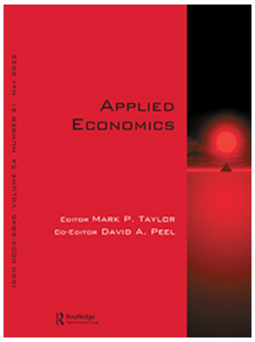

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Boosting the choice of energy-efficient home appliances: the effectiveness of two types of decision support

Julia E. Blasch [a], Massimo Filippini [b,c], Nilkanth Kumar [b] and Adan L. Martinez-Cruz [d]

[a]Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, Netherlands; [b]Centre of Economic Research (CER-ETH), ETH Zürich, Zurich, Switzerland; [c]Università della Svizzera italiana, Lugano, Switzerland; [d]Department of Forest Economics, and Centre for Environmental and Resource Economics (CERE), Swedish University of Agricultural Sciences (SLU), Umeå, Sweden

ABSTRACT
Consumers' limitations in assessing the lifetime cost of household appliances may sustain the much-cited energy efficiency gap. We analyse the impact of an individual's energy and investment literacy and two different types of decision support on the ability to identify the appliance with the lower lifetime cost in an online randomized controlled trial among two independently chosen samples of the Swiss population. In a decision task, participants choose between appliances with different lifetime cost. One treatment offers a short education programme on how to calculate the lifetime cost of an appliance – via a set of information slides. The second treatment provides access to an online lifetime-cost calculator tool. We find that pre-treatment energy and investment literacy are positively associated with the probability of identifying the appliance with the lowest lifetime cost. Evidence in this paper suggest that both decision aids boost identification of energy-efficient appliances. We discuss strategies to scale up these boosters.

KEYWORDS
Energy efficiency; bounded rationality; deliberation cost; boosting; online tools; energy and investment literacy

JEL CLASSIFICATION
D12; D80; Q41; Q48

I. Introduction

As shown by Attari et al. (2010) for the US, by Brounen, Kok, and Quigley (2013) for the Netherlands and by Blasch et al. (2017) for Switzerland, the level of energy-related knowledge and investment literacy in the population tends to be relatively low. Moreover, Blasch, Filippini, and Kumar (2019) show that a significant share of individuals do not seem to consider the lifetime cost of electrical appliances when choosing between two appliances. From an energy policy point of view, it would therefore be desirable to improve the level of investment literacy among consumers and to reduce their deliberation cost, i.e. their cognitive cost of assessing different investment options, so that consumers are more likely to engage in lifetime cost calculations. To this end, educational programmes and decision-support tools that aim to increase the literacy among consumers or to reduce deliberation cost can be thought as 'boosts' —i.e. as tools that improve people's competence to make their own choices (Hertwig 2017). In other contexts, it has been demonstrated that setting up education programmes and providing high-quality decision aids in the decision situation can empower consumers to make better financial decisions (Bernheim, Garrett, and Maki 2001; Goda, Manchester, and Sojourner 2014; Savikhin 2013). The increasing distribution of internet access within households opens the opportunity to propose educational materials that can be accessed quickly and easily.

Recent research in the energy domain has shown that a household's level of energy, investment or financial literacy can positively influence its level of energy efficiency by supporting individuals' choices of more efficient electrical appliances and lighting (Blasch, Filippini, and Kumar 2019; Blasch et al. 2017; Brounen, Kok, and Quigley 2013; Brent and Ward 2018; Blasch et al. 2021). In fact, identifying the most cost-effective, and ideally also most energy-efficient, electrical appliance can be challenging for the consumer. To make an economically rational choice, an individual should perform an investment analysis, taking into account not only the purchase price of the appliances but also their future operating costs. The latter depend on the electricity consumption of the appliance, the

CONTACT Nilkanth Kumar nkumar@ethz.ch E14, Zürichbergstrasse 18, Zürich 8092, Switzerland

expected intensity and frequency of use, the expected lifetime of the appliance as well as current and future electricity prices. There is ample evidence from other domains such as financial investments, credit card use and pension decisions, that many individuals make suboptimal decisions when confronted with complex calculations (Agarwal and Mazumder 2013; Altman 2013). Calculating the expected lifetime cost of an electric appliance creates 'deliberation cost' (Pingle 2015), often also referred to as 'decision-making cost' or 'optimization cost'(Conlisk 1996). The concept is closely related to the concept of 'bounded rationality' (Simon 1959; Sanstad and Howarth 1994; Conlisk 1996), which implicitly presumes that information acquisition is costly and the processing of information is cognitively burdensome, impeding optimization as postulated for the rational homo economicus.

While previous literature evaluates the relationship between energy and financial literacy and appliance choices or energy use (Blasch, Filippini, and Kumar 2019; Blasch et al. 2017; Brounen, Kok, and Quigley 2013; Brent and Ward 2018; Blasch et al. 2021) or studies the socioeconomic determinants of energy-related investment literacy (Blasch et al. 2021; Filippini, Kumar, and Srinivasan 2020), this study analyzes whether targeted interventions in the form of a short online educational programme and an online calculator tool have the potential to increase 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 and investment literacy. The second intervention, a simple online calculator that compares the lifetime costs of two appliances, potentially minimizes the cognitive effort that an individual needs to spend on the calculation. These interventions differ from those used in previous studies focused on the impact of efficiency labels or labels providing additional energy use information on the choice of household appliances (Andor, Gerster, and Sommer 2020; Davis and Metcalf 2016; Hille et al. 2018; Houde 2018; Newell and Siikamäki 2014). Rather than testing the impact of providing information, we test the impact of instruments that help consumers process the available information. For these types of interventions, the term 'boosting' has recently been introduced, which refers to behavioural policy measures that 'target the individual's skills and knowledge, the available set of decision tools, or the environment in which decisions are made' (Grüne-Yanoff and Hertwig 2016, 152)).

The 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 choose between two appliances differing in purchase price and energy consumption. The participants are not asked to choose their preferred appliance, but to identify the electrical appliance that minimizes the total lifetime cost. The first sample (HSEU-Bern sample) comprises 916 households residing in the city of Bern, whereas the second sample (SHEDS sample) comprises 5, 015 households randomly sampled from households residing in the German- and French-speaking parts of Switzerland. By estimating several probit models, we find evidence across both samples suggesting that both decision aids are effective in increasing the probability that an individual identifies the electrical appliance with the lowest lifetime cost.

Given the documented effect from the online tool and the relatively low cost from developing such a tool, we suggest that online investment calculators provided through mobile phone applications can effectively boost consumers' decisions, be it in the domain of electrical appliances or other domains that require solving complex, intertemporal 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 II discusses the role of decision aids and energy and investment literacy and proposes a simple theoretical framework to study their impact on appliance choice. The dataset and the experimental design are presented in Section III. Section IV presents the results and Section V concludes.

II. Boosting individual decisions toward energy-efficient appliance choices

So far, very few studies have evaluated the effectiveness of decision-support tools in directing consumers towards purchasing more efficient electric appliances. Allcott and Taubinsky (2015), for example, show that disclosing lifetime cost of light bulbs in the purchase situation increased consumers' willingness to pay for compact fluorescent light bulbs. Allcott and Sweeney (2017) test whether energy efficiency information through sales agents in the purchase situation positively impacts on consumers' purchases of energy-efficient appliances but do not find any effect. Furthermore, studies by Dwyer (2011) and Zografakis, Menegaki, and Tsagarakis (2008) show that an introduction of energy literacy curricula at schools can positively impact on the energy-related behaviour of students. Attari and Rajagopal (2015) compare and discuss various decision aids to help consumers make effective decisions (e.g. 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).

