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Consumers' Preferences for Electricity-Saving Programs: Evidence from a Choice-Based Conjoint Study

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Abstract

Electric utilities play a crucial role in deploying electricity conservation programs. As people can freely choose whether to participate in such programs, a better understanding of what types of programs would appeal to specific groups of customers is fundamental. We therefore explore preferences of likely subscribers for electricity-saving programs listing a set of different program features (based on goal setting, tailored feedback provision, as well as reward and penalty schemes) and use a latent class approach to capture heterogeneity in preferences and detect groups of people that share similar preferences. We subsequently profile the different segments of likely program subscribers and likely non-subscribers in terms of socio-demographic, psychographic, and behavioral characteristics. Overall, our results show that there is considerable heterogeneity in tastes for different features of electricity-saving programs. By identifying individual characteristics that influence the likelihood to participate in different forms of such programs, our findings may help electric utilities in better satisfying customer needs by designing electricity-saving programs in line with people's preferences and in more effectively tailoring marketing and communication programs to the specific target groups.

Keywords: Market segmentation; Choice-based conjoint analysis; Electricity-saving programs; Latent class analysis

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1. Introduction

Electricity represents one quarter of overall energy used in Switzerland (SFOE, 2017), and reducing electricity demand thus seems a decisive factor in achieving the country's long-term energy conservation targets. The Swiss Energy Strategy 2050 indeed foresees a reduction in total electricity consumption by 13% by 2035 and 18% by 2050 compared to 1990 levels (Energie Schweiz, 2015). In this respect, the residential sector plays a crucial role, given that it is responsible for 32.8% of total final electricity demand (SFOE, 2017). On the one hand, demand for residential electricity can be decreased through technological advancements in energy efficiency of the services provided (e.g., equipping households with energy-efficient appliances) (Burger et al., 2015). On the other hand, enhancing efficiency does not necessarily warrant a reduction in electricity demand because of the rebound effect, which can partially offset the benefits of technological advancements (e.g., Greening et al., 2000; Hediger et al., 2016; Weber and Farsi, 2014). Therefore, a combined dual strategy based on improving efficiency and encouraging curtailment is necessary to achieve the intended electricity-saving targets (Hille, 2016).

Electric utilities play a crucial role in the deployment of electricity-saving programs (e.g., by providing households with electricity consumption feedback, making use of goal-setting techniques, or using financial instruments to promote electricity-saving achievements) (Abrahamse et al., 2005; Bertoldi et al., 2013; Harding and Hsiaw, 2014). Indeed, research shows that the combination of different approaches results in most significant behavior changes, given that different barriers prohibit different households from action (Abrahamse et al., 2007). Nevertheless, using a one-size-fits-all combination of strategies for all consumers might not be the silver bullet to success. Using more than one approach simultaneously can result in a complicated and less focused message (Schultz, 2014). Given that certain programs depend on user engagement (Buchanan et al., 2015) and may appeal more strongly to certain segments of the population than others, it is "important to match the tool to the audience and the behavior" (Schultz, 2014, p. 107). Thus, a better understanding of the needs of different segments is critical to encourage as many electricity consumers as possible to participate in electricity-saving programs.

By means of a choice-based conjoint (CBC) experiment, we aim to explore likely subscribers' preferences for different electricity-saving program features, including the level of the savings target to be achieved, the size and form of the reward customers would receive on achieving the target, and the prevalence of additional information in the form of feedback to allow

tracking of progress toward the target. Moreover, we investigate the acceptance of a possible penalty that would accrue in case the agreed-on target is missed. We use a latent class approach to capture heterogeneity in preferences and to detect groups of people who share similar preferences. Our findings should help utilities to better satisfy customers' needs by designing electricity-saving programs that are in line with their preferences.

Households can freely opt to participate in electricity-saving programs or not; who would voluntarily participate in such programs remains an open research question. To unravel the drivers of likely subscription versus non-subscription of electricity-saving programs, we analyze whether consumers who intend to participate in such programs ("likely subscribers") differ from those who are unlikely to do so ("likely non-subscribers") in terms of socio-demographic (e.g., age) and psychographic (e.g., values) characteristics. In addition, we profile the segments of likely subscribers to different types of programs to identify characteristics that explain segment affiliation. Such knowledge should provide guidance to electric utilities on designing appropriate marketing and communication measures to foster adoption. Such insight is crucial considering that effective marketing and communication is a more important driver in increasing participation rates in such programs than, for example, the size of the reward (Stern et al., 1986).

The remainder of the paper proceeds as follows. Section 2 provides a brief overview of relevant studies that have investigated different strategies for promoting electricity savings. Section 3 describes the methodological approach and the design of the CBC survey. Section 4 presents the empirical results. Section 5 discusses the policy implication of our results and concludes.

2. Strategies for promoting electricity curtailment

2.1. Goal setting

Prior studies show that setting specific goals can be powerful in influencing behavior, particularly when combined with a reward (e.g., Locke & Latham, 2002). A goal refers to a sought-after end state that one aims to achieve and thus acts as a baseline of acceptable performance against which the actual performance can be measured (e.g., Lee et al., 1989). Setting goals can be effective in four ways (Locke & Latham, 2002): (1) goals direct attention to goal-relevant activities, (2) goals energize people and motivate them to invest greater efforts, (3) goals increase persistence and induce prolonged efforts, and (4) goals increase seeking of knowledge and innovative strategies. Goal setting has been effective in influencing

a range of different behaviors, including energy conservation behavior (Dwyer et al., 1993). Thus, giving people specific energy-saving goals such as “reduce electricity usage by 5% as compared to last year” rather than loosely encouraging them to “conserve energy” helps reduce energy consumption more effectively. However, it has also been shown that goals should be carefully calibrated: If set too low or too high, goals may cause detrimental effects on saving behavior (e.g., Loock et al., 2013).

2.2. Combining goal setting with rewards-based strategies

The goal-setting theory postulates that rewards can increase acceptance of goals, which in turn enhances performance (Locke et al., 1988). Monetary but also non-monetary rewards, such as public recognition, exert a positive influence on a person’s willingness to accept a goal (Reeve, 2005). Indeed, Slavin et al. (1981) shows that goals combined with rewards are an effective strategy for reducing energy use.

In fact, a few utilities introducing electricity-saving programs have made use of both goal setting and rewards (Prasanna et al., 2017). For example, during the Toronto Hydro 2009 Summer Challenge, multiple utilities offered 10% bill credit to customers who reduced their electricity usage by at least 10% (Bishop et al., 2010). The California statewide 20/20 demand reduction program also offered a 20% reduction on electricity bills during the summer period to households who managed to decrease their electricity demand by 20% (Wirtshafter Associates, 2006). Similar programs have been introduced in Swiss (Bern and Geneva) and German (Frankfurt and Heidelberg) cities. Households who decreased their electricity usage by 10% (Bern), 4/8% (Geneva), 10% (Frankfurt), or 15% (Heidelberg) were granted a reward in the form of a rebate of 15% (Bern), 10%/20% (Geneva), 20€ (Frankfurt), or 15€ (Heidelberg) on their next bill (Energie Wasser Bern, 2015; Leuser et al., 2014; Services Industriels de Genève, 2017; Stadt Frankfurt am Main, 2015).

Reward-based strategies are one of the earliest and most prominent ways to promote pro-environmental behavior (Porter et al., 1995). Rewards can promote pro-environmental behavior even among people who would not otherwise engage in such behavior from environmental concerns alone (Schultz, 2014). Rewards for electricity curtailment are however not widely used, which stands in stark contrast with the area of renewable energies, in which rewards at the level of the operation of renewable energy installations in the form of feed-in tariffs are widespread (Bertoldi et al., 2013). A series of studies have also shown that

financial rewards can lead to a reduction in electricity demand (e.g., Dolan & Metcalfe, 2015; Slavin et al., 1981).

