Journal of Cleaner Production 220 (2019) 800–815

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Consumers' preferences for electricity-saving programs: Evidence from a choice-based conjoint study

Stefanie Hille [a], Sylvain Weber [b,*], Tobias Brosch [c]

[a] University of St. Gallen, Institute for Economy and the Environment, Tigerbergstrasse 2, 9000, St. Gallen, Switzerland
[b] University of Neuchâtel, Institute of economic research, A.L. Breguet 2, 2000, Neuchâtel, Switzerland
[c] University of Geneva, Department of Psychology, Boulevard du Pont d'Arve 40, 1205, Geneva, Switzerland

ARTICLE INFO

Article history:
Received 30 August 2018
Received in revised form
16 January 2019
Accepted 13 February 2019
Available online 21 February 2019

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

ABSTRACT

Electric utilities play a crucial role in designing and deploying electricity conservation programs. However, because people can freely decide to participate in such programs or not, better understanding what types of programs appeal to specific groups of customers is fundamental. The authors therefore explore preferences of likely subscribers for electricity-saving programs defined by various features (such as goal setting, tailored feedback provision, or reward and penalty schemes), and use a latent class approach to capture heterogeneity and detect segments of people that share similar preferences. The segments are subsequently profiled in terms of socio-demographic and psychographic characteristics. Overall, results show that there is considerable heterogeneity in tastes for different features of electricity-saving programs. The findings allow identifying individual characteristics that influence the likelihood to adopt different forms of programs. On this basis, electric utilities may design electricity-saving programs that better satisfy customer needs and effectively tailor marketing and communication programs to the specific target groups.

1. Introduction

Electricity represents one quarter of overall energy used in Switzerland (SFOE, 2017). 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 may be decreased through technological advancements in energy efficiency of the services provided (e.g., equipping households with energy-efficient appliances; see 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., 2018; Ruzzenenti and Bertoldi, 2017; Weber and Farsi, 2014). Therefore, a combined dual strategy based on improving efficiency and encouraging curtailment through behavioral changes 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). 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, given that using more than one approach simultaneously may result in a complicated and less focused message (Schultz, 2014). 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 therefore "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 consumers as possible to participate in electricity-saving programs.

* Corresponding author.
E-mail address: sylvain.weber@unine.ch (S. Weber).

https://doi.org/10.1016/j.jclepro.2019.02.142
0959-6526/

By means of a choice-based conjoint (CBC) experiment, the authors explore households' preferences for several electricity-saving program features, including the reduction target, the size of the reward and its form, and the provision of additional feedback. Moreover, the authors investigate the acceptance of a possible penalty that would accrue in case the agreed-on target is missed. A latent class approach is used to capture heterogeneity in preferences and to detect groups of people who share similar preferences. The findings could help utilities to better satisfy customers' needs by designing electricity-saving programs that are in line with their preferences.

Currently, the Swiss electricity market is liberalized for large industrial consumers only (above 100,000 kWh/year). Small and residential consumers are, in contrast, bound to subscribing to an electricity tariff from a unique supplier based on its geographical location, often defined by cantonal boundaries. Nevertheless, most suppliers offer a variety of tariffs from which their customers can choose from. The default tariff is usually mainly composed of hydropower, but consumers can decide to change to a more expensive tariff where electricity is sourced from new renewable energies (solar, wind, etc.). In the same spirit, if suppliers were to offer electricity-saving programs, households could freely opt to participate or not, and 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, the authors 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, the segments of likely subscribers are profiled 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.

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 experiment. Section 4 presents the empirical results. Section 5 discusses the policy implications of the 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 and 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 and Latham, 2002): (1) goals direct attention to 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 appears effective in influencing a range of different behaviors, including energy conservation (Dwyer et al., 1993). Thus, one can infer that giving people specific goals such as "reduce electricity usage by 5% as compared to last year" rather than loosely encouraging them to "conserve energy" helps reduce 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 reward-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) show that goals combined with rewards are an effective strategy for reducing energy use.

Few utilities have made use of both goal setting and rewards to design electricity-saving programs (Prasanna et al., 2018). For example, during the Toronto Hydro 2009 Summer Challenge, multiple utilities offered a 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 bill (EWB, 2015; Leuser et al., 2014; SIG, 2018; 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 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. It is indeed common to financially support producers of renewable energy in the form of feed-in tariffs (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 and 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 to baseline levels after the reward scheme is discontinued (Katzev and Johnson, 1984; Weber et al., 2017b). Evidence from outside the energy context shows that consumers who have high intrinsic motivation can react negatively when extrinsic rewards are introduced (crowding-out effect, see 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 (moral licensing effect, see Tiefenbeck et al., 2013). Dolan and 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, economic incentives 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 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 and 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).

It has been shown that providing feedback is an effective tool for achieving electricity savings (e.g., Allcott, 2011; Costa and Kahn, 2013; Weber et al., 2017b), even though wide discrepancies arise 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 occur 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). In a recent and exhaustive literature review, Bertoldi et al. (2016) collect more than 100 feedback applications and confirm that higher savings are associated with direct as compared to indirect feedback (7% versus 5% on average). 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). Differences across studies might also arise because the selection of study participants ranges from random samples to self-selected volunteers (Buchanan et al., 2015; Hargreaves et al., 2013). Volunteers are likely more motivated than typical individuals to reduce their energy demand, which in turn jeopardizes external validity of the trials concerned. In fact, Delmas et al.'s (2013) meta-analysis reveals that the highest quality studies found savings of only 2% on average. However, households particularly interested or involved in conserving energy commonly use feedback systems and are willing to learn from them, which can lead to significantly larger 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 the agreed-on target is missed. For example, Gächter et al. (2009) report that penalties can sometimes be more powerful than rewards. 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 many people who want to engage in a positive behavior voluntarily subscribe to a “commitment contract” (there were more than 400′000 such commitments on www.stickk.com at the time this paper was written) that may contain a financial penalty (see also Giné et al., 2010).

In the energy context, Prasanna et al. (2018) are the first to discuss the idea of combining goal setting and penalties. They suggest introducing electricity tariffs that contain 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), imposing a fine in case a target is missed may be a stronger incentive than a potential reward for reaching a similar target. Based on a stated-choice experiment, Mahmoodi et al. (2018) indeed find that penalties have a stronger influence than rewards in the choice of an electricity tariff.

3. Method

3.1. Market segmentation based on CBC analysis

To explore Swiss households' preferences for various features of electricity-saving programs, the authors 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 and Sarigöllü, 2000). In a CBC, study participants are presented a series of different product options, described by several predefined features, and asked to make a choice among the offered options. The choice tasks are designed such that study participants need to tradeoff 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 based on demographic or socio-economic characteristics (DeSarbo et al., 1995).

3.2. Survey structure and design of CBC experiment

The CBC analyzed in this paper was inserted in the second wave of the Swiss Household Energy Demand Survey (SHEDS), which was fielded in April and May 2017 (for a detailed description of SHEDS, see Weber et al., 2017a). Each wave of this survey collects information from around 5,000 respondents representative of the Swiss population (excluding the Italian-speaking part of Switzerland). 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. The choice experiment on electricity-saving programs was included as an add-on module of SHEDS and answered by a random subsample of 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 L 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 series of hypothetical electricity-saving programs.