Outside of the energy context, studies show that providing simple decision aids in the decision-making situation can help individuals make better choices. Goda, Manchester, and Sojourner (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 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 programmes is provided by Bernheim, Garrett, and Maki (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.

It has been shown that 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, Stenner, and Hobman 2015; Andor, Gerster, and Sommer 2020). One explanation for heuristic decision-making is that the decision-maker incurs cognitive cost related to gathering all the necessary information for an optimization, and also to performing the optimization itself. The literature refers to this barrier to optimization as 'deliberation cost' (Pingle 2015), 'decision-making cost' or 'optimization cost' (Conlisk 1996). Hence, there seems to be a substantial potential for supporting consumers in the purchase situation through the provision of effective decision aids. We are interested to study how to empower consumers to overcome heuristic decision-making by means of two different types of decision aids that qualify as 'boosts', i.e. behavioural interventions that improve individuals' competences to make own choices (Grüne-Yanoff and Hertwig 2016; Hertwig 2017).

Previous research has shown that energy, investment or financial literacy can positively influence the level of energy efficiency of a household (Blasch et al. 2017) by supporting consumers' choices of more efficient electrical appliances and heating systems (Blasch, Filippini, and Kumar 2019; Brounen, Kok, and Quigley 2013; Brent and Ward 2018; Blasch et al. 2021). Blasch, Filippini, and Kumar (2019) documents that displaying information about the future energy consumption of electrical appliances in monetary terms – rather than physical units (kWh) – on a modified energy label increases the probability that an individual makes a calculation and identifies the appliance with the lowest lifetime cost. Brent and Ward (2018) use a choice experiment to show that an individual's level of financial literacy determines energy efficiency investments. In Boogen et al. (2020), the influence of customized monetary information on the operating costs of appliances and lighting sources is tested in a field experiment using home energy audits. Blasch et al. (2017) and Brounen, Kok, and Quigley (2013) investigate the impact of an individual's level of energy-related financial literacy on energy consumption. Blasch et al. (2021) explore whether consumers scoring high on energy-related financial literacy are more likely to invest in LED light bulbs at home.

In this paper, we propose that intervening in the decision-making of the individual by means of an educational programme or a calculator tool impacts differently on the appliance choice. While we expect both types of decision support increase the chances that an individual identifies the appliance with the lowest lifetime cost, we expect that the educational programme increases the level of energy- and investment literacy of the decision-maker, whereas the lifetime-cost calculator tool would only reduce the complexity of the decision task. Both interventions aim to reduce 'deliberation cost', albeit through different channels.

This reasoning is in line with a simple model of expectation formation developed and formalized by Blasch, Filippini, and Kumar (2019), relying on previous work of Conlisk (1988).[1] In this framework, an educational programme will impact on the choice primarily through an individual's level of energy and investment literacy. As literacy is potentially enhanced by the programme, 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. On the contrary, a calculator tool may not directly influence an individual's level of energy or investment literacy but will substantially reduce the task complexity. This too will lower the unit costs of decision-making such that the probability to choose an optimization strategy increases.

We therefore set up the following two hypotheses:

H1: Reading information slides on how to properly calculate lifetime costs of an appliance – thereby presumably enhancing the decision-maker's level of energy and investment literacy – will increase the decision-maker's propensity to identify the appliance with the lowest lifetime cost.

H2: Using a calculator tool that calculates the lifetime costs of an appliance – thereby implicitly minimizing task complexity for the decision-maker – will increase the decision-maker's propensity to identify the appliance with the lowest lifetime cost.

In the empirical part, we also analyse the role of the preexisting energy and investment literacy of respondents on their ability to correctly identify the appliance with the lower lifetime cost.

III. Data and experimental design

To test our hypotheses empirically, we gather data 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 in Section 3.3, is the same in both samples, as are most of the survey questions that captured demographic and socio-economic information used in our empirical analysis.

The methodology for data collection underlying these two samples is briefly described below.

HSEU-Bern

The first dataset comes from a large web-based household survey on energy use conducted in cooperation with 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.

[1]A similar theoretical approach is followed by Houde (2018), who presents a model of information acquisition for energy-intensive durables in which consumers optimize over the effort to collect and process energy information.

EWB customers were invited with a letter accompanying one of their electricity (or gas) bills to access an online questionnaire.[2] 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%).[3] 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]

SHEDS

The second dataset analysed 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 (Weber 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 French- and German-speaking regions of Switzerland[6] —which hosted around 94% of the population in Switzerland in 2015 (FSO 2016).[7] SHEDS' sample has been constructed to be representative of the population residing in those regions, according to pre-selected characteristics and quotas as follows: age — 18–34 = 30%, 35–54 = 40%, 55+ = 30%—; gender – males = 49%, females = 51%—; living situation – tenants = 62.5%, owners = 37.5%—; and region – French-speaking = 25%, German-speaking = 75% (Weber et al. 2017).

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 Intervista 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).

Experimental design

The online randomized controlled experiment was embedded within the two household surveys.[8] All respondents were randomly assigned[9] to one of the three groups – control group (CONTROL), a treatment group with educational slides (TRSLIDE), and another treatment group with access to an online calculator (TRCALC). Within HSEU-Bern, each respondent 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

[2]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.

[3]The response rate for this first dataset is very low primarily because of the underlying organizational specifics. The invitation to participate was sent on paper, including a link to the online survey. Moreover, this invitation letter was sent together with one of the regular utility bills which unfortunately lowered the probability that it caught customer's attention.

[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.

[5]From 2016 to 2020, SCCER-CREST has implemented five annual waves to generate a rolling panel dataset of 5,000 responses per wave. Further details are provided by Weber et al. (2017), and policy on data availability is posted in https://www.sccer-crest.ch/research/swiss-household-energy-demand-survey-sheds/.

[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)).

[8]Note that our online experiment is not a stated choice exercise as it does not request our respondents to state their preferences but to identify an appliance with the lowest lifetime cost.

[9]SurveyMonkey (for HSEU-Bern) and Qualtrics (for SHEDS) were used as software suites for the online surveys. Advanced software tools such as these provide randomization as a feature.

assigned to TRSLIDE, and another 500 assigned to TRCALC, with around 4,000 belonging to the control group.[10]

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 1). 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. We decided to abstract from discounting when introducing the task to our respondents, as the focus of our study lies on the impact of our treatments on objective criteria such as cognitive abilities and information processing, whereas time discounting expresses a subjective preference. Moreover, we anticipated that the average participant of our study is not familiar with the concept of discounting and would need a calculator to incorporate discounting in the analysis, they were asked to assume that 1 kWh of electricity will cost about 20 Rappen[11] 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.[12]

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 educational slides designed to improve the consumers' knowledge on how to do an investment analysis and to compare lifetime cost of appliances (Figure A1 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 exposed to the second intervention: access to a simple web-based tool in the form of an online calculator was provided 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.[13] We could not observe whether or how long the survey respondents were involved with the two decision aids but asked respondents in a follow-up question whether they considered the intervention 'useful' or not.[14]

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 1), 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

[10]SHEDS is a relatively longer 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.

[11]1 CHF = 100 Rappen; and 1 CHF = 0.97 USD, as of mid-April 2016.

[12]Other studies in this domain also abstract from the concept of discounting (Allcott and Taubinsky 2015). However, we cannot observe whether some of our participants discounted the future energy cost anyway. Typical discount rates used by Swiss consumers lie in the range of 2.5% to 27% (Alberini, Bareit, and Filippini 2016; Bruderer Enzler, Diekmann, and Meyer 2014). While Bruderer Enzler, Diekmann, and Meyer (2014) estimate the average discount rate based on survey data to be around 27%, the analysis of Alberini, Bareit, and Filippini (2016) estimates it to be around 2.5%, based on market data. Furthermore, at the time of carrying out the data collection, savings interest rates were close to zero (EY 2016), which makes another potential motivation to apply high discount rates less relevant.