However, research has also provided evidence that rewards can have unintended consequences. For example, the effects of financial rewards may be short-lived, in that the altered behavior often reverts back to baseline levels after discontinuation of the reward scheme (Katzev & Johnson, 1984; Weber et al., forthcoming). Evidence from outside the energy context also shows that consumers who have high intrinsic motivation can react negatively when extrinsic rewards are introduced (crowding-out effect) (Deci et al., 1999; Handgraaf et al., 2013). In addition, a person showing the desired behavior in response to an incentive might subsequently become less environmentally friendly in other domains (i.e., moral licensing effect; Tiefenbeck et al., 2013). Dolan & Metcalfe (2015) are not, however, able to confirm the crowding-out effect of monetary incentives related to energy conservation. Moreover, Thøgersen (2003) shows that in the case of using monetary incentives to promote recycling, the economic incentive can even strengthen intrinsic motivations. Some studies, however, still suggest that intrinsic rewards (e.g., praise, public recognition) or "in-kind" gifts are more effective than monetary rewards in encouraging sustainable behavior, particularly with highly intrinsically motivated consumers (Handgraaf et al., 2013).

2.3. Combining goal setting with the provision of feedback

Another key factor that affects performance toward achieving a goal is the provision of feedback. For consumers to pursue goals effectively, it is important that they are given a way to track their progress toward achieving their target (McCalley & Midden, 2002). For example, Abrahamse et al. (2007) show that setting an electricity-saving goal of 5%, combined with providing tailored information and feedback, led to a reduction in electricity consumption by up to 5.3% over a five-month period (see also Becker, 1978; Van Houwelingen &Van Raaij, 1989).

A wide range of studies indicates that providing feedback is an effective driver for achieving electricity savings (e.g., Allcott, 2011; Costa & Kahn, 2013; Weber et al., forthcoming). Several reviews (e.g., Darby, 2006; Ehrhardt-Martinez et al., 2010) have shown that feedback has a significant impact on promoting energy conservation behavior, even though they note wide discrepancies in terms of effectiveness due to different feedback channels (e.g., by post, online, by SMS, or through an in-home display unit) and differences in frequency (once, monthly, daily, or in real time). Darby's (2006) review reveals that savings occurs in the

region of 5–15% for direct feedback (e.g., in-home display units) but only 0–10% for indirect feedback (e.g., utility bills, including historical and comparative feedback). Recent smart metering trials across the European Union, however, show that savings of only 1.5–4% can typically be achieved by providing feedback (e.g., Schleich et al., 2013). The differences in the studies might be due to the study participants themselves, who are often volunteers participating in such trials (Buchanan et al., 2015; Hargreaves et al., 2013). Volunteers are likely to be motivated to reduce their energy demand, which in turn makes the findings of any trials difficult to replicate in the wider population (Buchanan et al., 2015). In fact, Delmas et al.'s (2013) meta-analysis reveals that robust studies found savings of only 2% on average. However, households actually interested or involved in conserving energy commonly use feedback systems and are willing to learn from them, which can lead to significant electricity savings (Wallenborn et al., 2011).

2.4. Combining goal setting with penalties

Recent research also shows that goal setting might be particularly effective in combination with penalties, that is, a punishment imposed in case a person misses the agreed-on target. For example, Gächter et al. (2009) report that penalty frames can sometimes be more effective than reward frames in motivating behavior. The website www.stickk.com offers the potential to register an envisioned target (e.g., lose weight, quit smoking), in which a penalty needs to be paid if the target is not met. Anecdotal evidence shows that a large number of people (more than 350'000 at the time of this writing, see www.stickk.com) who want to engage in a positive behavior voluntarily subscribe to a "commitment contract" that may contain a financial penalty (see also Giné et al., 2010).

In the energy context, Prasanna et al. (2017) were the first to discuss the idea of combining goal setting and penalties; they suggest introducing electricity tariffs that offer a combined approach of both an incentive for reaching a saving target and a disincentive for failing to reach this goal. According to them, such an approach would be particularly effective in terms of promoting electricity savings because of loss aversion. As losses loom larger than gains (Kahneman and Tversky, 1979), asking people to pay a fine if a target saving is not reached may be a stronger incentive for reaching a target than potentially forgoing an incentive for reaching such a target.

3. Method

3.1. Market segmentation based on CBC analysis

To explore Swiss households' preferences for different features of electricity-saving programs, we designed a choice-based conjoint (CBC) experiment. This technique belongs to the stated preference approach and is particularly appropriate in situations for which no real market data are available (Ewing & Sarigöllü, 2000). In a CBC, study participants are presented a series of different product options, described by several pre-defined features, and asked to make a choice among the offered options. The choice tasks are designed such that study participants need to trade off between different features, in that they must accept a lower level of one feature to obtain a higher level of another.

The data generated by the CBC can then be used for post hoc market segmentation purposes, in which market heterogeneity in preferences is captured to allow detection of segments of people that share similar preference structures (DeSarbo et al., 1995). Such a post hoc market segmentation approach differs from the a priori segmentation, which involves classifying people into segments on the basis of demographic or socio-economic characteristics (DeSarbo et al., 1995).

3.2. Survey structure and design of CBC experiment

Our CBC was inserted in wave 2 of the Swiss Household Energy Demand Survey (SHEDS), which was fielded between April and May 2017 (for a detailed description of SHEDS, see Weber et al., 2017). SHEDS respondents are requested to provide information about their equipment and usage in several energy consumption domains (heating, electricity, mobility). Household characteristics such as socio-demographic criteria and psychological characteristics are collected as well. Our choice experiment on electricity-saving programs was answered by 574 respondents.

At the onset of the choice experiment, respondents were informed that the focus was on the topic of electricity. Some information on how much money households could save in a year through electricity conservation was also provided. For example, it was stated that using a lid for the daily boil-up of 1.5 liters of water could save CHF 24 per year on electricity costs (i.e., approximately 4.3% of the annual electricity bill of a two-person household). The survey then continued with a detailed explanation of the CBC, in which respondents were asked to state their preferences for a new electricity-saving program. Under the scenario designed in the experiment, respondents were offered a bonus if they reached a certain percentage reduction

in their electricity consumption in comparison with the year before. It was specified that the bonus would be granted in addition to the realized cost savings that would accrue from the reduction in electricity consumption.

The experiment displayed the attributes and their levels using a full-profile design (i.e., electricity tariffs appeared with all five attributes at the same time). In every choice task, respondents had the possibility to obtain further information about the attributes through mouse-over pop-ups (basically the same information they had already been shown in the introduction of the CBC). Every respondent received eight choice tasks, each including three electricity program alternatives. In total, we designed 20 different questionnaire versions and randomly allocated respondents to one of the versions. Finally, we followed a dual-none response approach, which involved asking respondents first to make a choice between the three alternatives and then, in an additional question, to indicate whether they would actually opt for or decline the electricity tariff they had selected in the first stage if offered such a tariff for real (Brazell et al., 2006). Fig. 1 shows a sample choice task.

Fig. 1: Sample choice task.

Which of the following **three tariff options** would you **prefer most**?

Please note: *When you scroll over the specific characteristics of the electricity tariffs, you will be provided with additional information.*

1 of 8

	Option 1	Option 2	Option 3
Reduction target	5%	10%	15%
Electricity saving bonus	100 CHF	50 CHF	150 CHF
Form of bonus	Direct reduction from bill	Solar electricity	Efficiency voucher
Fine if target is missed	50 CHF	(-)	25 CHF
Improved information	Improved billing	Improved billing and in-home display unit	(-)
	1	2	3
Which option do you prefer?	○	○	○

If your utility provider would offer you the tariff that you have chosen above in real life, would you be willing to subscribe to such a tariff?