The experiment displayed the attributes and their levels using a full-profile design (i.e., electricity tariffs appeared with all 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 options. In total, the authors designed 20 different questionnaire versions and randomly allocated respondents to one of these versions. Finally, rather than offering the possibility to reject all options, a “dual-response” approach was followed (see Brazell et al., 2006), in which respondents first had to make a choice among the alternatives and then, in an additional question, they were asked to indicate whether they would really opt for or decline the selected electricity tariff. Fig. 1 shows a sample choice task.

The tariff options were defined by five relevant attributes, selected from the literature and expert interviews. Table 1 lists the five attributes and their levels. First, the tariffs entailed a

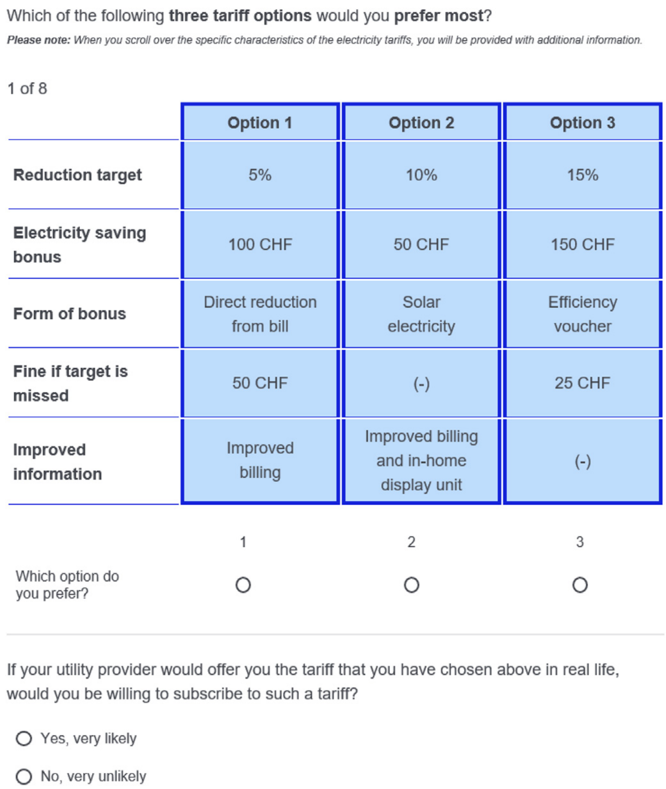

Fig. 1. Sample choice task.

reduction target in the electricity consumption compared with the year before. Given the possible demotivating effect that might occur with too ambitious targets (Locke et al., 1988), realistic reduction targets (5/10/15%) were presented. If reached, this reduction target would be rewarded with a monetary bonus. The scenario moreover specified that the bonus would be granted in addition to the realized cost savings that would accrue from the reduction in electricity consumption. Second, the tariffs differed in the size of the bonus that households would receive if they achieved the specific reduction target. Three incentive levels considered "significant" in the Swiss context (CHF 50/100/150) were included,[1] as previous research has shown that large enough incentives ensure that the price effect is larger than a potential negative crowding-out effect (e.g., Gneezy and Rustichini, 2000). Third, an attribute was included describing the form of bonus households would receive if they achieved the target. The bonus would be granted 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, an attribute was included indicating whether a fine must be paid in case households missed the agreed-on target. This attribute is rooted in research showing the powerful effect of loss aversion (Kahneman and Tversky, 1979). Three levels were therefore included: no fine, CHF 25, or CHF 50. The levels for the fine were set at a lower level than the levels for the bonus in order to avoid excessively strong disincentives. Fifth, the authors 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. Information is an important feature per se, as it improves households' knowledge of their electricity usage and therefore enables conservation (see e.g., Bernstein and Collins, 2014). In conjunction with other programs' attributes, in particular goal setting, tailored information would moreover allow households to keep track of their progress toward the target.

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 description

The CBC was taken by 574 respondents, who were randomly selected among all participants of the second wave of SHEDS (see Weber et al., 2017a, for additional details). Of these 574 respondents, 73 constantly indicated in their (eight) dual-responses that they were very unlikely to choose the offered electricity-saving programs in real life. These respondents form a group called the "likely non-subscribers", whereas the others qualify as "likely subscribers" because they stated at least once that they would accept the product if it was actually offered.

Further data cleansing has been implemented. Indeed, because answering a CBC experiment is a demanding and repetitive task, some respondents might be tempted to give up and simply tick one option at random. To minimize this potential issue, a selection procedure based on the root likelihood (RLH) value (Sawtooth Software, 2009) was applied for selecting the respondents into the final sample. RLH is an indicator of the goodness-of-fit of the model to the data, which provides, for each respondent, an indication of the responses consistency: Respondents answering randomly would display a low RLH. Within the 501 respondents who qualify as likely subscribers in the original sample, 100

[1] Swiss households consume around 3,000 kWh per year (see e.g., Weber et al., 2017b). Considering a price of 20 cents per kWh (see the statistics from the Swiss Federal Electricity Commission), the average annual bill is thus around CHF 600, and the bonuses go up to 25% of the annual electricity expenses. Such bonuses seem sufficiently high to create substantial incentives for motivating households.

Table 2
Summary of model fit.

Number of segments	CAIC	BIC
2	5,050	5,029
3	4,812	4,780
4	4,697	4,654
5	4,642	4,588
6	4,657	4,592
7	4,692	4,616

displayed an RLH value below 0.5. The authors therefore decided to discard these 100 respondents from the sample before proceeding with the analysis.[2]

The final sample is composed of 474 respondents, among which 401 likely subscribers and 73 likely non-subscribers. Preferences for the various electricity-saving program attributes will thus be investigated using 3,208 choices provided by the 401 likely subscribers (eight choices for each).

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

Hierarchical Bayes (HB) estimation was used to derive the individual utilities for each attribute level. Goodness-of-fit was established for the entire model by estimating the root likelihood (RLH) value (Sawtooth Software, 2009). Given that respondents were offered three alternatives, the RLH value that would be expected by chance is 1/3. In the estimated HB model, the average RLH was 0.76, which indicates a good model fit as it is more than twice the chance level.

Latent class analysis was then applied 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), based on two criteria: consistent Akaike information criterion (CAIC) and Bayesian information criterion (BIC). In the present case, both criterions were minimized for the five-segment solution.

Drawing on the resulting segment membership information, HB estimation was used to retrieve the average part-worth utilities (Fig. 2) and attribute importance scores (Fig. 3) for the five segments. Part-worth utilities indicate how much one attribute level contributes to the overall utility of an option (Orme, 2010). Importance scores reflect the impact of an attribute on decision-making. These scores are calculated on the basis of individual part-worth utility ranges and are expressed in relative terms (they sum to 100% across all attributes) to facilitate interpretation (Orme, 2010). Taken together, part worth utilities and importance scores allow portraying the respondents' segments. Below, these two elements are used to assign illustrative labels to each segment.

Fig. 2 depicts the part worth utilities (re-scaled and zero-centered to increase comparability between segments). Larger values indicate an increase in utility; smaller values indicate a decline in utility (Orme, 2010). Utility is expected to grow for the attributes "electricity-saving bonus" and "improved information". Indeed, everything else equal, any (rational) individual will prefer a larger bonus and more information. For these attributes, part worth utilities point in the expected direction, even though the sensitivity differs from one segment to another.[3] These findings provide confidence in the fact that respondents stated thoughtful and reliable answers.

Note: Even though attributes "Form of bonus" (3rd panel) and "Improved information" (5th panel) are ordinal, the different levels are connected to facilitate the reading of the chart. Detailed values corresponding to this Figure are provided in Appendix Table A.