[13]The online calculator required a user to input the purchase price and yearly energy consumption in kWh/year of two refrigerators(Figure A2 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).

[14]Figure A4 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 1. The refrigerator question in the identification task.

cost and to distinguish them from the respondents who followed another, possibly heuristic-based, decision-making strategy.[15]

Descriptive statistics

This sub-section reports descriptive statistics of variables informing the econometric specifications reported in Section IV. Control variables include gender, age, ownership of the house, income, and education.[16] In addition, all econometric specifications also control for respondents' pre-treatment energy and investment literacy – measured by an energy literacy index (ENLIT_IN) and an investment literacy indicator (INVLIT), respectively. 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. For descriptive statistics of the single items of the index see the Appendix, Table A3.[17] 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.[18] Compound interest rate calculations are usually used to assess an individual's financial literacy (Lusardi and Mitchell 2014; Brown and Graf 2013).[19]

Finally, all specifications include two variables reflecting the two treatments described earlier. TRSLIDE takes the value one if the respondent

[15]We tried to capture the self-declared decision strategy as a debriefing question, as this is potentially helpful in explaining a few underlying mechanisms through which the interventions may have affected the outcome of the identification task. In Section 4.2, we present a short discussion on this aspect.

[16]Details on these variables are included in the Appendix.

[17]Almost 77% of the respondents in the HSEU-Bern sample did not correctly report the average electricity price. This is in line with earlier findings of Blasch et al. (2017) from Switzerland who find that only about 27% of the surveyed respondents know the average price of electricity. Note that 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 (details reported in Table A3 in the Appendix).

[18]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.

[19]As the scales on these energy literacy and investment literacy variables are different, the empirical estimation would use the standardized versions (z-scores, with zero mean and unit standard deviation) of these variables.

Table 1. 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
AGE40 M	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
PRO_ENV_ATD	0.778	0.416	0.609	0.488	0	1
ORDEFF	0.477	0.499	—	—	0	1
L_FRENCH	—	—	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
idLowTLC	0.383	0.486	0.282	0.450	0	1

Note: This table reports the summary statistics for all variables used in the empirical analysis for the two datasets, HSEU-Bern and SHEDS. The outcome variable is idLowTLC. #ENLIT_IN varies from 0 to 9 in SHEDS.

received a short education programme 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 information slides nor with a calculator.

An overview of the summary statistics for the variables used in our econometric models for both datasets are presented in Table 1.[20] 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.

Our outcome variable measures whether a respondent has correctly identified the refrigerator with the lowest lifetime cost (idLowTLC = 1). According to the last row of Table 1, a higher share of respondents in HSEU-Bern sample (0.38) were able to correctly identify the refrigerator with the lower lifetime cost in comparison to those in the SHEDS sample (0.28).

To evaluate how well these two samples reflect the basic demographic characteristics of their respective geographic regions, we compared the sample characteristics to available population statistics (details are provided in the Appendix).

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.[21] 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. Also, as we document in Section IV, the results are generally consistent across both samples, regardless of the differences in sampling strategy and sampled population.

It is worth mentioning that the low share of respondents correctly identifying the refrigerator with the lower lifetime cost (Table 1) is not necessarily an indication of low calculation skills among the respondents, but partly also a reflection of the various

[20]Table A4 in the Appendix compares means and standard deviations across treatment and control groups as a check for the quality of randomization.
[21]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.

Table 2. Comparison of means.

	HSEU-Bern ($N = 916$)		SHEDS ($N = 5,015$)	
	N	*idLowTLC=1*	*N*	*idLowTLC=1*
CONTROL	311	0.306 (0.026)	4,031	0.267 (0.007)
TRSLIDE	291	0.402[a] (0.029)	494	0.328[a] (0.021)
TRCALC	314	0.443[a] (0.028)	490	0.363[a] (0.022)

Note: This table reports the means and standard errors (in parenthesis) for the share of correct responses across the control and treatment groups. idLowTLC = 1 implies that a respondent correctly identified the refrigerator with the lower lifetime cost.
[a]Difference in means compared to the CONTROL is significant at the 5% level (t-test). Difference in means between the two treatments is not significant at the 5% level (t-test).

decision-making strategies that can be applied in such a decision task. Not identifying the refrigerator with the lower lifetime cost can either be the result of failing in the lifetime cost calculation, or the result of following a heuristic decision-making strategy, such as choosing the appliance with the lowest electricity consumption, the lowest purchase price, or the best energy-efficiency rating on the energy label.[22]

IV. Empirical results

In this section, we first compare mean values of how respondents performed on the identification task across the randomly assigned control and treatment groups. Thereafter, given the binary nature of the outcome, we estimate a probit model and report the estimated coefficients and marginal effects. Considering these empirical findings as the main set of results, we discuss some heterogeneous effects in order to shed light on potential mechanisms and channels through which the difference in the outcome across the control and treatment groups could be explained. All analysis is performed on the two independent datasets, HSEU-Bern and SHEDS.[23]

Comparison of means

Table 2 presents the number of respondents in the control and treatment groups for the two data samples. It also shows the share of correct responses for the outcome variable (idLowTLC = 1).

From the table, we see that the share of respondents making a correct identification is significantly higher in either of the two treatment groups, TRSLIDE and TRCALC, when compared to the CONTROL group. Another interesting observation is that respondents with access to calculator correctly identify the refrigerator with the lower lifetime cost more often than those undergoing the education programme (44.3% versus 40.2% in HSEU-Bern and 36.3% versus 32.8% in SHEDS). However, the difference is not statistically significant. A difference in share of correct responses under the two interventions can be expected as the interventions are likely operating through different channels. In the TRSLIDE group, information slides shown to respondents explain how to compute and compare two energy consuming durable using an example, but the respondents would still need to correctly perform the necessary computations for the task at hand. On the other hand, the online calculator available to respondents in the TRCALC group enables them to directly perform the computations and hence substantially reduces the overall task complexity and the deliberation costs linked to performing the computations.

Given that the respondents were randomly assigned to one of the three groups, and that we observe a general balance of covariates across these groups as a check for quality of randomization (Table A4 in Appendix), the

[22]Note that the correct answer to the identification task in the experiment was not incentivized. We are aware that the outcomes might differ if respondents were taking an actual decision.
[23]For the sake of completion we also estimated a standard linear probability model, the results of which are reported in Table A5 in the Appendix. The signs and coefficients for our variables of interest are analogous.

above findings provide evidence of the positive impact of the two interventions in supporting respondents' decision on the identification task.

Probit estimates and marginal effects

We now undertake an econometric approach and fit a probit model on the binary outcome (correct or incorrect identification) where we control for several socio-demographic attributes. We are particularly interested in quantifying the impact of the two treatments and also the role of pre-treatment energy and investment literacy of respondents.

Table 3 reports results from two econometric specifications, one each for the two datasets. The first set of results is obtained through a probit estimated on the HSEU-Bern data and the second set of results is obtained through a probit estimated on the SHEDS data. As the reported parameter estimates in Table 3 are not interpretable as marginal effects, we present the discussion about the magnitude of the impacts afterward.

Table 3. Estimation results.

