strategy →	Lifetime cost comparison			Purchase price comparison		
Group (N)	*idLowTLC=0*	*idLowTLC=1*	*% Correct**	*idLowTLC=0*	*idLowTLC=1*	*% Correct*
CONTROL (311)	88	91	50.8%	4	0	0%
TRSLIDE (291)	93	102	52.3%	2	1	33.3%
TRCALC (314)	51	124	70.9%	5	3	37.5%

idLowTLC=1: Correct identification of the refrigerator with the lower lifetime cost.
*For those who declared to have found the intervention 'useful' or 'very useful': 50% (TRSLIDE) and 86.6% (TRCALC).

SHEDS (N=5,015)						
Decision Strategy →	Lifetime cost comparison			Purchase price comparison		
Group (N)	*idLowTLC=0*	*idLowTLC=1*	*% Correct***	*idLowTLC=0*	*idLowTLC=1*	*% Correct*
CONTROL (4,031)	839	767	47.8%	88	102	53.7%
TRSLIDE (494)	154	132	46.2%	11	2	15.4%
TRCALC (490)	82	135	62.2%	6	15	71.4%

**For those who declared to have found the intervention 'useful' or 'very useful': 47.4% (TRSLIDE) and 78.1% (TRCALC).

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