Note: Detailed values corresponding to this Figure are provided in Appendix Table B.

Fig. 3 illustrates the attribute importance scores for each segment. In conjunction with part worth utilities displayed in Fig. 2, attribute importance scores provide some descriptive insights of the segments and allow us to assign labels to each of them. The largest segment (Segment 1: "No fine", n = 136) considers the attribute "fine if target is missed" by far as the most important feature of an electricity-saving program. This segment would consider taking part in such a program only if punishments are excluded. The second-largest segment (Segment 2: "Direct deduction", n = 104) considers the form of the bonus as 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", n = 72) considers the size of the reduction target as the most important attribute, with a strong preference for the lowest target (i.e., 5%). It also appears important for this segment that no fine is charged. A smaller group (Segment 4: "Improved information", n = 45) 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", n = 44) 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 is the least sensitive to the fine component of the tariffs and would even consider an electricity-saving program 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 also 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*

The next step of the analysis is dedicated to investigating the determinants of willingness-to-subscribe to alternative electricity tariffs. To do so, the five likely subscriber segments and the likely non-subscriber segment are compares along specific

[2] The analysis was also conducted using the original sample of 574 respondents (among which 73 are likely non-subscribers and 501 are likely subscribers) without any data cleansing. The main findings (available on request) remain unaltered. The most important difference is the optimal number of segments, which is five in the analysis reported in the paper, while it is six with the full sample. In the alternative analysis based on the six-segment solution, the number of observations in some groups becomes small, and the additional group is difficult to characterize, which constitute another argument for cleaning the sample.

[3] Note that utility should be decreasing for most individuals with the level of a potential "fine if target is missed". This is indeed what is observed for Segments 1 to 4. However, some rational individuals may find it stimulating and therefore attractive to face the risk of paying a fine. To some extent, Segment 5 displays such a behavior (more on this below).

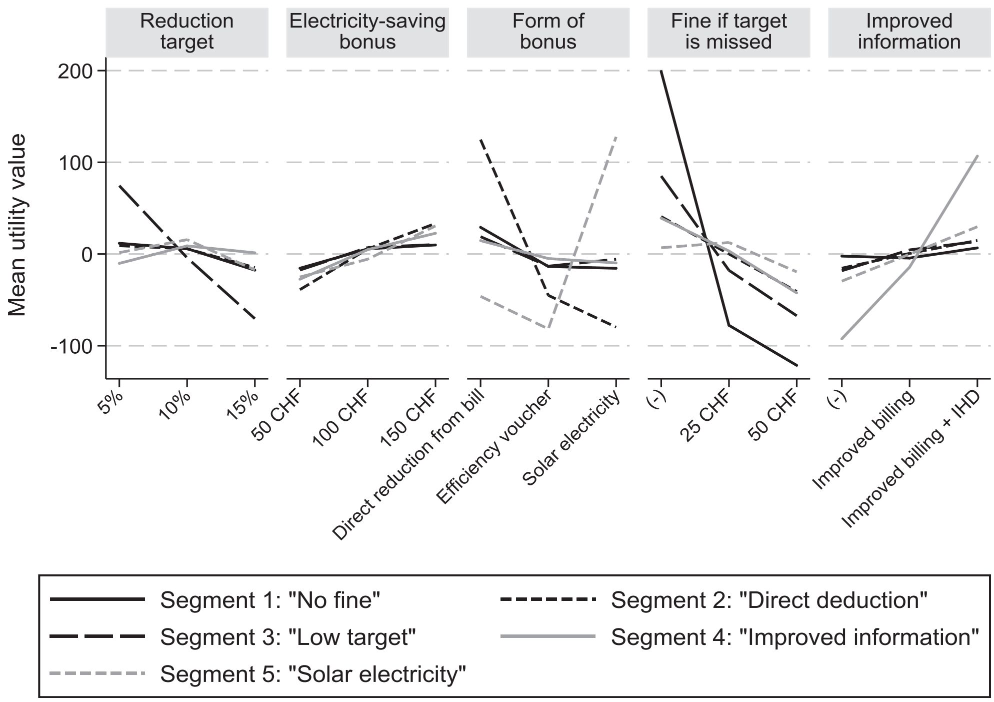

Fig. 2. HB estimation of part worth utilities for the five segments.

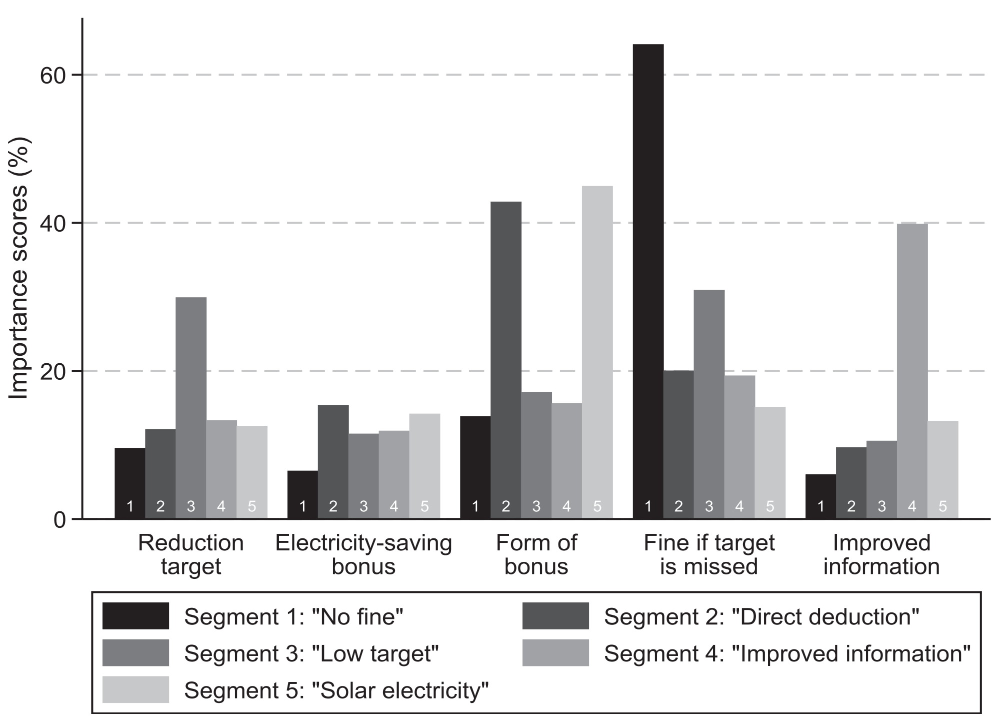

Fig. 3. Attribute importance scores for the five segments.

characteristics. The selected characteristics are described in Table 3. A first overview of these differences is provided by the descriptive statistics of each segment (see Appendix Table C1, where all likely subscribers are grouped together, and Appendix Table C2, where the five segments are separated).

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

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

and binary response models were estimated (both logit and probit) to explain variable y_i. Results are presented graphically in Fig. 4. Because interpreting the coefficients of such models is not straightforward, marginal effects at the means of all covariates are reported. Also, only the coefficients significant at least at the 10% level are displayed in Fig. 4. The complete results are reported in Appendix Table D.