	HSEU-Bern *Probit*	SHEDS *Probit*
FEMALE	−0.287***	−0.326***
	(0.097)	(0.040)
AGE40_59	−0.061	−0.089*
	(0.107)	(0.045)
AGE60P	−0.288**	−0.221***
	(0.133)	(0.057)
OWNER	0.024	0.033
	(0.118)	(0.044)
HHI6_12K	0.085	−0.073
	(0.108)	(0.045)
HHI12K	0.191	0.027
	(0.146)	(0.063)
UNIV	0.403***	0.228***
	(0.094)	(0.040)
PRO_ENV_ATD	−0.045	−0.093**
	(0.107)	(0.040)
ORDEFF	0.128	—
	(0.089)	
L_FRENCH	—	0.042
		(0.046)
ALPS	—	−0.014
		(0.049)
ST(ENLIT_IN)	0.142***	0.086***
	(0.046)	(0.019)
ST(INVLIT)	0.200***	—
	(0.049)	
TRSLIDE	0.268**	0.172***
	(0.111)	(0.063)
TRCALC	0.354***	0.283***
	(0.107)	(0.062)
N	916	5015

Notes: ***, **, * ⇒ Significance at 1%, 5%, 10% level. Robust standard errors in parenthesis. Constants not shown. ENLIT_IN and INVLIT were used in a standardized form (z-scores).

Table 4. Effects from discrete changes in binary variables (TRSLIDE and TRCALC) and marginal effects (ST(ENLIT_IN) and ST(INVLIT)).

	HSEU-Bern	SHEDS
TRSLIDE	0.0919**	0.0560***
	(0.0378)	(0.0205)
TRCALC	0.1214***	0.0921***
	(0.0360)	(0.0202)
ST(ENLIT_IN)	0.0486***	0.0281***
	(0.0155)	(0.0062)
ST(INVLIT)	0.0687***	—
	(0.0162)	

Notes: ***, **, * ⇒ Significance at 1%, 5%, 10% level. Robust standard errors in parenthesis. The reported effects are the average marginal effects for a probit model specification with idLowTLC as outcome. Literacy related variables, ENLIT_IN and INVLIT, were used in a standardized form (z-scores). In the context of binary variables, the marginal effects are in fact discrete effects as they refer to effects due to discrete changes.

We briefly comment on the signs of coefficients reflecting association with control variables. Coefficients on most attributes in the two samples appear to have similar signs and significance. In both samples, we observe that females identify the lower lifetime cost refrigerator with a lower probability than men; respondents older than 60 are less likely to identify the refrigerator with the lower lifetime cost in comparison to respondents younger than 40; and respondents with a university degree are more likely to correctly identify the refrigerator. In the case of SHEDS, we observe a negative coefficient for respondents exhibiting pro-environmental attitude. It could be that some of these respondents employ a heuristic approach such as looking 'only' at the annual electricity consumption without doing a lifetime cost calculation, which for this particular task would mean they end up incorrectly identifying the lower lifetime cost refrigerator. Our main variables of interests, the treatments and the energy and investment literacy, have a positive and significant coefficient in both the samples. These findings are also robust when we exclude participants who did not report their income.

Statements about the magnitude of effects are better drawn from the marginal effects estimates. Table 4 reports average marginal effects (for ST (ENLIT_IN) and ST(INVLIT)) and effects from discrete changes in binary variables (TRSLIDE and TRCALC) resulting from the probit model estimations.

From Tables 3 and 4, we learn that both treatments increase the probability that respondents in the two samples correctly identify the refrigerator with the lower lifetime cost. The magnitude of the treatment effects is found to be stronger in the HSEU-Bern sample than in the SHEDS sample, i.e. 9.2 percentage points (TRSLIDE) and 12.2 percentage points (TRCALC) for HSEU-Bern versus 5.6 percentage points (TRSLIDE) and 9.2 percentage points (TRCALC) for SHEDS. Furthermore, the effect due to the calculator treatment is larger than the education treatment by about 3 percentage points in HSEU-Bern and 3.6 percentage points in SHEDS. Note that the t-tests reported in Tables 2 and post-hoc power calculations suggest that while effects from the online calculator are identifiable under reasonable values of type I and type II errors, the effect from the educational slides treatment is identifiable only under mediocre statistical power scenarios.[24] Consequently, we interpret these point estimates as suggesting that the online calculator, in comparison to the educational slides treatment, can be expected to have a larger impact on the probability that individuals correctly select a refrigerator with lower lifetime costs.

It is worth noting that the treatment effects reported here are, in essence, intent to treat (ITT) effects (as opposed to average treatment effects on the 'treated' or ATT). Although respondents in the treatment groups were always shown the educational slides, or had access to the online calculator, we did not have a clear way to track whether they actually read through and used these decision aids.

Finally, we discuss the marginal associations from pre-treatment energy and investment literacy. Respondents with higher pre-treatment energy literacy exhibit a higher probability of recognizing the refrigerator with the lower lifetime cost, a result that holds across datasets —4.86 percentage points for HSEU-Bern, and 2.81 percentage points for SHEDS. An even stronger association, 6.87 percentage points for HSEU-Bern, was observed for pre-treatment investment literacy on the selection of the refrigerator with the lower lifetime cost.

We have also tried to capture the decision strategy of respondents in our surveys for the two samples, as this could be potentially helpful in explaining the underlying mechanisms through which the educational slides and calculator affects the outcomes. We asked respondents about their decision-making strategy, i.e. how they reached their conclusions in the identification task (Figure A5 in the Appendix). The answer options to this question (except the 'Other reason' option) were presented in a random order to avoid any order bias. Overall, we find that the treatments seem to induce more respondents into following a decision strategy based on comparison of the total lifetime cost (i.e. purchase price + lifetime energy cost).[25]

Heterogeneous effects

The findings presented until this point are clearly indicative of a positive role of the two decision-support interventions. The results also highlight the importance of energy and investment literacy. In this part, we would like to explore some heterogeneity-related aspects in order to shed light on potential mechanisms and channels through which we could better understand the differences in the outcome across the control and treatment groups.

[24]Based on the proportions reported in Table 2, we carried out post-hoc two-sample test power calculations. Keeping the type I error fixed at 0.05 and for the case of the HSEU-Bern sample, the power to identify differences between the control and the educational slides treatment is around 69%; and the power to identify differences between the control and the online calculator treatment is around 94%. Keeping the type I error fixed at 0.05 and for the case of the SHEDS sample, the power to identify differences between the control and the educational slides treatment is around 80%; and the power to identify differences between the control and the online calculator treatment is around 99%.

[25]In preliminary analysis steps, instead of considering a single binary outcome, we tried to jointly model two binary outcome variables – whether or not respondents opt for lifetime cost calculation as their self-declared decision strategy, and whether or not they correctly identify the refrigerator with lower lifetime cost. The overall essence of the obtained results in terms of the role of interventions and other variables of interest is very similar to the results presented here. However, our preliminary approach had two main limitations, first that the follow-up question on self-declared decision strategy may not have been entirely unambiguous to all respondents, and some of the respondents may have misinterpreted the question. Second, the simultaneous estimation of two decisions implied a complex model with stronger assumptions, and one that did not fully consider the fact that there were several decision strategies possible.

Table 5. Heterogeneous effects with interactions using linear probability model.