○ Yes, very likely

○ No, very unlikely

We selected relevant product attributes from the literature and expert interviews. Table 1 lists the five attributes considered and their levels. First, a reduction target with three levels (i.e., 5%, 10%, and 15%) indicated the percentage reduction of electricity consumption households needed to achieve within one year to be eligible for the bonus. We decided to choose realistic reduction targets, given the possible demotivating effect that might occur with too ambitious targets (Locke et al., 1988). Second, the tariffs differed in the size of the bonus that households would receive if they achieved the specific reduction target. We considered three "significant" levels (i.e., CHF 50/100/150) because research has shown that large enough incentives ensure that the price effect is larger than a potential negative crowding-out effect (e.g., Gneezy & Rustichini, 2000). Third, we included an attribute describing the form of bonus households would receive if they achieved the target. The bonus was provided at the end of the year, either in the form of a reduction on the next electricity bill or as an efficiency voucher that could be used for buying energy efficient equipment. As a third alternative, the bonus could be issued in the form of a supply of certified green electricity from regional solar plants equivalent to the size of the bonus. This non-monetary reward was motivated by previous research showing that non-monetary rewards may be more effective than monetary rewards in prompting sustainable behavior, particularly with highly intrinsically motivated consumers (Handgraaf et al., 2013). Fourth, we included an attribute indicating whether respondents would have to pay a fine in case they missed the agreed-on target. This attribute is rooted in research showing the powerful effect of loss aversion (Kahneman and Tversky, 1979). For this attribute, we included three levels (i.e., no fine, 25 CHF, and 50 CHF). Fifth, we also included an attribute indicating whether "improved information" would be provided. Where applicable, households would be provided with more informative electricity bills (including historical consumption data, feedback on how they compare with similar households, and electricity-saving tips) or with such improved billing and additionally an in-home display unit connected to a smart meter that would give them real-time electricity consumption feedback.

Table 1: Choice experiment design: Attributes and attribute levels.

Attribute	Attribute levels
Reduction target	• 5% • 10% • 15%
Electricity-saving bonus	• CHF 50 • CHF 100 • CHF 150
Form of bonus	• Direct reduction from the next electricity bill • Efficiency voucher • Certified green electricity from solar plants in the region
Fine if target is missed	• (-) • CHF 25 • CHF 50
Improved information	• (-) • Improved billing • Improved billing and in-home display unit

4. Results

4.1. Sample sescription

Our CBC was taken by 574 respondents, who were randomly selected among all respondents in the 2nd wave of SHEDS (see Weber et al., 2017, for additional details). Of the 574 respondents, 73 constantly indicated in the dual-none response questions that they were very unlikely to choose the offered electricity-saving programs in real life and were thus excluded from the analysis of the CBC data. These respondents, however, form the group of likely non-adopters and will be investigated thereafter. Moreover, further data cleansing was necessary because several respondents seem to have answered rather randomly. On the basis of each respondent's root likelihood (RLH) value, an indicator of the goodness of fit of the model to the data, 100 respondents were completely discarded, which left a sample of 401 respondents. The final CBC data set used for the analysis thus contains 3,208 choice observations (eight choices for each of the 401 respondents).

4.2. Estimation of utility values and importance scores for each segment

We used hierarchical Bayes (HB) estimation to derive the individual utilities for each attribute level. We established the goodness-of-fit for the entire model by estimating the root likelihood (RLH) value (Sawtooth Software, 2009). Given that we offered our respondents

three alternatives, the RLH value that would be expected by chance is 1/3. In the HB model we estimated, the RLH was 0.76, which indicates a good model fit as it is approximately 2.3 times better than the chance level.

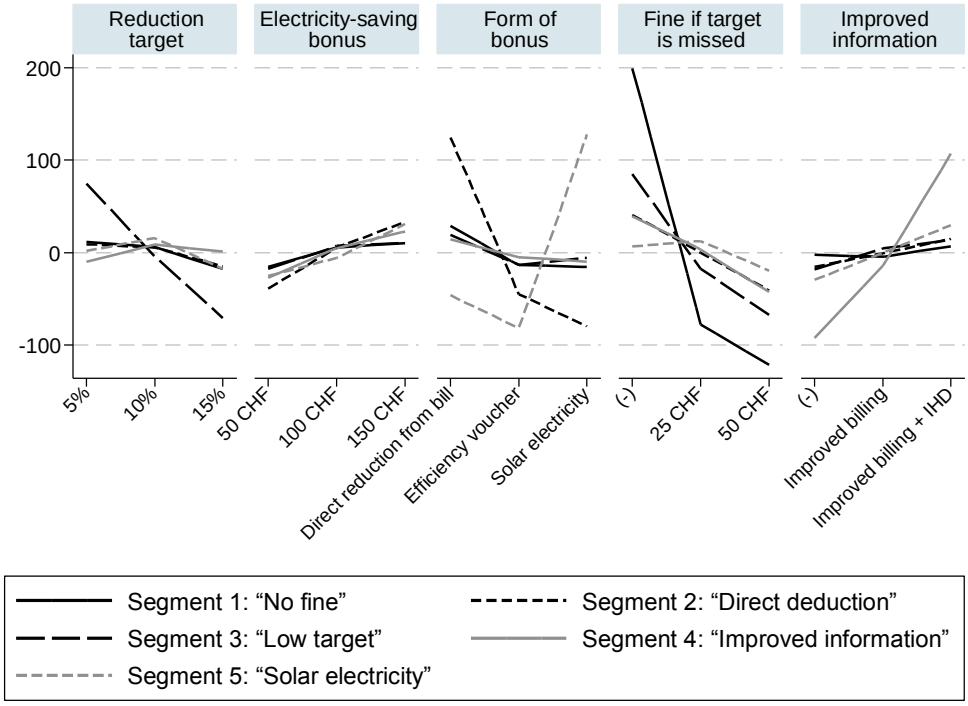
We then applied latent class module to identify segments of respondents that share similar preference structures in the choice data (Sawtooth Software, 2012). The best outcome of the latent class analysis was selected among six different possible groupings (from two to seven segments) (see Table 2). To determine best model fit, we considered two criteria: consistent Akaike information criterion (CAIC) and Bayesian information criterion (BIC). In our case, both criterions were minimized for the five-segment solution (see Table 2).

We then drew on the resulting segment membership information to calculate the average part-worth utilities and importance values for the five segments, which we estimated using the HB model. Fig. 2 depicts the results, and Table A in the Appendix shows the detailed mean utility values and the corresponding standard deviations. Positive values indicate an increase in utility; negative values signify a drop in utility (Orme, 2010). For the attributes "electricity-saving bonus" and "improved information", utility was expected to grow in a clear direction. Indeed, everything else equal, any (rational) individual will prefer a larger bonus and more information. For these two attributes and for all segments, we obtain values pointing in the expected direction, even though the sensitivity differs from one segment to another. These findings provide confidence in the fact that our respondents stated thoughtful and reliable answers.

Table 2: Summary of model fit.

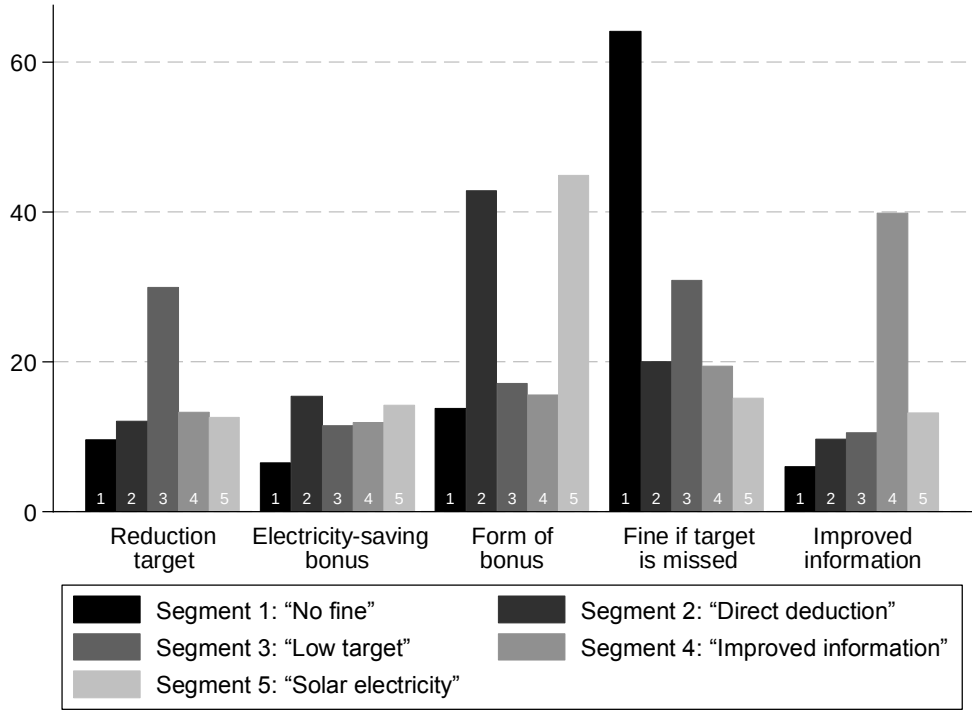
Number of segments	CAIC	BIC
2	5049.80	5028.80
3	4812.49	4780.49
4	4697.44	4654.44
5	4642.00	4588.00
6	4657.08	4592.08
7	4691.66	4615.66