Results reveal that socio-demographics, except house occupancy, had no significant impact on explaining subscription likelihood.[4] Respondents living in a house (instead of in an apartment) were less frequently among the likely subscribers ($p < .10$). In contrast, several psychographic variables were more powerful in explaining likely subscription to an electricity-saving program. For example, the higher the level of loss aversion (i.e., the higher the tendency to prefer avoiding losses to acquiring equivalent gains), the lower the likelihood to opt for an electricity-saving program ($p < .01$). Moreover, several affective variables influenced 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, displayed 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 behave 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 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 on intent to 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 ($p < .01$).

To investigate the segment affiliation within likely subscribers, multinomial regression models (logit and probit) were used to explain the composition of the segments:

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

Because the coefficients of such models are not directly interpretable and for the sake of space, the marginal effects at the means obtained in the probit model are reported.[5] The significant results are displayed in Fig. 5, while the complete results can be found in Appendix Table E.

Results reveal that 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 higher 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 lower the likelihood of being in Segment 1 ($p < .05$). 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 and Brosch, 2018).

Being female ($p < .01$) and being more educated ($p < .10$) 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 it ($p < .10$).

Being older ($p < .01$) and possessing a higher knowledge in the field of energy ($p < .10$) had 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 leads to a preference for lower saving targets (see Loock et al., 2013, for the detrimental effect of setting inadequate goals). Negative outcome affect also increased the probability of being in this segment.

Being older ($p < .05$) and living in a household with a larger number of people ($p < .05$) significantly influenced the likelihood of belonging to 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 plants located in the region, was increased by home ownership ($p < .05$) and by high self-efficacy ($p < .10$). It should be noted that the small size of the segments, in particular the last two, make it difficult to obtain significant coefficients.

5. Discussion and conclusions

Electricity-saving programs are not widespread in Switzerland. Therefore, little is known about consumers' preferences or their likelihood of subscribing to such programs. 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 designed in the choice experiment.

However, results show that different segments of electricity consumers have heterogeneous preferences for the various characteristics of such programs. Therefore, no single design of an

[4] Note that income is not included in the explanatory variables. Even though this variable was collected in the survey, it is missing for a substantial share of the respondents (around 10%). To include income, a good number of respondents would have been lost or missing values would have to be imputed. The results obtained using both procedures show that income is not significant while other coefficients are virtually unaltered (results available upon request). The authors have therefore decided to exclude income from the analysis.

[5] Tables with the full results are available on request.

Table 3
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, loss aversion is determined 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). Robustness checks are nevertheless conducted by (1) dropping these respondents and (2) considering 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 the results.	Adapted from Gächter et al. (2007)
Energy literacy [z]	An energy literacy index is constructed by counting the number of correct answers to the following five questions: 1 The biggest share of energy consumed in a Swiss household is for heating purposes. (True) 2 CO_2 emissions play a crucial role in global warming. (True) 3 Simply lowering the heating temperature in an average household by 1 °C can help to cut down the heating demand by 6%. (True) 4 Coal is a renewable energy resource. (False) 5 Hydroelectric power plants account for 10% of total Swiss electricity production. (False)	
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 and Brosch (2018)
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 and Brosch (2018)
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 and Brosch (2018)
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 and Brosch (2018)
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 and Brosch (2018)
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 Thøgersen (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 Thøgersen (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, and energy literacy, measured on a 6-point scale from 0 to 5). 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).

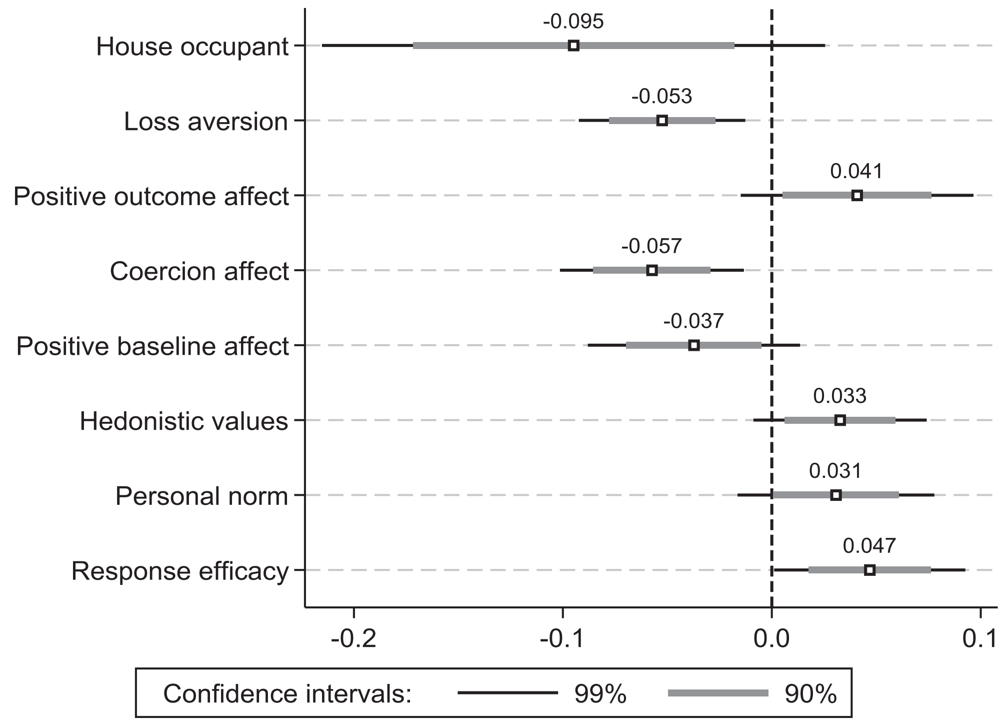

Fig. 4. Factors affecting the likelihood of subscription to electricity-saving tariffs (marginal effects obtained from a probit regression).
Note: Marginal effects obtained from a probit regression explaining likely subscriber (1) versus likely non-subscriber (0) status. Only the coefficients significant at least at the 10% level are displayed. Additional covariates are included. Complete regression results are reported in Appendix Table D. The variables are described in Table 3.

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 segments of the population are attracted by different features, which would limit the overall aggregate impact of one single specific measure. Discrepancies in preferences provide a strong argument for the introduction of different electricity-saving programs with various focal points. To reach the different consumer segments in the market effectively, a multitude of programs and marketing approaches would be required.

This research is also dedicated to ascertain drivers for subscription to an electricity-saving program by contrasting potential subscribers with likely non-subscribers 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.

Socio-demographic variables are not found to be 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, several significant differences between likely subscribers and non-subscribers are observed 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, the 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. More than a third of the energy bill payers were in favor of switching, but there was 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 or demographic factors. Moser et al. (2016) also studied whether unconventional non-monetary incentives induced consumers to change their energy-related behavior. Their findings indicate that people should be segmented based on psychological rather than socio-economic criteria.

These insights have significant implications for marketing strategies of electric utilities. For instance, 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 are more likely to subscribe. 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 for doing something laudable, have more money available due to lower electricity costs, and preserve the beautiful nature.