	HSEU-Bern *LPM*	SHEDS *LPM*
FEMALE	−0.091	−0.112***
	(0.057)	(0.014)
AGE40_59	−0.053	−0.026
	(0.061)	(0.017)
AGE60P	−0.112*	−0.057***
	(0.067)	(0.020)
OWNER	0.053	0.003
	(0.071)	(0.016)
HHI6_12K	0.024	−0.009
	(0.059)	(0.016)
HHI12K	0.034	0.032
	(0.083)	(0.024)
UNIV	0.176***	0.059***
	(0.053)	(0.015)
PRO_ENV_ATD	−0.012	−0.031**
	(0.037)	(0.013)
ORDEFF	0.038	—
	(0.031)	
L_FRENCH	—	0.014
		(0.015)
ALPS	—	−0.005
		(0.016)
ST(ENLIT_IN)	0.054**	0.029***
	(0.026)	(0.007)
ST(INVLIT)	0.058**	—
	(0.025)	
TRSLIDE	0.012	0.040
	(0.105)	(0.064)
TRCALC	0.200**	0.147**
	(0.100)	(0.060)
FEMALE × TRSLIDE	0.073	0.044
	(0.087)	(0.045)
FEMALE × TRCALC	−0.083	0.009
	(0.080)	(0.046)
AGE40_59 × TRSLIDE	0.069	−0.012
	(0.097)	(0.052)
AGE40_59 × TRCALC	0.022	−0.028
	(0.087)	(0.053)
AGE60P × TRSLIDE	0.087	−0.038
	(0.111)	(0.064)
AGE60P × TRCALC	−0.038	−0.085
	(0.107)	(0.062)
OWNER × TRSLIDE	−0.074	0.045
	(0.105)	(0.050)
OWNER × TRCALC	−0.075	0.038
	(0.100)	(0.050)
HHI6_12K × TRSLIDE	0.084	−0.045
	(0.090)	(0.052)
HHI6_12K × TRCALC	−0.058	−0.117**
	(0.085)	(0.051)
HHI12K × TRSLIDE	0.089	−0.109
	(0.128)	(0.073)
HHI12K × TRCALC	0.037	−0.127*
	(0.122)	(0.075)
UNIV × TRSLIDE	−0.095	0.081*
	(0.082)	(0.048)
UNIV × TRCALC	−0.002	0.105**
	(0.079)	(0.048)
ST(ENLIT_IN) × TRSLIDE	0.004	0.004
	(0.042)	(0.021)
ST(ENLIT_IN) × TRCALC	−0.011	−0.007
	(0.037)	(0.023)
ST(INVLIT) × TRSLIDE	0.001	—
	(0.039)	
ST(INVLIT) × TRCALC	0.026	—
	(0.037)	

Notes: ***, **,* ⇒ Significance at 1%, 5%, 10% level. Robust standard errors in parenthesis. Constants not shown.

Recall that we found evidence suggesting that certain attributes such as gender, age group and university education may also play a role in the determination of the outcome. It is also worth investigating whether the treatments have varying effects depending on some of these attributes. To this purpose, we explore the possibility of observed heterogeneity in the effects from our treatments. Our heterogeneity analysis accounts for interaction terms for our treatments with female, age categories, ownership, household income categories, university education, and energy and investment literacy. All interaction terms are jointly estimated in a linear probability model framework for directly obtaining the marginal effects. Table 5 reports the results on the two samples.

We observe significant coefficients on some of the respondent level attributes in the control group – age group, university education, and the preexisting energy literacy have significant estimates in both samples; preexisting investment literacy is significant in the HSEU-Bern sample; gender and pro-environmental attitude are significant in the SHEDS sample. In the HSEU-Bern sample, we find that none of the interaction terms yield statistically significant coefficients. This is an interesting finding given our randomized experimental setup. It implies that while we observe a significant role of age group, university education, and the preexisting energy and investment literacy in the control group, we do not find any statistically significant heterogeneous impact of the two interventions.

In the SHEDS sample though, we notice significant interactions related to income categories and university education. The negative coefficients on the income categories interacted with TRCALC imply that, compared to the reference income category, participants in these categories performed worse on the identification task in the presence of the calculator treatment. Similarly, the positive coefficients on the university education dummy interaction terms suggest higher impact of the two interventions on respondents with university education compared to those without university education. While the latter result makes intuitive sense, the former finding is a bit unusual. However, these findings on the heterogeneous effects of the treatment for SHEDS are not too robust.[26] Nevertheless, the differences in these effects across the two samples are reminiscent of the fact that these samples were neither drawn from the same population and nor were the surveys administered under the same setup.

Looking at the non-interacted treatment variables that resemble the effect on the reference participant in the interaction models – i.e. male, below 40 years of age, does not own their residence, belongs to the reference (lower) income category, and have lower levels of preexisting energy and investment literacy – we observe that the coefficients on the calculator treatment appear to be strong and positive – 20% points for HSEU-Bern, and 14.7% points for SHEDS. Whereas the coefficients on the educational slides treatment appear to be positive but insignificant. Overall, this difference across the two treatments is also indicative of our earlier observations on the post-hoc power calculations and that the effect due to the calculator treatment is larger.

V. Conclusion and policy implications

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.

Building upon previous research (Blasch, Filippini, and Kumar 2019; Blasch et al. 2017, 2021), we have explored the impact of two types of 'boosts' (Grüne-Yanoff and Hertwig 2016; Hertwig 2017) 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. 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 aim at reinforcing an individual's energy and investment literacy or at reducing task complexity, increase the rate at which individuals identify the appliance with the lowest lifetime cost.

A relevant nuance has become clear: while evidence from both samples suggest that the online calculator is effective at increasing the probability that an appliance with the lower lifetime cost is chosen, the evidence on the effect from the information slides is weaker. While we find evidence that the information slides boost individual's chances to perform a lifetime cost calculation, their overall effectiveness on an individual's probability to identify the least-cost appliance is lower in comparison to the online calculator. These results suggest that – even after having been taught how to perform an investment calculation – the cognitive effort of calculating and comparing lifetime costs remains a major barrier for the identification of efficient appliances. Evidence also suggest that pretreatment energy and investment literacy are positively associated identification of the appliance with the lowest lifetime cost. The impact of investment literacy is much stronger than that of energy literacy.

We would like to emphasize that the ability to perform a lifetime-cost calculation is of course a necessary but not sufficient condition for choosing an energy-efficient appliance. Several other factors clearly play a role in this decision as well. With our research, we are able to identify and isolate the ability to calculate the lifetime cost of an appliance as one factor that impedes the choice of more energy-efficient appliances, amongst others. Our findings 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

[26]We performed robustness checks on these interaction models for both samples by dropping respondents who did not report their income and by dropping speeders (available only in SHEDS). For SHEDS, the significant coefficients on the interaction terms tended to become either weakly significant, or insignificant, when we dropped participants who did not report their income, or when we dropped the quickest ten percent (group-specific) speeders within the randomized experiment. In the HSEU-Bern sample, the coefficients on the interaction terms remained robust when we dropped participants who did not report their income.

choice of investments, pension plans and appliances or other devices with hidden future operating costs.

The effectiveness of performing a lifetime cost calculation is linked closely to the level of energy and investment literacy of the decision-maker. This begs an important question – is it good to nudge people to undertake an intertemporal optimization decision if the underlying calculations are too complicated for them? New solutions are needed to overcome this barrier. The development and promotion of web-based educational programmes 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 not only regarding energy efficiency but also in various other areas of public health, public finance and environmental sustainability that involve intertemporal decision-making. From a policy point of view, these measures are low-cost and easy to implement. One example of such an online support tool is the webportal www.topten.eu, which offers a comparison of the lifetime cost of various household appliances for several EU countries, Argentina, Brazil, Chile and China. While www.topten.eu offers the comparison only for a pre-selection of appliances, user-friendly webtools or apps that can be applied to all products on the market, and allow consumers to specify their own assumptions regarding duration of use, electricity prices, etc., are hardly available. The latter would support individuals effectively in the selection of cost- and energy-efficient appliances, as our findings show. Due to the mixed-public good characteristics of such instruments, a strong role for governments in supplying and promoting them seems crucial to avoid under-provision.