Fig. 2: HB model estimation of mean utility values for the five segments.



Using the ranges of the estimated utilities, we then calculated relative importance scores. Importance percentages are calculated on the basis of individual part-worth utility ranges and sum to 100% across all attributes (Orme, 2010). The magnitude of importance scores reflects the impact of one characteristic on decision-making. Fig. 3 illustrates the results, and Table B in the Appendix includes the corresponding data details. Segments were assigned labels based on the importance scores they display for each attribute and on the mean utility values they get from each attribute level.

Fig. 3. Importance scores for the five segments.



The largest segment (Segment 1: “No fine”) considers the attribute “fine if target is missed” by far as the most important characteristic of an electricity-saving program. For this group, charging a penalty would be a no-go; this segment would consider taking part in such a program only if punishments are excluded. The second-largest segment (Segment 2: “Direct deduction”) considers the form of the bonus to be the most important attribute, with an importance score of 42.8%. This segment would primarily consider an electricity-saving program if the saving bonus were directly deducted from the next electricity bill, while they dislike other bonus forms. The third-largest group (Segment 3: “Low target”) considers the size of the reduction target as the most important attribute, with a strong preference for the lowest target (i.e., 5%). This segment also considers it important that no fine is charged if the target were missed. A smaller group (Segment 4: “Improved information”) considers that receiving feedback is the most important characteristic, with an importance score of 39.8%. This group would highly appreciate receiving more informative electricity bills as well as having access to an in-home display unit that would give them real-time consumption feedback. Finally, the smallest segment (Segment 5: “Solar electricity”) considers bonuses as the most important criterion. This segment would particularly appreciate if the bonus were paid in the form of certified green electricity supplied by solar plants located in the region. Of note, this segment would consider an electricity-saving program even slightly more attractive

if it were to contain a small penalizing element. Such a finding is in line with the success rates of platforms such as Stickk.com, on which people voluntarily commit to achieving a target even though they risk paying a fine if they do not meet the target. Both Segments 4 and 5 would deem a more challenging target of 10% instead of 5% as slightly more attractive. These segments may be mindful of the need to commit to the reduction of energy consumption (Harding and Hsiaw, 2014).

4.3. Profiling the Different Segments

In the next step of our analysis, we investigated whether the five potential subscriber segments and the likely non-subscriber segment can be distinguished by specific characteristics. The selected characteristics are described in Table C in the Appendix. Tables D1 and D2 (see Appendix) give a first overview of these differences, by displaying the descriptive statistics of each segment (in Table D1, all likely subscribers are grouped together, while the five segments are separated in Table D2).

To estimate which characteristics influence non-subscription (versus subscription) of electricity-saving programs, we constructed the following binary variable:

$$y_i = \begin{cases} 0 & \text{if individual i is a likely adopter} \\ 1 & \text{if individual i is a likely non} - \text{adopter} \end{cases}$$

and estimated binary response models (both logit and probit) to explain variable y_i. Results are reported in Table 3. Because interpreting the coefficients of such models is not straightforward, we also report marginal effects at the means of all covariates.

Table 3: Binary models and marginal effects for likely adopters (0) vs likely non-adopters (1)

	Logit		**Probit**	
	Coefficients	Marginal effects	Coefficients	Marginal effects
Gender	-0.001	-0.000	0.009	0.002
	(0.329)	(0.029)	(0.177)	(0.032)
Age	0.002	0.000	0.001	0.000
	(0.011)	(0.001)	(0.006)	(0.001)
Years of education	0.102	0.009	0.062	0.011
	(0.078)	(0.007)	(0.043)	(0.008)
Household size	0.066	0.006	0.022	0.004
	(0.131)	(0.012)	(0.073)	(0.013)
House occupant	0.769**	0.082*	0.450**	0.095**
	(0.349)	(0.044)	(0.193)	(0.047)
Home owner	-0.270	-0.023	-0.160	-0.028
	(0.354)	(0.029)	(0.193)	(0.032)
Loss aversion ^{z}	0.535***	0.048***	0.292***	0.053***
	(0.168)	(0.014)	(0.087)	(0.015)
Energy literacy ^{z}	-0.203	-0.018	-0.101	-0.018
	(0.152)	(0.013)	(0.085)	(0.015)
Positive outcome affect ^{z}	-0.374*	-0.033*	-0.225*	-0.041*
	(0.212)	(0.019)	(0.119)	(0.021)
Negative outcome affect ^{z}	-0.303	-0.027	-0.151	-0.027
	(0.215)	(0.019)	(0.119)	(0.021)
Goal frustration affect ^{z}	-0.114	-0.010	-0.071	-0.013
	(0.203)	(0.018)	(0.111)	(0.020)
Coercion affect ^{z}	0.554***	0.049***	0.314***	0.057***
	(0.174)	(0.015)	(0.095)	(0.017)
Positive baseline affect ^{z}	0.375*	0.033*	0.203*	0.037*
	(0.196)	(0.018)	(0.107)	(0.019)
Altruistic values ^{z}	0.261	0.023	0.127	0.023
	(0.208)	(0.018)	(0.115)	(0.021)
Biospheric values ^{z}	0.326	0.029	0.196	0.035
	(0.235)	(0.021)	(0.129)	(0.023)
Egoistic values ^{z}	0.073	0.007	0.041	0.007
	(0.170)	(0.015)	(0.094)	(0.017)
Hedonistic values ^{z}	-0.317*	-0.028*	-0.183**	-0.033**
	(0.165)	(0.015)	(0.091)	(0.016)
Descriptive norm ^{z}	-0.077	-0.007	-0.046	-0.008
	(0.164)	(0.015)	(0.090)	(0.016)
Injunctive norm ^{z}	0.050	0.004	0.050	0.009
	(0.183)	(0.016)	(0.099)	(0.018)
Personal norm ^{z}	-0.319*	-0.028*	-0.172*	-0.031*
	(0.181)	(0.016)	(0.102)	(0.019)
Self-efficacy ^{z}	0.263	0.023	0.144	0.026
	(0.207)	(0.018)	(0.113)	(0.020)
Response efficacy ^{z}	-0.483***	-0.043***	-0.267***	-0.048***
	(0.183)	(0.016)	(0.101)	(0.018)
Constant	-3.929***	-	-2.258***	-
	(1.349)		(0.741)	
Pseudo-R^2	0.218		0.219	
Count R^2 (adjusted)	0.297		0.297	
Log-Likelihood	-159.197		-159.134	
AIC	364.394		364.267	
BIC	460.102		459.975	
# Obs.	474		474	

Standard errors in parentheses. */**/***: significant at 10/5/1%. Marginal effects computed at the sample means (discrete change from the base level for binary variables). ^{z}: the variable is standardized (z-score).