Moreover, adoption is found 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 comfort loss) need to be

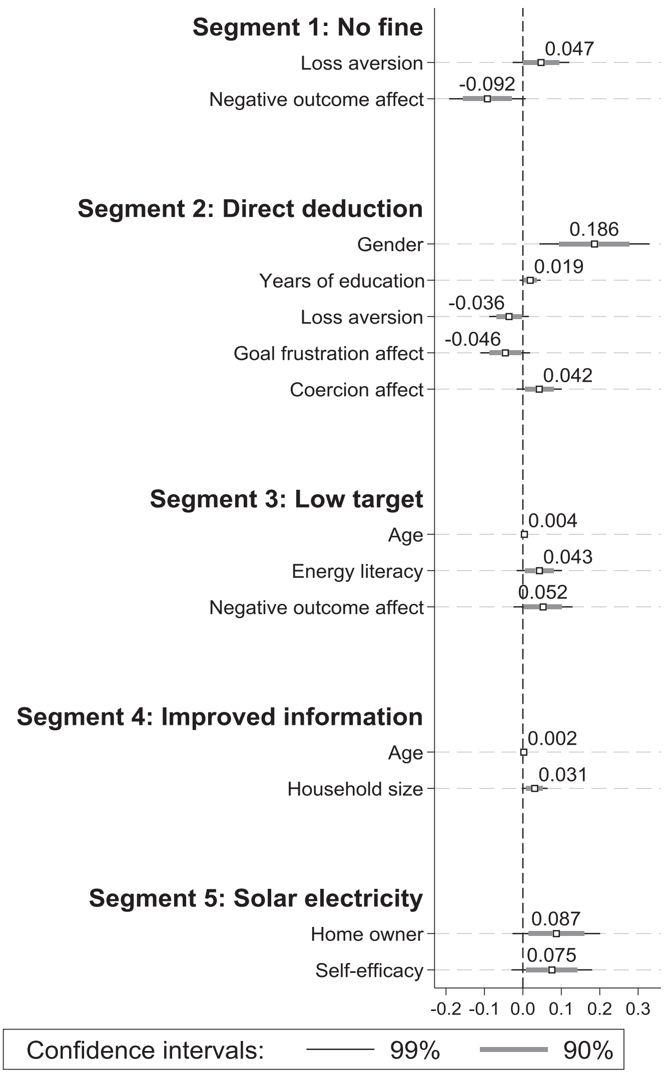

Fig. 5. Significant factors affecting the composition of segments (marginal effects obtained from a multinomial probit model).
Note: Marginal effects obtained from a multinomial probit regression explaining the segments' composition. Only the coefficients significant at least at the 10% level are displayed. Additional covariates are included. Complete regression results are reported in Appendix Table E. The variables are described in Table 3.

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 for new customers (see, e.g., Ebeling and Lotz, 2015).

Finally, the two cognitive variables personal norms and perceived response efficacy seem related to increased program subscription. Individuals who express an intent to subscribe to an electricity-saving program feel more personally obliged to behave in an environmentally friendly manner than likely non-subscribers, and also believe 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).

The results obtained in this study furthermore yield insights into the structure of the 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, older individuals tend to prefer 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 appear to be more inclined to opt for electricity-saving programs when they encompass 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 opt for an electricity-saving tariff have a 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., 2018; Mahmoodi et al., 2018) and is indeed considered an attractive tariff element by some consumers (such as Segment 5 in the current study), a financial penalty is perceived as repelling by most potential subscribers.

Interestingly, people scoring low on loss aversion prefer programs where reaching the savings target is associated with a direct deduction from 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 must be acknowledged. As in any other stated-preference survey, this research faces the potential risk of a gap between stated and actual preferences. Potential surveying biases were limited by indirectly eliciting people's preferences using a carefully designed choice experiment and by surveying real electricity consumers. Because each respondent was requested to make several choice tasks, it is moreover possible to detect and exclude those who responded inconsistently. Nevertheless, it must be acknowledged 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, 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 rather than at the end of the year) would lead to changes in preferences. It may also be worth assessing preferences for alternative non-monetary rewards, such as public praise (Handgraaf et al., 2013).

Finally, a legitimate question might arise regarding a possible conflict between electricity providers' role in promoting energy saving behavior and their traditional business models, given that utilities' revenue is typically a direct result of the amount of energy sold (Blumer et al., 2014). Indeed, no utility-centered energy efficiency policy frameworks exist in Switzerland in contrast to other European countries or several states in the U.S. (e.g., based on white certificate schemes coupled with saving obligations; see Bertoldi and Rezessy, 2008, or Bertoldi et al., 2010). Still, many utilities in Switzerland promote voluntarily services or products to encourage consumers to save energy (Blumer et al., 2014). One of the possible reasons for this pro-active approach is that most utilities are owned by public bodies, which have to align their business models with policy objectives. In fact, more than 80 percent of the Swiss electricity providers are owned by the public sector, in particular by cantons and municipalities (SFOE, 2017). In addition, the energy literature discusses alternative incentives for utilities to engage in energy-saving programs, including the possibility to be perceived as a “green” company which may in turn improve a utility's public image (Blumer et al., 2014; Cooremans, 2011). The literature also argues that promoting energy-saving behavior could cost less than building new power plants or could limit the requirement for an upgrade of the transmission and distribution network (Allcott and Rogers, 2014; Boogen et al., 2017).

Overall, the present 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. The 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, the findings may help electric utilities to more effectively tailor marketing and communication strategies to specific target groups.

Acknowledgements

This research is part of the activities of SCCER CREST (Swiss Competence Center for Energy Research), which is financially supported by the Swiss Commission for Technology and Innovation (CTI) under Grant No. KTI. 1155000154. The involvement of Stefanie Hille in this paper dates back from her research work at the University of St. Gallen before she joined the European Commission in Luxembourg in October 2017. The information set out in this paper are solely those of the authors and do not reflect the official opinion of the European Commission.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.02.142.

Appendix

Table A
HB estimation of part worth utilities for the five segments.

	Segment 1: “No fine”		Segment 2: “Direct deduction”		Segment 3: “Low target”		Segment 4: “Improved information”		Segment 5: “Solar electricity”	
	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)	1.5	(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)	−70.4	(36.9)	1.3	(34.4)	−17.2	(31.5)
Electricity-saving bonus										
50 CHF	−15.5	(12.6)	−38.8	(26.3)	−17.5	(34.3)	−27.4	(23.9)	−25.1	(36.4)
100 CHF	5.6	(7.5)	5.5	(12.5)	7.1	(14.5)	4.8	(13.1)	−5.6	(15.5)
150 CHF	9.9	(13.5)	33.3	(24.7)	10.4	(33.1)	22.6	(22.5)	30.7	(44.9)
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	(32.9)	−79.7	(36.9)	−5.7	(43.9)	−9.7	(34.5)	127.8	(71.3)
Fine if target is missed										
(−)	199.0	(47.5)	40.8	(43.6)	85.0	(38.9)	39.1	(42.2)	6.9	(45.3)
25 CHF	−77.7	(19.7)	0.1	(25.9)	−17.8	(27.5)	3.3	(25.5)	12.5	(23.3)
50 CHF	−121.4	(30.2)	−40.9	(26.9)	−67.3	(22.3)	−42.4	(31.3)	−19.4	(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)	0.7	(11.7)	4.5	(15.4)	−14.3	(22.2)	−0.2	(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)

Notes: Standard deviations in parentheses. Fig. 2 provides an illustration corresponding to this Table.

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”
	n = 136	n = 104	n = 72	n = 45	n = 44
Reduction target	9.6	12.1	29.9	13.3	12.5
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	19.3	15.1
Improved information	6.0	9.7	10.5	39.8	13.2
Total	100.0	100.0	100.0	100.0	100.0

Note: Fig. 3 provides an illustration corresponding to this Table.

Table C1
Descriptive statistics (means and standard deviations) comparing likely subscribers to likely non-subscribers.