In our decision experiment, the application of heuristics led to the choice of the more energy-efficient appliance, which raises the question whether deviations from rational and fully informed decision-making should always be corrected, as in some cases they may be welfare-enhancing. Results as those reported in Wichman (2017) and Brent and Ward (2019) demonstrate that consumer misinformation can be welfare enhancing whenever it results in public benefits that exceed the private costs due to misinformation. In the absence of an energy-efficiency gap, i.e. when the purchase of energy-efficient devices is not privately optimal, a situation in which it might be beneficial to not interfere with consumers' heuristic or otherwise irrational decision-making could arise. However, under the assumption that the purchase of energy-efficient devices is also privately optimal, enhancing consumers' skills to make rational and fully informed decisions will be welfare enhancing. This is also a matter of consumer sovereignty (Waldfogel 2005; Redmond 2000). To what extent should governments care to eliminate consumer irrationality if it keeps individuals from making privately optimal choices? The literature on nudging and boosting clearly argues that nudges and boosts should aim to increase the decision-maker's welfare (Sunstein and Thaler 2003; Grüne-Yanoff and Hertwig 2016). Our proposed interventions are aimed at achieving this.

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ORCID

Julia E. Blasch http://orcid.org/0000-0002-1082-9272
Massimo Filippini http://orcid.org/0000-0002-5972-4439
Nilkanth Kumar http://orcid.org/0000-0002-5055-5798
Adan L. Martinez-Cruz http://orcid.org/0000-0001-7865-5339

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Appendix

HSEU-Bern sample

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 A1) obtained from the Swiss Cities Association (SSV).

Table A1. 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

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

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. With respect to household income, available statistics for the population appear to exist only at the national level (and are reported together with the discussion on the SHEDS sample). 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.

SHEDS sample

Table A2. 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[a]	0.60
Household Income (%):-		
lower than 6K CHF	26.9	29.3[b]
6K-12K CHF	44.5	45.0[b]
higher than 12K CHF	13.7	25.7[b]
missing	14.9	–
Region (%):-		
French-speaking	25.00	21.00
German-speaking	75.00	74.00
Home-ownership (%):-		
tenants	62.50	62.50
owners	37.50	37.50

Data source: Switzerland's population in 2015 (FSO, (2016)) and Statistik der Schweizer Städte 2017 (FSO, (2017b)).
[a]Number of rooms including kitchen.
[b]Household income for Swiss population in 2009-2011 (BFS Haushaltsbudgeterhebung (HABE) 2009-2011, 2014).

Table A2 compares the SHEDS sample statistics with the corresponding Swiss population statistics. The proportion of males and females reached by SHEDS closely replicates 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.[27]

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*. Despite this feature, SHEDS appears to closely replicate the national average figures for people per room. For Switzerland, the average gross monthly household income in 2014 was 10,079 CHF.[28] Given the category-wise household income statistics (for years 2009–2011) in the table, our observed household income distribution in the SHEDS sample appears reasonable.

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 Rehdanz 2010; Rehdanz 2007).

Data preparation

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 (AGE40 M 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.[29] 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).[30] 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 L_FRENCH which takes the value one if the respondent speaks French as main 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 PRO_ENV_ATD is one if the respondent chose 'agree' or 'strongly agree'.

ORDEFF is a binary variable that controls for the random assignment of the presentation order of the two appliances in the identification task, i.e. in Figure 1 half of the respondents sees that Fridge – A's purchase price is 3300 CHF and Fridge – B's is 2800 CHF, while the other half sees that Fridge – A's purchase price is 2800 CHF and Fridge – B's is 3300 CHF.[31]

For construction of the energy literacy index (ENLIT_IN), Table A3 reports the individual survey items and the share of correct responses to each item. The number of correct responses were weighted, with more difficult questions receiving higher weights. The assigned weights were as follows: 1 point each for the three pairwise comparison question (Q3) on knowledge of electricity consumption of various household appliances; 2 points for the knowledge of the average price of electricity (Q1), and 3 points each for the two questions on knowledge of the usage cost (Q2) of different household appliances. Therefore, the final energy literacy index ranges from 0 to 11 in the HSEU-Bern sample. As the question on knowledge of average electricity price was not asked in the SHEDS survey, it ranges from 0 to 9 in the SHEDS sample.

[27]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.

[28]https://www.eda.admin.ch/aboutswitzerland/en/home/wirtschaft/soziale-aspekte/haushaltseinkommen-und–ausgaben.html Accessed on 02.Oct.2019.

[29]When it comes to purchase decision of large household appliances, the ownership is perhaps a more crucial attribute than electricity consumption itself. Almost two-third Swiss live in rented housing that generally comes prefixed with larger electrical appliances like oven, fridge and dishwasher, and any change is usually responsibility of either the landlord or the rental agency.

[30]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.

[31]Although randomization of presentation order was implemented in both surveys, the variable ORDEFF is available only for the HSEU-Bern dataset.

Table A3: Energy literacy survey questions.

	HSEU-Bern (N = 916)		SHEDS (N = 5,015)	
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*
Q1: How much do you think 1 Kilowatt hour (kWh) of electricity currently costs in Switzerland (on average)? Please indicate your best guess without checking your bill or other resources.	0.23	0.421	—	—
Q2: How much do you think it costs in terms of electricity to run:				
(2a) a desktop PC for 1 hour?	0.467	0.499	0.305	0.46
(2b) a washing machine (load of 5kg at 60C)?	0.202	0.402	0.15	0.357
Q3: In the following pairs, which of the two consumes more electricity?				
(3a) Pair 1: Bringing 1 litre of water to a boil in an average pot with lid **v/s** Running a washing machine with a load of 5kg at 60C	0.837	0.369	0.733	0.442
(3b) Pair 2: Bringing 1 litre of water to a boil in an average pot with lid **v/s** Bringing 1 litre of water to a boil in an electric kettle	0.731	0.443	0.618	0.486
(3c) Pair 3: Running a desktop PC for 1 hour **v/s** Running a laptop for 1 hour	0.632	0.482	0.476	0.499

Table reports the summary statistics on individual survey items used to construct the energy literacy index. All individual questions are treated as dichotomous with 1 implying a correct response, and 0 otherwise. Q1 had a numeric box to input the amount (Amount in Rappen/Centimes) and a 'I do not know' choice. A range from 15–25 has been considered as a correct response. Q2 had a drop-down with choices as: 0-19/20-39/40-59/60-79/80-100/More than 100/I do not know. The correct responses are: (2a) 0–19; and (2b) 0–19 or 20–39. Q3 had four answer choices – one for each item in the pair followed by 'Both consume about the same' and 'I do not know'. The correct responses are: (3a) second item in the pair; (3b) first item in the pair; and (3c) first item in the pair.

The investment literacy index (INVLIT), available only in the HSEU-Bern sample, is dichotomous and takes the value 1 if respondents correctly answered a compound interest question that read as: Let us say you have 200 CHF in a savings account. The account earns 10% interest per year. How much would you have in the account at the end of 2 years? (Answer choices: 204/220/240/242/Don't know).