Results reveal that socio-demographics, except house occupancy, had no significant impact on explaining subscription likelihood. Respondents living in a house (instead of in an apartment) were more likely to be represented in the likely non-subscriber group ($p<.10$). In contrast, several psychographic variables were more powerful in explaining likely non-subscription to an electricity-saving program. For example, the higher the level of loss aversion of a respondent (i.e., the higher the tendency to prefer avoiding losses to acquiring equivalent gains), the lower the likelihood to opting for an electricity-saving program ($p<.01$). Moreover, several affective variables predicted the likelihood of subscription. Participants with high positive outcome affect, i.e., a high tendency to experience positive emotions (e.g., pride) as a consequence of actions with a positive impact on the environment, reported a higher likelihood to opt for an electricity-saving program ($p<.10$). Participants with high coercion affect, i.e., a high tendency to experience negative emotions when feeling forced to perform in an environmentally friendly manner) reported a lower likelihood to opt for such a program ($p<.01$). Similarly, participants with high positive baseline affect, a pronounced tendency to experience positive emotions (e.g., awe) vis-à-vis the current state of the environment, indicated a lower likelihood to opt for such a program. In this case, positive emotions toward the environmental status quo may have signaled the absence of the need to engage in pro-environmental behaviors.

Furthermore, hedonistic values showed an impact, in that people who highly rated the importance of pleasure and enjoying life as guiding principles in their lives were more likely to opt for an electricity-saving program ($p<.10$). Similarly, personal norms had an impact, in that respondents feeling personally obliged to save as much energy as possible were more likely to opt for an electricity-saving program ($p<.10$). Finally, the level of response efficacy had a strong impact likely subscription. Respondents believing that acting in an environmentally friendly way is effective for nature protection as well as for preventing global warming would also be likely to adopt an electricity-saving program in the future ($p<.01$).

Next, we turn to the explanation of segment affiliation within the likely subscribers. To do so, we employed multinomial (logit and probit) regression models to explain segments' composition:

$$y_i = \begin{cases} 1 & \text{if individual i belongs to segment 1: "No fine"} \\ 2 & \text{if individual i belongs to segment 2: "Direct deduction"} \\ 3 & \text{if individual i belongs to segment 3: "Low target"} \\ 4 & \text{if individual i belongs to segment 4: "Direct deduction"} \\ 5 & \text{if individual i belongs to segment 5: "Solar electricity"} \end{cases}$$

Again, because the coefficients of such models are not directly interpretable and for the sake of space, we only report the marginal effects at the means obtained in the probit model.1 Results are displayed in Table 4.

Results reveal that the level of loss aversion had a significant impact on the likelihood of being in Segment 1: “No fine” ($p<.10$). People who prefer to avoid losses as much as possible are also those who strongly want to avoid the risk of paying a fine. In addition, the lower the level of negative outcome affect (i.e., the tendency to experience negative emotions such as anger as a consequence of actions with a negative impact on the environment), the higher the likelihood of being in Segment 1: “No fine” ($p<.05$). This is consistent with previous research showing a link between higher levels of negative outcome affect and the willingness to constrain one’s resource consumption for the sake of the environment (Hahnel et al., 2017).

Furthermore, being female ($p<.01$) and being younger ($p<.10$) positively influenced the likelihood to be in Segment 2: “Direct deduction”. Higher levels of loss aversion and goal frustration affect reduced the likelihood to be in this segment (both ps<.10), while higher levels of coercion affect increased the likelihood ($p<.10$).

Being older ($p<.05$) and possessing a higher knowledge in the field of energy ($p<.10$) has a positive impact on the likelihood to be in Segment 3: “Low target”, which may reflect the fact that knowing about the difficulty associated with saving energy entails leads to a preference for relatively low saving targets (see Loock et al., 2013, for the detrimental effect of setting inadequate goals).

Furthermore, being older ($p<.05$) and living in a household with a larger number of people ($p<.01$) significantly influences likelihood to be in Segment 4: “Improved information”.

Finally, the likelihood of being in Segment 5: “Solar electricity”, defined by a preference for electricity saving bonus paid in the form of a supply with certified green electricity from solar

[1] The full results’ tables are available on request.

plants located in the region, was increased by lower levels of education (p<.05), by home ownership (p<.10), and by high self-efficacy (p<.10).

Table 4: Marginal effects obtained in multinomial probit model for likely adopters

	(1) No fine	**(2) Direct deduction**	**(3) Low target**	**(4) Improved information**	**(5) Solar electricity**
Gender	-0.075	0.190***	-0.065	0.001	-0.051
	(0.056)	(0.054)	(0.044)	(0.036)	(0.032)
Age	-0.001	-0.004*	0.004**	0.003**	-0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Years of education	-0.008	0.021*	0.005	-0.005	-0.014*
	(0.014)	(0.013)	(0.011)	(0.009)	(0.008)
Household size	-0.001	-0.001	-0.023	0.036***	-0.012
	(0.025)	(0.022)	(0.020)	(0.014)	(0.015)
House occupant	-0.076	0.034	0.059	-0.007	-0.010
	(0.066)	(0.066)	(0.059)	(0.041)	(0.037)
Home owner	-0.001	-0.002	-0.045	-0.032	0.080*
	(0.062)	(0.057)	(0.047)	(0.034)	(0.042)
Loss aversion ^{z}	0.052*	-0.043*	-0.029	0.011	0.009
	(0.027)	(0.025)	(0.021)	(0.018)	(0.015)
Energy literacy ^{z}	-0.026	0.015	0.043*	-0.009	-0.023
	(0.029)	(0.027)	(0.025)	(0.019)	(0.016)
Positive outcome affect ^{z}	0.001	0.025	-0.034	0.000	0.007
	(0.039)	(0.037)	(0.032)	(0.025)	(0.024)
Negative outcome affect ^{z}	-0.087**	0.013	0.056*	0.006	0.012
	(0.036)	(0.033)	(0.030)	(0.023)	(0.021)
Goal frustration affect ^{z}	0.038	-0.059*	0.013	0.006	0.002
	(0.034)	(0.031)	(0.027)	(0.021)	(0.018)
Coercion affect ^{z}	-0.013	0.050*	0.009	-0.029	-0.017
	(0.030)	(0.027)	(0.024)	(0.020)	(0.017)
Positive baseline affect ^{z}	0.023	-0.046	-0.012	0.028	0.007
	(0.033)	(0.030)	(0.027)	(0.023)	(0.020)
Altruistic values ^{z}	0.015	-0.017	-0.033	0.004	0.031
	(0.035)	(0.033)	(0.028)	(0.023)	(0.023)
Biospheric values ^{z}	0.002	0.019	-0.019	-0.021	0.018
	(0.040)	(0.038)	(0.033)	(0.027)	(0.025)
Egoistic values ^{z}	-0.019	0.015	0.006	0.021	-0.023
	(0.028)	(0.026)	(0.022)	(0.018)	(0.016)
Hedonistic values ^{z}	0.040	-0.035	0.026	-0.015	-0.015
	(0.030)	(0.028)	(0.023)	(0.019)	(0.016)
Descriptive norm ^{z}	0.020	0.015	-0.022	-0.015	0.001
	(0.030)	(0.028)	(0.025)	(0.019)	(0.017)
Injunctive norm ^{z}	-0.003	0.022	-0.041	0.020	0.003
	(0.031)	(0.029)	(0.026)	(0.020)	(0.017)
Personal norm ^{z}	-0.026	0.006	0.023	0.028	-0.030
	(0.036)	(0.033)	(0.030)	(0.026)	(0.022)
Self-efficacy ^{z}	-0.005	-0.019	0.011	-0.033	0.046*
	(0.037)	(0.034)	(0.031)	(0.024)	(0.023)
Response efficacy ^{z}	-0.039	0.015	0.005	0.016	0.003
	(0.034)	(0.032)	(0.027)	(0.024)	(0.022)
# Obs.	401	401	401	401	401

Standard errors in parentheses. */**/***: significant at 10/5/1%. Marginal effects computed at the sample means (discrete change from the base level for binary variables). ^{z}: the variable is standardized (z-score).