	(1)	(2)	(3)
	Likely subscribers	Likely non-subscribers	Total
Gender	0.461	0.466	0.462
	(0.499)	(0.502)	(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, and energy literacy measured on a 6-point scale from 0 to 5). All these variables were transformed to z-scores before they were included in the estimations. The variables are described in Table 3.

Table C2
Descriptive statistics (means and standard deviations) comparing the five segments of likely subscribers.

	(1)	(2)	(3)	(4)	(5)
	No fine	Direct deduction	Low target	Improved information	Solar electricity
Gender	0.426	0.577	0.333	0.467	0.500
	(0.496)	(0.496)	(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, and energy literacy measured on a 6-point scale from 0 to 5). All these variables were transformed to z-scores before they were included in the estimations. The variables are described in Table 3.

Table D
Binary models and marginal effects for likely subscribers (1) vs likely non-subscribers (0)

	Logit		Probit	
	Coefficients	Marginal effects	Coefficients	Marginal effects
Gender	−0.009	−0.001	−0.015	−0.003
	(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	−0.023	−0.004
	(0.131)	(0.012)	(0.073)	(0.013)
House occupant	−0.770**	−0.082*	−0.450**	−0.095**
	(0.349)	(0.044)	(0.193)	(0.047)
Home owner	0.269	0.023	0.160	0.028
	(0.354)	(0.029)	(0.193)	(0.032)
Loss aversion ^{z}	−0.534***	−0.048***	−0.291***	−0.053***
	(0.168)	(0.015)	(0.087)	(0.015)
Energy literacy ^{z}	0.198	0.018	0.098	0.018
	(0.148)	(0.013)	(0.083)	(0.015)
Positive outcome affect ^{z}	0.377*	0.034*	0.226*	0.041*
	(0.213)	(0.019)	(0.120)	(0.022)
Negative outcome affect ^{z}	0.309	0.027	0.154	0.028
	(0.219)	(0.019)	(0.121)	(0.022)
Goal frustration affect ^{z}	0.113	0.010	0.070	0.013
	(0.201)	(0.018)	(0.110)	(0.020)
Coercion affect ^{z}	−0.562***	−0.050***	−0.318***	−0.057***
	(0.176)	(0.015)	(0.097)	(0.017)
Positive baseline affect ^{z}	−0.382*	−0.034*	−0.207*	−0.037*
	(0.200)	(0.018)	(0.109)	(0.020)
Altruistic values ^{z}	−0.258	−0.023	−0.125	−0.023
	(0.206)	(0.018)	(0.114)	(0.021)
Biospheric values ^{z}	−0.328	−0.029	−0.197	−0.035
	(0.235)	(0.021)	(0.130)	(0.023)
Egoistic values ^{z}	−0.073	−0.006	−0.041	−0.007
	(0.169)	(0.015)	(0.094)	(0.017)
Hedonistic values ^{z}	0.315*	0.028*	0.181**	0.033**
	(0.164)	(0.014)	(0.090)	(0.016)
Descriptive norm ^{z}	0.078	0.007	0.047	0.008
	(0.166)	(0.015)	(0.091)	(0.016)
Injunctive norm ^{z}	−0.052	−0.005	−0.051	−0.009
	(0.186)	(0.017)	(0.101)	(0.018)
Personal norm ^{z}	0.315*	0.028*	0.170*	0.031*
	(0.178)	(0.016)	(0.100)	(0.018)
Self-efficacy ^{z}	−0.261	−0.023	−0.143	−0.026
	(0.206)	(0.018)	(0.112)	(0.020)
Response efficacy ^{z}	0.471***	0.042***	0.260***	0.047***
	(0.178)	(0.016)	(0.098)	(0.018)
Constant	4.014***	–	2.306***	–
	(1.351)		(0.742)	
Pseudo-R^2	0.218		0.219	
Count R^2 (adjusted)	0.297		0.297	
Log-Likelihood	−159.197		−159.131	
AIC	364.393	.	364.262	.
BIC	460.101	.	459.970	.
# 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). The variables are described in Table 3. The coefficients significant at least at the 10% level are displayed in Fig. 4.

Table E
Marginal effects obtained in multinomial probit model for likely subscribers

	(1) No fine	(2) Direct deduction	(3) Low target	(4) Improved information	(5) Solar electricity
Gender	−0.065	0.186***	−0.048	0.004	−0.077
	(0.060)	(0.056)	(0.040)	(0.031)	(0.052)
Age	−0.000	−0.002	0.004***	0.002**	−0.003
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Years of education	−0.002	0.019*	0.008	−0.003	−0.022
	(0.015)	(0.011)	(0.010)	(0.007)	(0.014)
Household size	0.005	0.002	−0.018	0.031**	−0.019
	(0.026)	(0.018)	(0.020)	(0.013)	(0.026)
House occupant	−0.073	0.030	0.058	−0.002	−0.013
	(0.072)	(0.051)	(0.050)	(0.035)	(0.066)
Home owner	−0.000	−0.002	−0.051	−0.034	0.087**
	(0.064)	(0.047)	(0.053)	(0.037)	(0.044)
Loss aversion z	0.047*	−0.036*	−0.030	0.007	0.012
	(0.029)	(0.020)	(0.020)	(0.015)	(0.027)
Energy literacy z	−0.017	0.016	0.043*	−0.004	−0.037
	(0.030)	(0.021)	(0.023)	(0.015)	(0.029)
Positive outcome affect z	−0.000	0.019	−0.032	−0.000	0.013
	(0.041)	(0.030)	(0.030)	(0.021)	(0.041)
Negative outcome affect z	−0.092**	0.011	0.052*	0.005	0.024
	(0.039)	(0.028)	(0.030)	(0.020)	(0.037)
Goal frustration affect z	0.034	−0.046*	0.009	0.003	0.001
	(0.035)	(0.025)	(0.025)	(0.017)	(0.031)
Coercion affect z	−0.006	0.042*	0.012	−0.022	−0.028
	(0.032)	(0.023)	(0.023)	(0.018)	(0.030)
Positive baseline affect z	0.019	−0.037	−0.014	0.021	0.010
	(0.036)	(0.025)	(0.026)	(0.021)	(0.035)
Altruistic values z	0.003	−0.018	−0.036	−0.000	0.051
	(0.037)	(0.027)	(0.027)	(0.019)	(0.040)
Biospheric values z	−0.003	0.010	−0.020	−0.018	0.031
	(0.042)	(0.031)	(0.031)	(0.023)	(0.043)
Egoistic values z	−0.009	0.016	0.010	0.019	−0.036
	(0.030)	(0.021)	(0.021)	(0.016)	(0.028)
Hedonistic values z	0.042	−0.025	0.024	−0.012	−0.029
	(0.031)	(0.022)	(0.022)	(0.016)	(0.028)
Descriptive norm z	0.021	0.011	−0.020	−0.012	0.001
	(0.032)	(0.023)	(0.024)	(0.016)	(0.029)
Injunctive norm z	−0.002	0.017	−0.037	0.016	0.006
	(0.033)	(0.023)	(0.025)	(0.017)	(0.029)
Personal norm z	−0.015	0.011	0.027	0.025	−0.048
	(0.037)	(0.026)	(0.029)	(0.022)	(0.037)
Self-efficacy z	−0.024	−0.023	0.002	−0.030	0.075*
	(0.040)	(0.028)	(0.029)	(0.022)	(0.041)
Response efficacy z	−0.038	0.011	0.006	0.013	0.007
	(0.036)	(0.026)	(0.025)	(0.019)	(0.037)
Segment size	136	104	72	45	44

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). The variables are described in Table 3. The coefficients significant at least at the 10% level are displayed in Fig. 5.