Additional figures and tables

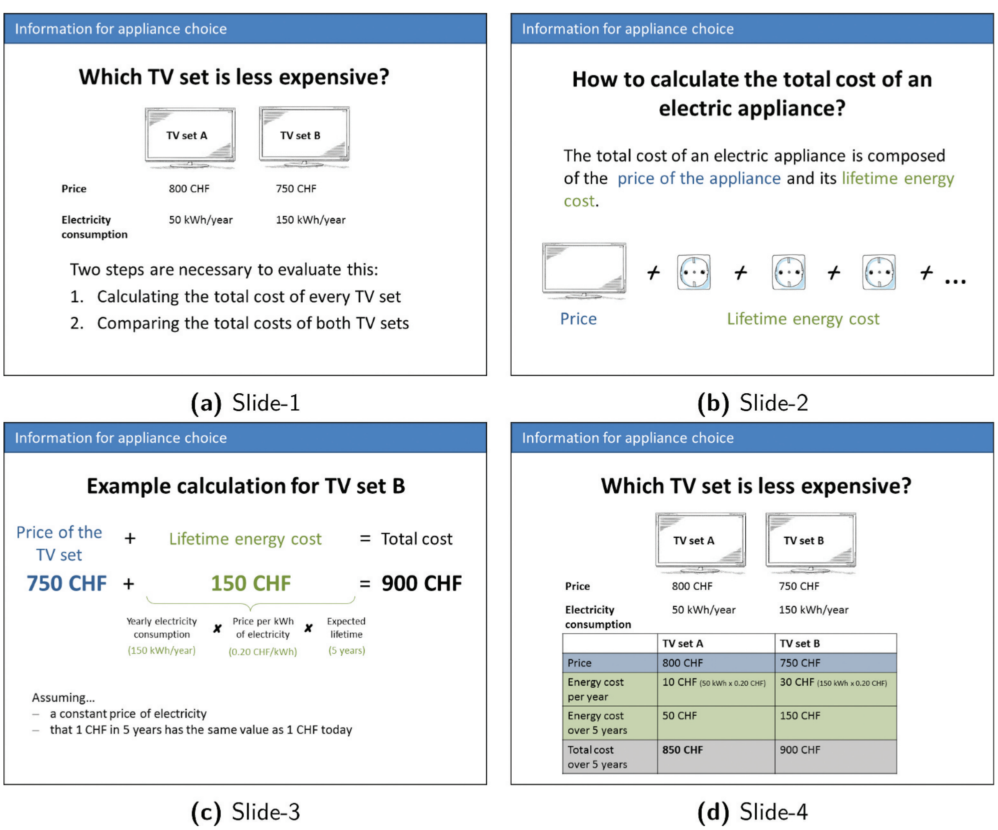


Figure A1: Information slides as intervention for the TRSLIDE treatment group.

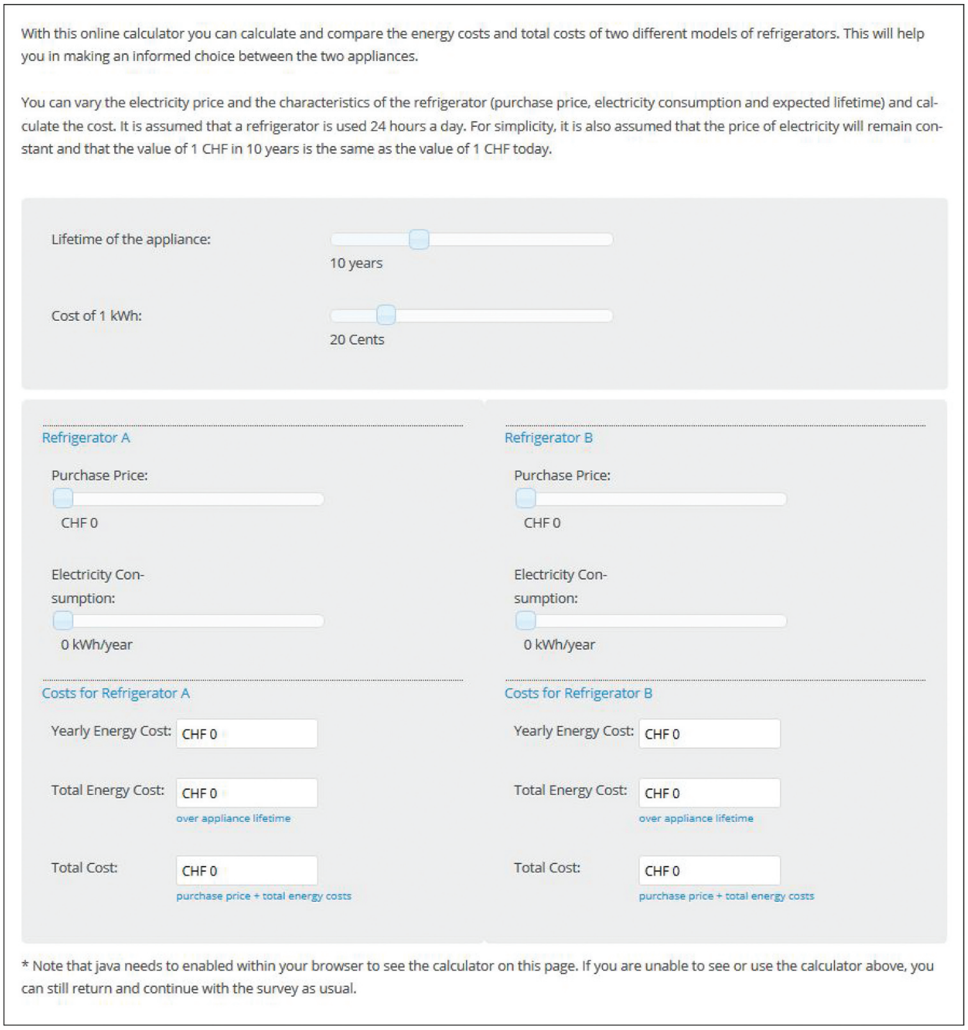
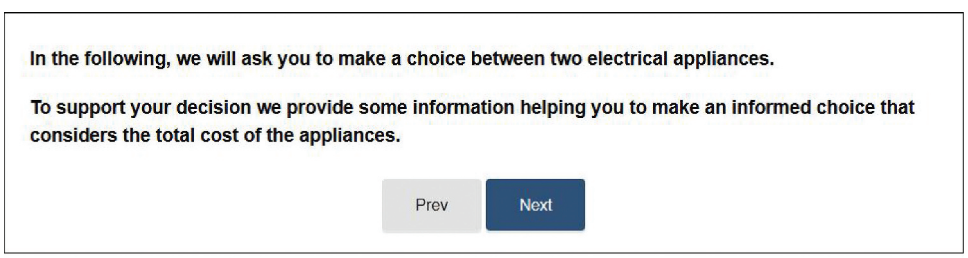
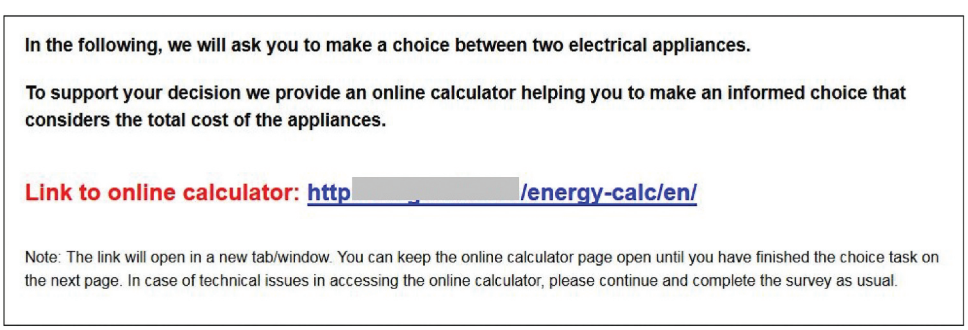


Figure A2: Online calculator as intervention to the TRCALC treatment group.