5. Discussion and Conclusions

Electricity-saving programs are not widespread in Switzerland. Therefore, little is known about consumers' preferences for such programs or their likelihood of subscribing to them. One central finding of this study is that there is a great amount of interest of Swiss electricity consumers in participating in electricity-saving programs, with a large majority of respondents stating they would be likely to opt in if they were offered programs such as the ones we designed in our choice experiment.

However, the results also show that different segments of electricity consumers have quite heterogeneous preferences for the various characteristics of such programs. Therefore, no one design of an electricity-saving program, or "silver bullet," would be highly preferred across the entire customer base, speaking against a one-size-fits-all approach to design programs. Different intervention types are more or less attractive to different segments of the population, which would limit the overall aggregate impact of a single specific measure. The large discrepancy in preferences provides a strong argument for the introduction of different electricity-saving programs with various focal points. To reach the different segments in the market effectively, a multitude of programs and marketing approaches would therefore be required, as supported by our data analyses.

This research was also dedicated to ascertain drivers for subscription to an electricity-saving program by contrasting potential subscribers with likely non-adopters of such programs on several factors, including a set of different socio-economic variables (e.g., gender, age) and psychographic and behavioral factors (e.g., values, emotions), in order to provide marketers and policy makers with detailed information on how to foster the market penetration of such programs.

We find that socio-demographic variables were not very powerful in determining whether consumers would be willing to subscribe to an electricity-saving program. Only occupation of a flat (and not a house) seemed to be a positively influence subscription likelihood. Thus, targeting mainly occupants of flats seems to be a promising strategy for any electricity-saving program.

In contrast, we found several significant differences between likely subscribers and non-subscribers in terms of psychographic variables, related to affective variables such as loss aversion, positive outcome affect, coercion affect, positive baseline affect, and hedonistic values, as well as related to more cognitive variables such as personal norms and response

efficacy. Overall, our findings are well in line with those obtained in other studies. Nicolson et al. (2017) investigated the willingness of British energy bill payers to switch from flat-rate to time of use electricity tariffs. They found that more than a third of the energy bill payers are in favor of switching, but there is substantial variation among individuals' willingness to switch. Moreover, their results suggest that these differences are driven by differences in loss aversion and ownership of demand-flexible appliances rather than standard socio-economic/demographic factors. Moser et al. (2016) studied whether unconventional non-monetary incentives induced consumers to change their energy-related behavior in order to save electricity. Their findings also indicate that people should be targeted based on psychological rather than socio-economic criteria in order to induce behavioral changes.

These insights have significant implications for marketing strategy of electric utilities. For instance, our results show that individuals with pronounced hedonistic values, i.e., people who put much value on enjoying life, are more likely to adopt electricity-saving programs. Similarly, individuals with a pronounced tendency to experience positive emotions as a consequence of pro-environmental actions were more likely to adopt. Thus, one marketing strategy resulting from these findings would focus on hedonic aspects and positive emotions, presenting electricity saving as a "lifestyle choice" and emphasizing that the adoption of an electricity-saving program is associated with a number of pleasurable outcomes (subscribers will feel good, have more money available, and preserve the beautiful nature).

We moreover obtained that adoption was less likely for individuals with a pronounced tendency to feel positive towards the current state of the environment, reflecting the perception that the environment is in a sufficiently good state and may not deserve too much attention. As a consequence, it may be important to also emphasize the message that there is an urgent need to act and to reduce electricity consumption in order to combat climate change.

Additional marketing implications derive from the observed important role of loss aversion as a predictor of non-adoption of electricity-saving programs. Worries about potential negative consequences of these programs (e.g., a loss in comfort) need to be addressed and downplayed. However, loss aversion may also exert its effect via a general reluctance to change, the so-called status quo bias (Kahneman et al., 1991). Thus, more loss-averse individuals may resist change and simply prefer to stick with their standard electricity tariff instead of trying out something new. Such decision inertia would most efficiently be addressed with nudging techniques such as making an electricity-saving program the default choice that is proposed to new customers (see, e.g., Ebeling & Lotz, 2015).

Finally, the two cognitive variables personal norms and perceived response efficacy were related to increased program subscription. Individuals who subscribed to an electricity-saving program felt more personally obliged to behave in an environmentally friendly manner than likely non-subscribers, and also believed that saving electricity is an efficient measure to protect our planet and to prevent the consequences of global warming. Marketing campaigns can target both variables in order to increase potential subscription rates. Personal norms are driven by an individual's knowledge of the potential consequences of related action and non-action (i.e., the consequences of saving energy versus not saving energy at a global scale) and an individual's perceived personal responsibility for the respective behavior (Schwartz, 1977). A marketing campaign conveying that participation in electricity-saving programs would reduce the negative impact of electricity production and consumption while emphasizing the individual responsibility of each consumer in addressing this issue, may translate into higher interest in program participation (see Doran and Larsen, 2016).

Our results furthermore yield insights into the structure of the individual segments of potential subscribers, which allow for targeted marketing campaigns to promote electricity-saving programs focused on the specific program features covered here (goal setting, tailored feedback, reward and penalty schemes). For example, while younger individuals were more likely to prefer programs offering direct deductions as a form of bonus, older individuals preferred programs with low saving targets and programs providing improved information. The message delivered by electricity providers and the proposed electricity-saving programs could therefore be customized based on the age of the consumers. Moreover, homeowners appeared to be more inclined to opt for electricity-saving programs when they encompassed a bonus distributed in form of green and local electricity. To maximize adoption rate among the subpopulation of owners, emphasis should be put on aspects such as the composition and the geographical origin of the electricity supplied.

In addition to the demographic variables discussed above, interesting results arose from the psychographic variables. Again emphasizing the importance of loss aversion, loss averse people who opted for an electricity-saving tariff had a strong preference for tariffs without potential financial penalties. Therefore, while adding a financial penalty may be an effective way to promote energy saving (Prasanna et al., 2017), and is indeed considered an attractive tariff element by some consumers (such as Segment 5 in the current study), for many potential adopters a financial penalty is perceived as repelling.

Interestingly, those people scoring low on loss aversion preferred programs where reaching the savings goal was associated with a direct financial reduction of their energy bill. These people may perceive electricity-saving tariffs as a gamble in which financial gains are possible, so emphasizing the game-like character of such a tariff may appeal to this subgroup.

A few limitations of the current research need to be mentioned. As in any other stated-preference survey, our research faces the potential risk of a gap between stated and actual preferences. We tried to limit potential surveying biases by indirectly eliciting people's preferences using an innovative research methodology, and by surveying real electricity consumers. Nevertheless, we acknowledge that the willingness to participate measured in the present study may be over-estimated, given that the stated preference approach cannot cover all aspects prevalent in the market. Factors such as transaction cost, lack of awareness, availability of products, and consumer inertia may have an impact on adoption rates and should be considered when interpreting the results of this research (Kaenzig et al., 2013; Tabi et al., 2014).

Future research may additionally address aspects such as the possibility to adjust the electricity-saving target for climatic and other external or exogenous conditions (e.g., change in occupancy levels, weather variations, see Bertoldi et al., 2013). In addition, one may investigate whether altering the time of paying the bonus (e.g., upon signing up for the program) would lead to changes in preferences. Finally, it would be worth assessing preferences for alternative non-monetary rewards, such as public praise (Handgraaf et al., 2013).

Overall, the current study illustrates the market potential for electricity-saving programs using innovative features to engage customers, increase their motivation and boost the potential for effective savings. Our results show that there is considerable heterogeneity in consumer tastes for different features of electricity-saving programs. Taking into account this heterogeneity, together with the identified individual socio-demographic, psychographic, and behavioral characteristics that partly determine these preferences, our findings may help electric utilities to more effectively tailor marketing and communication strategies to specific target groups.

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Appendix

Table A: HB model estimation of mean utility values for five segments.