References

Abrahamse, W., Steg, L., Vlek, C., Rothengatter, T., 2005. A review of intervention studies aimed at household energy conservation. J. Environ. Psychol. 25 (3), 273–291.

Abrahamse, W., Steg, L., Vlek, C., Rothengatter, T., 2007. The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents. J. Environ. Psychol. 27 (4), 265–276.

Allcott, H., 2011. Social norms and energy conservation. J. Publ. Econ. 95 (9), 1082–1095.

Allcott, H., Rogers, T., 2014. The short-run and long-run effects of behavioral interventions: experimental evidence from energy conservation. Am. Econ. Rev. 104, 3003–3037.

Becker, L.J., 1978. Joint effect of feedback and goal setting on performance: a field study of residential energy conservation. J. Appl. Psychol. 63 (4), 428–433.

Bernstein, M., Collins, M., 2014. Saving energy through better information: a new energy paradigm? Contemp. Econ. Policy 32 (1), 219–229.

Bertoldi, P., Rezessy, S., 2008. Tradable white certificate schemes: fundamental concepts. Energy Efficiency 1, 237–255.

Bertoldi, P., Rezessy, S., Lees, E., Baudry, P., Jeandel, A., Labanca, N., 2010. Energy supplier obligations and white certificate schemes: comparative analysis of experiences in the European Union. Energy Policy 38 (3), 1455–1469.

Bertoldi, P., Rezessy, S., Oikonomou, V., 2013. Rewarding energy savings rather than energy efficiency: exploring the concept of a feed-in tariff for energy savings. Energy Policy 56, 526–535.

Bertoldi, P., Serrenho, T., Zangheri, P., 2016. Consumer feedback systems: how much energy saving will they deliver and for how long? ACEEE Summer Study on Energy Efficiency in Buildings.

Bishop, A., Tse, H., Schruder, N., 2010. Toronto Hydro 2009 Summer Challenge Program Impact Evaluation Report. Ontario Power Authority.

Blumer, Y.B., Mühlebach, M., Moser, C., 2014. Why some electricity utilities actively promote energy efficiency while others do not – a Swiss case study. Energy efficiency 7, 697–710.

Boogen, N., Datta, S., Filippini, M., 2017. Demand-side management by electric utilities in Switzerland: analyzing its impact on residential electricity demand. Energy Econ. 64, 402–414.

Brazell, J.D., Diener, C.G., Karniouchina, E., Moore, W.L., Séverin, V., Uldry, P.-F., 2006. The no-choice option and dual response choice designs. Market. Lett. 17, 255–268.

Buchanan, K., Russo, R., Anderson, B., 2015. The question of energy reduction: the problem(s) with feedback. Energy Policy 77, 89–96.

Burger, P., Bezencon, V., Bornemann, B., Brosch, T., Carabias-Hütter, V., Farsi, M., et al., 2015. Advances in understanding energy consumption behavior and the governance of its change: outline of an integrated framework. Front. Energy