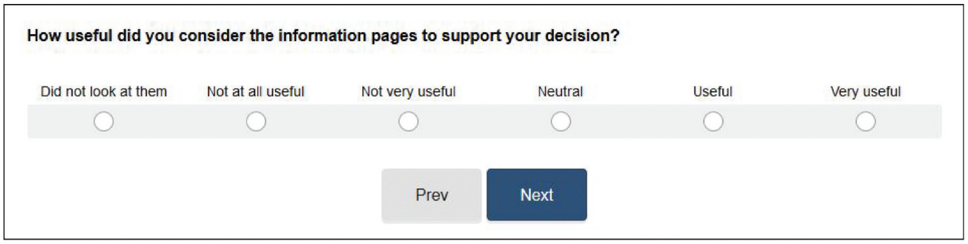


(a) TRSLIDE group

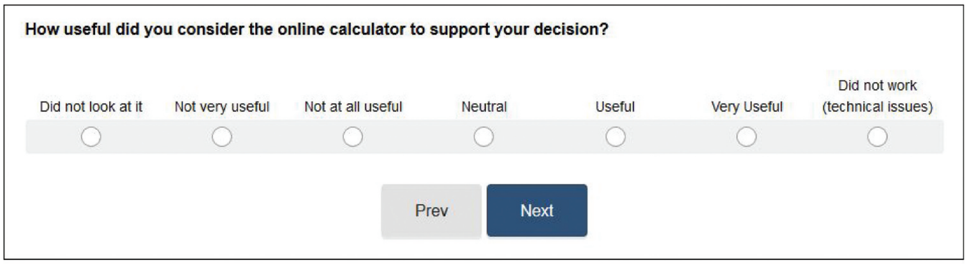


(b) TRCALC group

Figure A3: Pages shown to the two treatment groups prior to the experiment.



(a) TRSLIDE group



(b) TRCALC group

Figure A4: Debriefing questions specific to the two treatment groups.

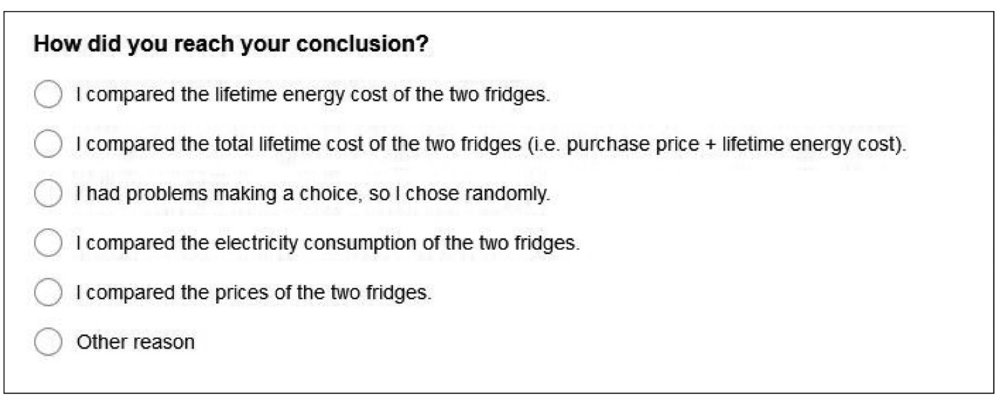


Figure A5: Debriefing question about the decision-making strategy.

Table A4: Comparison of variable means across control and treatment groups.

	HSEU-Bern ($N = 916$)			SHEDS ($N = 5{,}015$)		
	CONTROL	*TRSLIDE*	*TRCALC*	*CONTROL*	*TRSLIDE*	*TRCALC*
FEMALE	0.492	0.450	0.459	0.509	0.496	0.516
	(0.501)	(0.498)	(0.499)	(0.500)	(0.500)	(0.500)
AGE40M	0.415	0.385	0.417	0.391	0.385	0.400
	(0.493)	(0.487)	(0.494)	(0.488)	(0.487)	(0.490)
AGE40_59	0.363	0.354	0.382	0.393	0.415	0.376
	(0.482)	(0.479)	(0.487)	(0.488)	(0.493)	(0.485)
AGE60P	0.222	0.261	0.201	0.216	0.200	0.224
	(0.416)	(0.440)	(0.401)	(0.412)	(0.401)	(0.418)
OWNER	0.215	0.278	0.252	0.365	0.362	0.367
	(0.412)	(0.449)	(0.435)	(0.482)	(0.481)	(0.483)
HHI6k	0.309	0.234	0.252	0.269	0.259	0.284
	(0.463)	(0.424)	(0.435)	(0.444)	(0.439)	(0.451)
HHI6_12k	0.395	0.495	0.516	0.445	0.453	0.447
	(0.490)	(0.501)	(0.501)	(0.497)	(0.498)	(0.498)
HHI12k	0.183	0.175	0.121	0.137	0.134	0.131
	(0.388)	(0.381)	(0.327)	(0.344)	(0.341)	(0.337)
HHI_MISS	0.113	0.0962	0.111	0.149	0.154	0.139
	(0.317)	(0.295)	(0.315)	(0.356)	(0.361)	(0.346)
UNIV	0.514	0.519	0.538	0.402	0.423	0.402
	(0.501)	(0.501)	(0.499)	(0.490)	(0.495)	(0.491)
PRO_ENV_ATD	0.743	0.801	0.793	0.612	0.587	0.612
	(0.438)	(0.400)	(0.406)	(0.487)	(0.493)	(0.488)
ORDEFF	0.482	0.440	0.506	—	—	—
	(0.500)	(0.497)	(0.501)			
L_FRENCH	—	—	—	0.260	0.277	0.245
				(0.439)	(0.448)	(0.430)
ALPS	—	—	—	0.215	0.206	0.214
				(0.411)	(0.405)	(0.411)
ENLIT_IN#	4.492	4.680	4.834	3.195	3.148	3.204
	(2.837)	(2.647)	(2.885)	(2.450)	(2.547)	(2.370)
INVLIT	0.691	0.735	0.726	—	—	—
	(0.463)	(0.442)	(0.447)			

Note: The means and standard deviations (in parentheses) are reported here for all covariates. We also compared the means across the CONTROL, TRSLIDE and TRCALC groups using a t-test. The quality of randomization is found to be very good. The only exceptions are the two income categories, HHI6_12K and HHI12K, in HSEU-Bern sample where the t-test rejects the null hypothesis (that the difference in means is zero) for 'CONTROL v/s TRSLIDE' and for 'CONTROL v/s TRCALC'. The null hypothesis is not rejected for 'TRSLIDE v/s TRCALC'. We can not think of an explanation for this as the randomization was inbuilt within the software suite and appears to work quite well across all other variables in HSEU-Bern.

#ENLIT_IN varies from 0 to 11 in HSEU-Bern and from 0 to 9 in SHEDS.

Table A5: Estimation results for linear probability model.

	HSEU-Bern *LPM*	SHEDS *LPM*
FEMALE	-0.101***	-0.107***
	(0.034)	(0.013)
AGE40_59	-0.020	-0.029*
	(0.037)	(0.015)
AGE60P	-0.096**	-0.070***
	(0.044)	(0.018)
OWNER	0.003	0.011
	(0.041)	(0.014)
HHI6_12K	0.025	-0.024*
	(0.036)	(0.014)
HHI12K	0.065	0.010
	(0.052)	(0.021)
UNIV	0.144***	0.077***
	(0.033)	(0.013)
PRO_ENV_ATD	-0.019	-0.030**
	(0.037)	(0.013)
ORDEFF	0.045	—
	(0.031)	
L_FRENCH	—	0.013
		(0.015)
ALPS	—	-0.005
		(0.016)
ST(ENLIT_IN)	0.050***	0.029***
	(0.016)	(0.007)
ST(INVLIT)	0.066***	—
	(0.016)	
TRSLIDE	0.087**	0.058***
	(0.038)	(0.022)
TRCALC	0.118***	0.097***
	(0.036)	(0.022)
N	916	5015

***, **, * ⇒ Significance at 1%, 5%, 10% level. Robust standard errors in parenthesis. Constants not shown. ENLIT_IN and INVLIT were used in a standardized form (z-scores).