	Segment 1: "No fine"	**Segment 2: "Direct deduction"**	**Segment 3: "Low target"**	**Segment 4: "Improved information"**	**Segment 5: "Solar electricity"**
Segment size	n=136	n=104	n=72	n=45	n=44
Reduction target					
5%	11.7 (23.7)	9.1 (32.1)	74.5 (49.5)	-10.2 (35.1)	1.6 (32.6)
10%	5.9 (11.5)	5.7 (17.5)	-4.0 (25.2)	8.9 (25.6)	15.7 (20.6)
15%	-17.6 (23.1)	-14.8 (32.5)	-70.5 (36.9)	1.3 (34.4)	-17.2 (31.5)
Electricity-saving bonus					
50 CHF	-15.51 (12.6)	-38.8 (26.3)	-17.5 (34.3)	-27.5 (23.9)	-25.2 (36.4)
100 CHF	5.60 (7.54)	5.5 (12.5)	7.1 (14.5)	4.8 (13.1)	-5.6 (15.5)
150 CHF	9.91 (13.54)	33.3 (24.8)	10.4 (33.1)	22.6 (22.6)	30.7 (45.0)
Form of bonus					
Direct reduction from bill	29.1 (33.4)	124.7 (45.1)	18.9 (40.2)	14.6 (43.5)	-46.1 (66.3)
Efficiency voucher	-13.6 (24.2)	-45.0 (34.0)	-13.2 (31.4)	-4.9 (34.2)	-81.7 (29.0)
Solar electricity	-15.5 (33.0)	-79.7 (36.9)	-5.7 (43.9)	-9.7 (34.4)	127.8 (71.3)
Fine if target is missed					
(-)	199.1 (47.5)	40.8 (43.6)	85.0 (38.9)	39.1 (42.2)	6.87 (45.4)
25 CHF	-77.7 (19.7)	.1 (25.9)	-17.8 (27.5)	3.3 (25.6)	12.54 (23.3)
50 CHF	-121.4 (30.2)	-40.9 (26.9)	-67.3 (22.3)	-42.4 (31.3)	-19.41 (30.2)
Improved information					
(-)	-2.3 (15.6)	-15.5 (23.5)	-18.2 (26.3)	-92.4 (28.6)	-29.5 (22.5)
Improved billing	-4.4 (7.6)	-.7 (11.7)	4.5 (15.4)	-14.3 (22.2)	-.2 (12.8)
Improved billing + IHD	6.7 (18.0)	14.8 (23.6)	13.7 (26.3)	106.8 (45.0)	29.7 (22.7)

Standard deviations are in parentheses.

Table B: Attribute importance scores for the five segments.

	Segment 1: "No fine"	**Segment 2: "Direct deduction"**	**Segment 3: "Low target"**	**Segment 4: "Improved information"**	**Segment 5: "Solar electricity"**
Segment size	n=136	n=104	n=72	n=45	n=44
Reduction target	9.6%	12.1%	29.9%	13.3%	12.6%
Electricity-saving bonus	6.5%	15.4%	11.5%	11.9%	14.2%
Form of bonus	13.8%	42.8%	17.1%	15.6%	44.9%
Fine if target is missed	64.1%	20.0%	30.9%	19.4%	15.1%
Improved information	6.0%	9.7%	10.5%	39.8%	13.2%
Total	100%	100%	100%	100%	100%

Table C: Variables selected to characterize segments.

Category and variable	Description	Source
Demographic characteristics		
Gender	0=Male; 1=Female	
Age	Respondent's age (in years)	
Years of education	Inferred from the highest level of education achieved: 1=Less than compulsory school (7 years); 2=Compulsory school (9 y.); 3=Domestic school (11 y.); 4=Basic vocational school (11 y.); 5=Vocational/general school (12 y.); 6=Apprenticeship (12 y.); 7=Full-time vocational school (14 y.); 8=High school (13 y.); 9=University, ETH, university of applied sciences (16 y.)	
Household size	Number of people living in the household	
House occupant	The household lives in a house (0 = flat, 1 = house)	
Home owner	The household owns its dwelling (0 = tenant, 1 = owner)	
Psychographic characteristics [z]		
Loss aversion [z]	Respondents were asked to imagine a situation in which they could participate in a game in which a coin was tossed. With a probability of 50%, "tail" appears and they would get paid CHF 6. With a probability of 50%, "head" appears and they have to pay some amount (X) in CHF. Then they were asked whether they would take part in a game where X would be CHF 2, 3, 4, 5, 6, 7. A loss aversion index is computed on a scale from 0 (least averse individuals, who accept all games), 1 (individuals who accept games with potential loss up to CHF 6 but reject the game with potential loss of CHF 7), … to 6 (most averse individuals, who reject all games). 62 respondents provided inconsistent answers, in the sense that they stated they reject a game with a low potential loss but would accept a game with a larger potential loss. For these respondents, we determine loss aversion by considering the first turning point only. For example, a respondent stating he would not accept games where he could lose CHF 2 to 5, accept a game where he could lose CHF 6, and then again not accept a game in which he could lose CHF 7 is assigned a loss aversion of 1. The rationale for implementing this procedure is that most inconsistent answers appear to arise because respondents likely misinterpreted the question and simply provided a single answer, which likely correspond to the last game they would accept (such as the above-mentioned example). We nevertheless conducted robustness checks in which we (1) drop these respondents and (2) consider these responses as missing values and implement multiple-imputation methods to conduct full-information estimations. These robustness checks (available on request) revealed no substantial change in our results.	Adapted from Gächter et al. (2007)

Positive outcome affect [z]	Respondents rated their tendency to experience positive emotions as a consequence of actions (their own or someone else's) with a positive impact on the environment across 4 scenarios (e.g., pride when they commit an environmentally friendly action) on a 5-point scale ranging from 1 = *totally disagree* to 5 = *totally agree*.	Hahnel et al. (2017)
Negative outcome effect [z]	Respondents rated their tendency to experience negative emotions as a consequence of actions (their own or someone else's) with a negative impact on the environment across 5 scenarios (e.g., anger when they observe someone polluting the environment) on a 5-point scale ranging from 1 = *totally disagree* to 5 = *totally agree*.	Hahnel et al. (2017)
Goal frustration effect [z]	Respondents rated their tendency to experience negative emotions when their intention to perform environmentally friendly behaviors is obstructed across 3 scenarios (e.g., frustration when they would like to recycle something, but there were no containers around) on a 5-point scale ranging from 1 = *totally disagree* to 5 = *totally agree*.	Hahnel et al. (2017)
Coercion affect [z]	Respondents rated their tendency to experience negative emotions when they are feeling forced to perform in an environmentally friendly manner across 3 scenarios (e.g., feeling annoyed when someone expects them to make a donation for an environmental organization) on a 5-point scale ranging from 1 = *totally disagree* to 5 = *totally agree*.	Hahnel et al. (2017)
Positive baseline affect [z]	Respondents rated their tendency to experience positive emotions vis-à-vis the current state of the environment across 3 scenarios (e.g., awe towards the beauty of nature) on a 5-point scale ranging from 1 = *totally disagree* to 5 = *totally agree*.	Hahnel et al. (2017)
Altruistic values [z]	Respondents rated the importance of 4 values (equality, a world at peace, social justice, helpful) "as guiding principles in their lives" on a 5-point scale ranging from 1 = *totally disagree* to 5 = *totally agree*.	Adapted from Steg et al. (2014)
Biospheric values [z]	Respondents rated the importance of 4 values (respecting the earth, unity with nature, protecting the environment, preserving nature) "as guiding principles in their lives" on a 5-point scale ranging from 1 = totally disagree to 5 = totally agree.	Adapted from Steg et al. (2014)
Egoistic values [z]	Respondents rated the importance of 5 values (social power, wealth, authority, influential, ambitious) "as guiding principles in their lives" on a 5-point scale ranging from 1 = totally disagree to 5 = totally agree.	Adapted from Steg et al. (2014)
Hedonistic values [z]	Respondents rated the importance of 3 values (pleasure, enjoying life, self-indulgent) "as guiding principles in their lives" on a 5-point scale ranging from 1 = totally disagree to 5 = totally agree.	Adapted from Steg et al. (2014)