Res. 3, 1–19.
Cooremans, C., 2011. Make it strategic! Financial investment logic is not enough. Energy Efficiency 4, 473–492.
Costa, D.L., Kahn, M.E., 2013. Energy conservation "nudges" and environmentalist ideology: evidence from a randomized residential electricity field experiment. J. Eur. Econ. Assoc. 11 (3), 680–702.
Darby, S., 2006. The Effectiveness of Feedback on Energy Consumption: A Review for DEFRA of the Literature on Metering, Billing and Direct Displays. Oxford University, Environmental Change Institute, Oxford.
Deci, E.L., Koestner, R., Ryan, R.M., 1999. A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. Psychol. Bull. 25 (6), 627–668.
Delmas, M.A., Fischlein, M., Asensio, O.I., 2013. Information strategies and energy conservation behavior: a meta-analysis of experimental studies from 1975 to 2012. Energy Policy 61, 729–739.
DeSarbo, W.S., Ramaswamy, V., Cohen, S.H., 1995. Market segmentation with choice-based conjoint analysis. Market. Lett. 6 (2), 137–147.
Dolan, P., Metcalfe, R.D., 2015. Neighbors, Knowledge, and Nuggets: Two Natural Field Experiments on the Role of Incentives on Energy Conservation. Becker Friedman Institute for Research in Economics Working. Paper No. 2589269.
Doran, R., Larsen, S., 2016. The relative importance of social and personal norms in explaining intentions to choose eco-friendly travel options. Int. J. Tour. Res. 18 (2), 159–166.
Dwyer, W.O., Leeming, F.C., Cobern, M.K., Porter, B.E., Jackson, J.M., 1993. Critical review of behavioral interventions to preserve the environment: research since 1980. Environ. Behav. 25, 275–321.
Ebeling, F., Lotz, S., 2015. Domestic uptake of green energy promoted by opt-out tariffs. Nat. Clim. Change 5 (9), 868.
Energie Schweiz, 2015. Fakten zu Energie Nr. 5: energiestrategie 2050. http://www.bfe.admin.ch/php/modules/publikationen/stream.php?extlang=de&name=de_215949035.pdf.
EWB, 2015. Stromsparen lohnt sich jetzt doppelt. Energie Wasser Bern. http://www.ewb.ch/umwelt-schonen/stromsparbonus/spielregeln.html.
Ewing, G., Sarigöllü, E., 2000. Assessing consumer preferences for clean-fuel vehicles: a discrete choice experiment. J. Publ. Pol. Market. 19 (1), 106–118.
Gächter, S., Johnson, E.J., Hermann, A., 2007. Individual-level Loss Aversion in Riskless and Risky Choices. Inst. Study Labor Discuss. Paper 2961. Inst. Study Labor, Bonn, Germany.
Gächter, S., Orzen, H., Renner, E., Starmer, C., 2009. Are experimental economists prone to framing effects? A natural field experiment. J. Econ. Behav. Organ. 70 (3), 443–446.
Giné, X., Karlan, D., Zinman, J., 2010. Put your money where your butt is: a commitment contract for smoking cessation. Am. Econ. J. Appl. Econ. 2 (4), 213–235.
Gneezy, U., Rustichini, A., 2000. Pay enough or don't pay at all. Q. J. Econ. 115 (3), 791–810.
Greening, L.A., Greene, D.L., Difiglio, C., 2000. Energy efficiency and consumption – the rebound effect – a survey. Energy Policy 28 (6), 389–401.
Hahnel, U.J., Brosch, T., 2018. Environmental trait affect. J. Environ. Psychol. 59, 94–106.
Handgraaf, M.J., de Jeude, M.A.V.L., Appelt, K.C., 2013. Public praise vs. private pay: effects of rewards on energy conservation in the workplace. Ecol. Econ. 86, 86–92.
Harding, M., Hsiaw, A., 2014. Goal setting and energy conservation. J. Econ. Behav. Organ. 107, 209–227.
Hargreaves, T., Nye, M., Burgess, J., 2013. Keeping energy visible? Exploring how householders interact with feedback from smart energy monitors in the longer term. Energy Policy 52, 126–134.
Hediger, C., Farsi, M., Weber, S., 2018. Turn it up and open the window: on the rebound effects in residential heating. Ecol. Econ. 149, 21–39.
Hille, S.L., 2016. The myth of the unscrupulous energy user's dilemma: evidence from Switzerland. J. Consum. Pol. 39 (3), 327–347.
Kaenzig, J., Heinzle, S.L., Wüstenhagen, R., 2013. Whatever the customer wants, the customer gets? Exploring the gap between consumer preferences and default electricity products in Germany. Energy Policy 53, 311–322.
Kahneman, D., Knetsch, J.L., Thaler, R.H., 1991. Anomalies: the endowment effect, loss aversion, and status quo bias. J. Econ. Perspect. 5 (1), 193–206.
Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47 (2), 263–291.
Katzev, R.D., Johnson, T.R., 1984. Comparing the effects of monetary incentives and foot-in-the-door strategies in promoting residential electricity conservation. J. Appl. Soc. Psychol. 14 (1), 12–27.
Kim, S., Jeong, S.H., Hwang, Y., 2012. Predictors of pro-environmental behaviors of American and Korean students: the application of the theory of reasoned action and protection motivation theory. Sci. Commun. 35 (2), 168–188.
Lee, T.W., Locke, E.A., Latham, G.P., 1989. Goal setting theory and performance. In: Pervin, L.A. (Ed.), Goal Concepts in Personality and Social Psychology. Lawrence Erlbaum, Hillsdale, NJ, pp. 291–326.
Leuser, L., Duscha, M., Brischke, L.-A., 2014. Optionen zur Gestaltung von Rahmenbedingungen für Energiesuffizienz in Haushalten durch Kommunen am Beispiel der Stromsparprämie der Stadtwerke Heidelberg. https://energiesuffizienz.files.wordpress.com/2015/02/20150123-arbeitspapier-einsparbonus.pdf.
Locke, E.A., Latham, G.P., 2002. Building a practically useful theory of goal setting and task motivation: a 35-year odyssey. Am. Psychol. 57 (9), 705–717.
Locke, E.A., Latham, G.P., Erez, M., 1988. The determinants of goal commitment. Acad. Manag. Rev. 13 (1), 23–39.
Loock, C.-M., Staake, T., Thiesse, F., 2013. Motivating energy-efficient behavior with green IS: an investigation of goal setting and the role of defaults. MIS Q. 37 (4), 1313–1332.
Mahmoodi, J., Prasanna, A., Hille, S., Patel, M.K., Brosch, T., 2018. Combining "carrot and stick" to incentivize sustainability in households. Energy Policy 123, 31–40.
McCalley, L.T., Midden, C.J., 2002. Energy conservation through product-integrated feedback: the roles of goal-setting and social orientation. J. Econ. Psychol. 23 (5), 589–603.
Moser, C., Cometta, C., Frick, V., 2016. How do different residential consumer groups react to monetary and unconventional non-monetary incentives to reduce their electricity consumption? Swiss Federal Office of Energy SFOE. Final report 24 October 2016.
Nicolson, M., Huebner, G., Shipworth, D., 2017. Are consumers willing to switch to smart time of use electricity tariffs? The importance of loss-aversion and electric vehicle ownership. Energy Research & Social Science 23, 82–96.
Orme, B.K., 2010. Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research. Research Publishers, Madison, WI.
Porter, B.E., Leeming, F.C., Dwyer, W.O., 1995. Solid waste recovery: a review of behavioral programs to increase recycling. Environ. Behav. 27, 122–152.
Prasanna, A., Mahmoodi, J., Brosch, T., Patel, M.K., 2018. Recent experiences with tariffs for saving electricity in households. Energy Policy 115, 514–522.
Reeve, J., 2005. Understanding Motivation and Emotion. John Wiley & Sons, New York.
Ruzzenenti, F., Bertoldi, P., 2017. Energy conservation policies in the light of the energetics of evolution. In: Labanca, N. (Ed.), Complex Systems and Social Practices in Energy Transitions. Green Energy and Technology. Springer International Publishing, Cham.
Sawtooth Software, 2009. The CBC/HB system for hierarchical Bayes estimation version 5.0 technical paper. https://www.sawtoothsoftware.com/support/technical-papers/hierarchical-bayes-estimation/cbc-hb-technical-paper-2009.
Sawtooth Software, 2012. Latent class v4.5. https://www.sawtoothsoftware.com/download/techpap/lclass_manual.pdf.
Schleich, J., Klobasa, M., Gölz, S., Brunner, M., 2013. Effects of feedback on residential electricity demand – findings from a field trial in Austria. Energy Policy 61, 1097–1106.
Schultz, P.W., 2014. Strategies for promoting proenvironmental behavior: lots of tools but few instructions. Eur. Psychol. 19, 107–117.
Schwartz, S.H., 1977. Normative influences on altruism. J. Exp. Soc. Psychol. 10, 221–279.
SIG, 2018. Tarifs électricité. Services Industriels de Genève.
SFOE, 2017. Schweizerische Elektrizitätsstatistik 2016. Swiss Federal Office of Energy.
Slavin, R.E., Wodarski, J.S., Blackburn, B.L., 1981. A group contingency for electricity conservation in master-metered apartments. J. Appl. Behav. Anal. 14 (3), 357–363.
Stadt Frankfurt am Main, 2015. Frankfurt spart Strom – Förderprogramm für Haushalte. http://www.frankfurt.de/sixcms/detail.php?id=4576&_ffmpar%5B_id_inhalt%5D=7431319.
Steg, L., Dreijerink, L., Abrahamse, W., 2005. Factors influencing the acceptability of energy policies: a test of VBN theory. J. Environ. Psychol. 25 (4), 415–425.
Steg, L., Perlaviciute, G., Van der Werff, E., Lurvink, J., 2014. The significance of hedonic values for environmentally relevant attitudes, preferences, and actions. Environ. Behav. 46 (2), 163–192.
Tabi, A., Hille, S.L., Wüstenhagen, R., 2014. What makes people seal the green power deal? – customer segmentation based on choice experiment in Germany. Ecol. Econ. 107, 206–215.
Thøgersen, J., 2003. Monetary incentives and recycling: behavioural and psychological reactions to a performance-dependent garbage fee. J. Consum. Pol. 26 (2), 197–228.
Tiefenbeck, V., Staake, T., Roth, K., Sachs, O., 2013. For better or for worse? Empirical evidence of moral licensing in a behavioral energy conservation campaign. Energy Policy 57, 160–171.
Van Houwelingen, J.H., Van Raaij, W.F., 1989. The effect of goal-setting and daily electronic feedback on in-home energy use. J. Consum. Res. 16 (1), 98–105.
Wallenborn, G., Orsini, M., Vanhaverbeke, J., 2011. Household appropriation of electricity monitors. Int. J. Consum. Stud. 35 (2), 146–152.
Weber, S., Burger, P., Farsi, M., Martinez-Cruz, A.L., Puntiroli, M., Schubert, I., Volland, B., 2017a. Swiss Household Energy Demand Survey (SHEDS): Goals, Design, and Implementation. CREST Working Paper.
Weber, S., Farsi, M., 2014. Travel Distance and Fuel Efficiency: an Estimation of the Rebound Effect Using Micro-data in Switzerland. IRENE Working paper 14-03. University of Neuchâtel.
Weber, S., Puddu, S., Pacheco, D., 2017b. Move it! How an electric contest motivates households to shift their load profile. Energy Econ. 68, 255–270.
Wirtshafter Associates, 2006. Evaluation of the California statewide 20/20 demand reduction programs. http://www.calmac.org/publications/2005_20-20_evaluation_report.pdf.