Descriptive norms [z]	Respondents rated the extent to which they agree with the statement "I believe that most of my acquaintances save energy wherever it is possible" on a 5-point scale ranging from 1 = totally disagree to 5 = totally agree.	Adapted from Thørgersen (2006)
Injunctive norms [z]	Respondents rated the extent to which they agree with the statement "Most of my acquaintances expect that I save energy wherever it is possible" on a 5-point scale ranging from 1 = totally disagree to 5 = totally agree.	Adapted from Thørgersen (2006)
Personal norms [z]	Respondents rated the extent to which they agree with the statement "I feel personally obliged to save as much energy as possible" on a 5-point scale ranging from 1 = totally disagree to 5 = totally agree.	Steg et al. (2005)
Self-efficacy [z]	Respondents rated the extent to which they agree with the two statements "I can participate in behaviors to protect the environment if I really wanted to" and "I will take steps to adopt environmentally friendly behaviors even if it causes daily inconveniences" on a 5-point scale ranging from 1 = totally disagree to 5 = totally agree.	Kim et al. (2012)
Response efficacy [z]	Respondents rated the extent to which they agree with the two statements "Acting environmentally friendly is effective to protect our planet and its nature" and "Acting environmentally friendly will help to prevent the consequences of global warning for our planet and its inhabitants" on a 5-point scale ranging from 1 = totally disagree to 5 = totally agree.	Kim et al. (2012)

[z] All psychographic variables are measured on a 5-point scale, from 1 to 5 (except loss aversion, measured on a 7-point scale, from 0 to 6). To facilitate interpretation, these variables were transformed to z-scores (i.e., standardized variables with mean 0 and standard deviation 1) before they were included in the estimations (Section 4.3).

Table D1: Descriptive statistics (means and standard deviations) comparing likely subscribers to likely non-subscribers.

	(1) **Likely subscribers**	**(2)** **Likely non-subscribers**	**(3)** **Total**
Gender	0.464	0.452	0.462
	(0.499)	(0.501)	(0.499)
Age	45.923	48.932	46.386
	(15.171)	(16.759)	(15.446)
Years of education	13.808	13.904	13.823
	(1.930)	(2.116)	(1.958)
Household size	2.112	2.110	2.112
	(1.170)	(1.208)	(1.175)
House occupant	0.195	0.315	0.213
	(0.396)	(0.468)	(0.410)
Home owner	0.299	0.233	0.289
	(0.459)	(0.426)	(0.454)
Loss aversion	3.643	4.712	3.808
	(1.934)	(1.783)	(1.948)
Energy literacy	3.564	3.219	3.511
	(1.225)	(1.566)	(1.288)
Positive outcome affect	3.968	3.455	3.889
	(0.783)	(0.955)	(0.832)
Negative outcome affect	3.441	2.959	3.367
	(0.841)	(0.912)	(0.869)
Goal frustration affect	3.438	3.201	3.402
	(0.943)	(0.986)	(0.953)
Coercion affect	2.521	3.096	2.610
	(0.931)	(0.985)	(0.961)
Positive baseline affect	4.165	4.210	4.172
	(0.809)	(0.719)	(0.796)
Altruistic values	3.890	3.791	3.874
	(0.748)	(0.728)	(0.745)
Biospheric values	4.012	3.908	3.996
	(0.761)	(0.827)	(0.771)
Egoistic values	2.677	2.641	2.672
	(0.709)	(0.718)	(0.710)
Hedonistic values	3.761	3.566	3.731
	(0.752)	(0.906)	(0.779)
Descriptive norm	3.145	3.123	3.141
	(0.932)	(0.985)	(0.940)
Injunctive norm	3.120	2.973	3.097
	(1.059)	(1.080)	(1.062)
Personal norm	4.052	3.534	3.973
	(0.927)	(1.191)	(0.989)
Self-efficacy	3.788	3.521	3.747
	(0.725)	(0.868)	(0.754)
Response efficacy	3.946	3.445	3.869
	(0.866)	(1.009)	(0.907)
# Obs.	401	73	474

Psychographic variables measured on a 5-point scale, from 1 to 5 (except loss aversion, measured on a 7-point scale, from 0 to 6). All these variables were transformed to z-scores before they were included in the estimations.

Table D2: Descriptive statistics (means and standard deviations) comparing the five segments of likely subscribers.

	(1) No fine	(2) Direct deduction	(3) Low target	(4) Improved information	(5) Solar electricity
Gender	0.426	0.587	0.333	0.467	0.500
	(0.496)	(0.495)	(0.475)	(0.505)	(0.506)
Age	45.412	42.452	48.569	50.533	46.659
	(13.432)	(15.123)	(16.467)	(16.752)	(15.080)
Years of education	13.721	14.106	13.903	13.578	13.455
	(1.946)	(1.874)	(1.973)	(2.017)	(1.823)
Household size	2.074	2.058	2.028	2.533	2.068
	(1.113)	(1.261)	(1.007)	(1.517)	(0.900)
House occupant	0.162	0.192	0.236	0.222	0.205
	(0.370)	(0.396)	(0.428)	(0.420)	(0.408)
Home owner	0.279	0.269	0.292	0.311	0.432
	(0.450)	(0.446)	(0.458)	(0.468)	(0.501)
Loss aversion	3.882	3.442	3.333	3.889	3.636
	(1.982)	(1.940)	(1.906)	(1.874)	(1.831)
Energy literacy	3.441	3.538	3.806	3.667	3.500
	(1.293)	(1.097)	(1.083)	(1.187)	(1.517)
Positive outcome affect	3.849	4.007	3.865	4.100	4.278
	(0.765)	(0.769)	(0.817)	(0.791)	(0.726)
Negative outcome affect	3.246	3.471	3.492	3.573	3.759
	(0.849)	(0.887)	(0.783)	(0.767)	(0.750)
Goal frustration affect	3.380	3.359	3.426	3.600	3.659
	(0.965)	(0.906)	(0.946)	(0.806)	(1.065)
Coercion affect	2.547	2.638	2.593	2.363	2.212
	(0.941)	(0.984)	(0.858)	(0.834)	(0.932)
Positive baseline affect	4.120	4.045	4.111	4.363	4.477
	(0.855)	(0.819)	(0.767)	(0.619)	(0.802)
Altruistic values	3.840	3.851	3.764	4.006	4.222
	(0.792)	(0.732)	(0.756)	(0.652)	(0.638)
Biospheric values	3.947	3.945	3.944	4.122	4.369
	(0.780)	(0.746)	(0.772)	(0.676)	(0.714)
Egoistic values	2.682	2.723	2.697	2.720	2.477
	(0.730)	(0.699)	(0.698)	(0.688)	(0.702)
Hedonistic values	3.833	3.740	3.759	3.637	3.712
	(0.750)	(0.671)	(0.830)	(0.791)	(0.770)
Descriptive norm	3.162	3.212	2.944	3.156	3.250
	(0.913)	(0.972)	(0.963)	(0.852)	(0.918)
Injunctive norm	3.059	3.154	2.944	3.356	3.273
	(1.052)	(1.068)	(1.060)	(1.004)	(1.086)
Personal norm	3.949	4.019	4.028	4.311	4.227
	(0.999)	(0.935)	(0.839)	(0.874)	(0.831)
Self-efficacy	3.680	3.736	3.778	3.844	4.205
	(0.706)	(0.753)	(0.691)	(0.698)	(0.668)
Response efficacy	3.820	3.913	3.917	4.078	4.330
	(0.892)	(0.860)	(0.927)	(0.715)	(0.739)
# Obs.	136	104	72	45	44

Psychographic variables measured on a 5-point scale, from 1 to 5 (except loss aversion, measured on a 7-point scale, from 0 to 6). All these variables were transformed to z-scores before they were included in the estimations.